Resource Misallocation and Productivity Gaps in Malaysia

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Abstract

The reallocation of resources from low- to high-productivity firms can generate large aggregate productivity gains. The paper uses data from the Malaysian manufacturing census to measure the country’s hypothetical productivity gains when moving toward the level of within-sector allocative efficiency in the United States to be between 13 and 36 percent. Across three census periods in 2000, 2005, and 2010 (the most recent available), the productivity gaps appear to have somewhat widened. This suggests that the “catching-up” process remains a challenge and a potential opportunity, particularly if total factor productivity is expected to be the dominant source of future economic growth. The simulations, based on different magnitudes of the realization of hypothetical productivity gains, show that Malaysia’s gross domestic product growth can potentially increase by 0.4 to 1.3 percentage points per year over five years. The analysis accounts only for resource misallocation within sectors. There may be other, possibly large, resource misallocation across sectors. If so, closing those gaps could boost total factor productivity and gross domestic product growth even further.
Resource Misallocation and Productivity Gaps in Malaysia

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1.0 Introduction

The economics literature amply documents the importance of total factor productivity (TFP) as a source of sustained economic growth. TFP differs greatly across countries. Dissecting the sources of TFP into various micro components reveals that these differences are also persistent across firms that operate within narrowly defined industries. What accounts for these productivity differences across countries or firms? One possible explanation is that frontier technologies and best practice methods are slow to diffuse to some countries. Recent literature argues that misallocation of resources, which is the focus of this paper, explains part of these productivity differences.

Previous studies have suggested that both slow technological diffusion and misallocation of resources are potentially relevant, but more conventional discussion about productivity centers on technology, which requires a different set of policy prescriptions. Policies geared toward increasing technological diffusion and innovation include measures that promote research and development (R&D) and the creation of new ideas. These policies are usually complemented with ones that incentivize learning, upgrading of skills, and investment in education. However, recent views focus on the benefits of reallocation of inputs from less to more productive firms as an important component of aggregate productivity growth. Policies associated with allocative efficiencies emphasize correcting or reducing market distortions.

The conceptual idea of allocation efficiency was translated into an empirical framework by Hsieh and Klenow (2009). In their framework, they argue that the overall TFP of an industry depends not only on the TFP of individual firms, but also on how resources are being allocated across firms. In an economy with low levels of distortion, productive firms will have access to more resources—namely, labor and capital—compared to less productive ones, and this leads to an increase in the overall productivity of the sector. Therefore, to achieve maximum allocation efficiency, two firms within a narrowly defined industry should be able to access resources up to the point where they attain the same marginal revenue product. Large dispersions in marginal revenue products among firms operating within a narrowly defined industry will imply misallocation of resources in the industry.

Many studies and anecdotal details showed how corruption, regulation, or direct government involvement distort the allocation of resources from their most efficient use, especially in lower-income economies. For example, it could be the case that the government subsidizes some firms, but not others. State-owned enterprises could also be enjoying preferential interest rates, while non-state-owned enterprises face market interest rates. While distortions explain the unequal access to resources, other factors are also at play. For example, the size of a firm can affect its bargaining power; thus, larger firms may be able to borrow at lower interest rates.

Therefore, measuring the extent of resource misallocation in an economy is important because it allows us to answer three key questions. First, how important is resource misallocation in causing the productivity gaps in the manufacturing sector and industries in the sector? Second, what are the main causes of misallocation of resources? Third, what is the cost of misallocation of resources to overall economic growth?

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1 See Cole et al. (2016); OECD (2015); Syverson (2011); and Restuccia and Rogerson (2008).
This paper attempts to measure allocation efficiency across firms operating in narrowly defined manufacturing industries in Malaysia, and the potential productivity gains that can be made by removing distortions that impede allocation efficiency. We find that distortions in both the output and capital markets lower the productivity of Malaysia’s manufacturing sector. If resources were being allocated "perfectly," such that all marginal revenue products across all firms in the narrowly defined industries were equalized, Malaysia’s manufacturing productivity would be higher by as much as 94% in 2010. If we benchmark Malaysia against the level of allocative efficiency in the United States in 1997, hypothetical productivity gains are estimated to be 36%.

This paper contributes to the literature in three ways. It is the first attempt to measure the extent of resource misallocation in Malaysia using firm-level census data. Previous studies of Malaysia have tended to focus on the traditional drivers of aggregate productivity, as well as the role of capital accumulation in growth and development. From a firm-level approach, we find that Malaysia’s productivity loss of 94% is comparable to that of China, an upper middle-income country, but lower than that of India, which is perceived to experience larger market distortions. We also extend the analysis to investigate the misallocation of resources within 2-digit industry groupings. We find misallocation to be rather significant in the food and beverage industry, but less apparent in the export-oriented industries, such as textiles, wood and wood products, and the machinery, electrical, and electronics industries.

Second, the availability of the three periods of census data allows us to examine trends in resource misallocation. We find that the allocative efficiency gap between the United States, the benchmark economy, and Malaysia worsened during these census periods. This suggests that the catching up process, particularly with respect to the United States, remains a challenge. Decomposing the sources of misallocation, we find that distortions in the output market appear to have a stronger effect on productivity compared to distortions in the capital or labor markets.

Third, we simulate three possible growth paths based on the magnitude of the realization of productivity gains. A realization of a 10% gain resulting from moderate reforms can lift growth by 0.4 percentage points over five years. More aggressive and purposeful market reforms can increase the realization of productivity gains and further lift growth. This is an important source of growth for Malaysia because we expect TFP to be the single most important contributor of future growth. Higher productivity growth is essential to accommodate the impact of demographic changes, to boost competitiveness, and to enable Malaysia to escape the middle-income trap that is afflicting many emerging economies.

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2 The focus is on the manufacturing sector because we have access only to data on manufacturing firms in Malaysia. This does not mean that resource misallocation does not exist in other sectors such as services, construction, or agriculture.

3 See Sarel (1997); Ahmed (2009); and Anand et al. (2014).

4 See Hsieh and Klenow (2009).

5 The estimation of productivity gaps for industries is based on the 2-digit Standard Industrial Classification (SIC) of industries, while productivity gaps for the overall manufacturing sector is based on the 3-digit Malaysia Standard Industrial Classification (MISC) codes. Both are harmonized to ensure consistency. A 2-digit level classification of industries will define industries less narrowly compared to a 3-digit level classification. For example, the 2-digit level classification "36" represents firms in the electronics, computers, and electrical equipment industry. The 3-digit representation will breakdown the electronics industry into electronic components, computers and peripherals, consumer electronics, and so on.
Two caveats are in order. First, our analysis accounts only for resource misallocation within sectors. There may be other, possibly large, resource misallocation across sectors. If so, closing those gaps could boost TFP and GDP growth even further. Second, as will be clear later, because of the lack of quantity data on both outputs and inputs, the Hsieh and Klenow framework makes assumptions regarding demand, such as constant elasticity of substitution (CES) aggregation and equalized markup across firms in the same sector. Because of these assumptions, what we attribute to misallocation in this paper could be partly caused by different markups, which in turn could be driven by differential quality and/or demand for the firms’ products. To the extent that there is no substantial variation in quality or demand for firms’ products within the same narrow industry, the Hsieh and Klenow approach provides a good approximation of resource misallocation. In subsequent papers, we will try to disentangle improvements in physical productivity with other quality and demand factors, thanks to newly obtained data on outputs and material inputs for Malaysian manufacturing firms.

This paper is organized as follows. Section 2.0 provides an overview of the Malaysian economy, particularly the manufacturing sector. Section 3.0 reviews literature on the role of misallocation as a source of productivity differences across firms. Section 4.0 discusses Hsieh and Klenow’s (2009) estimation framework, and describes the profile of firms in the three census periods and the data treatment for the estimation procedure. Section 5.0 discusses the findings. Section 6.0 concludes by discussing a few broad policy options.

2.0. Background

The manufacturing sector is one of Malaysia’s engines of growth, registering an average growth of 7.8% and contributing approximately 1.5 percentage points (ppts) to overall GDP growth during 1988–2016. This is higher than the average growth in gross domestic product (GDP) of 6.1%. Development of the manufacturing sector first focused on import substitution. Then, from the mid-1980s, increasing openness to foreign investment drove export-led growth. The shift was made as the government saw the importance of technology embodied in FDIs as a way to develop and shape the country’s industrial base. In this regard, the Promotion of Investment Act (PIA) 1986 was instrumental in attracting foreign direct investment (FDI) through a spectrum of tax incentives, particularly in areas of services, manufacturing and agriculture. Consequently, the manufacturing sector’s share of GDP increased steadily from 16.5% in 1988 to 21.2% in 1995, peaking at 26% in 2006. The growth of the manufacturing sector facilitated the diversification of Malaysia’s economic base by reducing the economy’s dependence on the agriculture and mining sectors. The share of manufactured exports to total gross exports increased from 22% in 1973 to 82% in 2016.

The growth in the manufacturing sector was disrupted by three major events: the Asian Financial Crisis (AFC) in 1997–98; the burst of the U.S. technology bubble in 2001–02; and the global financial crisis (GFC) of 2007-08 (figure 1). During each of these downturns, the manufacturing sector registered a sharper decline compared to the overall economic growth.

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6 See, for example, Restuccia, Yang, and Zhu (2008); McMillan and Rodrik (2011).
7 Tax incentives such as the Pioneer Status and Investment Tax Allowance were aimed at promoting the export sector. At the same time, the government had also undertaken measures to liberalize the equity requirements for foreign investment to support the objectives outlined in PIA 1986.
Figure 1: Malaysia’s Real GDP and Manufacturing Sector Growth, 1988–2016

![Graph showing Malaysia’s Real GDP and Manufacturing Sector Growth from 1988 to 2016.](image)

Source: Haver Analytics.

Note: AFC = Asian Financial Crisis; GFC = global financial crisis.

The expansion of the manufacturing sector has created employment opportunities in the economy. It has become the second largest source of employment after the services sector (57%), accounting for 19% of total employment, on average, between 2000 and 2016. More importantly, it overtook the agriculture sector as the second largest source of employment in 1992, reflecting the transformation of Malaysia’s economic structure (figure 2).

**Figure 2: Share of Employment in Major Sectors of the Malaysia Economy, 1982–2016**

![Graph showing the share of employment in major sectors of the Malaysia economy from 1982 to 2016.](image)

Source: Department of Statistics Malaysia.

The Third Industrial Masterplan (IMP3) 1996–2020 highlights the importance of ensuring that Malaysia’s manufacturing sector remains competitive on the global market. While Malaysia has coped well with the progressive trade liberalization and opening of markets, the country is facing increasing competition from emerging markets such as China, India, Central European economies, and Latin America.
A key challenge highlighted by IMP3 and other national plans is the need to raise the productivity of the manufacturing sector. In particular, the IMP3 outlines several recommendations, including upgrading of knowledge and skills of the workforce, adopting and absorbing new technologies, fostering innovation, and benchmarking to best management practices. It also emphasizes developing technological capabilities and enhancing innovation through research and development (R&D). However, a strategy of promoting innovation and greater absorption of technology must be complemented by other policies. This paper highlights the importance of ensuring well-functioning product, labor, and credit markets. It also notes the need to institute policies that foster greater domestic competition so that resources can be allocated efficiently and unproductive firms or sectors do not overutilize the available resources in the economy.

3.0 Literature Review

As granular data become more readily available, micro data are increasingly being used to ascertain why some firms are more productive than others, and more recently, why productivity differences persist even in narrowly defined industries. Specifically, many studies examine whether resource misallocation is a significant channel in explaining productivity differences across firms or countries.

3.1 The Direct Measure of Misallocation

Studies that assess the implications of misallocation on productivity can be divided into two categories: those that adopt the direct approach, and others that adopt the indirect approach. Studies using the direct approach attempt to obtain a direct measure of factors or specific regulations that cause misallocation of inputs. These studies build a case for the importance of misallocation by assessing the implications of these regulations on sectors of the economy.

For example, Hopenhayn and Rogerson (1993) show that firing taxes distort the allocation of labor across firms, which results in TFP loss of about 2% and output loss of 5%. Lagos (2006) also studies the implications of labor market regulation such as unemployment insurance and employment protection on the allocative efficiency of resources. Lileeva and Trefler (2010) study the impact of reductions on trade tariffs on firm productivity in Canada. Along the same lines, Epifani and Gancia (2011) argue that trade barriers influence the degree of competition and hence affect markups. These varying markups are sources of distortions and misallocation of resources. Eslava et al. (2013) focus on whether large changes of tariffs in Colombia are associated with misallocation of resources.

Other studies attempt to link credit market imperfections with misallocation. Banerjee and Duflo (2005) provide evidence that suggests that misallocation of capital arising from credit constraints and institutional failures is an important source of productivity differences across countries. Other related studies such as Erosa (2001), Buera, Kaboski, and Shin (2011), and Midrigan and Xu (2010) have all produced estimates of the effects of varying measures of

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8 The Second National Science Technology Policy (2002-2010) and many of the Malaysia Plans beginning in the mid-1980s also discuss the importance of R&D initiatives in driving growth and competitiveness.

9 Hopenhayn and Rogerson (1993) use the general equilibrium model of Hopenhayn (1992), where the parameters in the model are calibrated based on the US manufacturing firm level dataset.

10 See Boyd and Prescott (1986); Jeong and Townsend (2007); and Cole, Greenwood, and Sanchez (2016).
credit market imperfections on TFP. The results from these studies show a wide range of effects on the importance of credit market imperfections in explaining TFP. Udry (2012) reviews the microeconomic evidence of the role of credit constraints in explaining the large productivity gaps between the high-income and low-income countries. He argues that while evidence suggests that credit constraints have some influence on manufacturing productivity in developing countries, the role of credit is not significant in explaining the low productivity in the agriculture sector in low-income countries. Adamopoulos and Restuccia (2014) suggest that other distortionary factors cause the low productivity in agriculture, including inheritance rules, progressive taxes, agricultural subsidies, land reform, and tenancy restrictions.

An advantage of the direct approach is that it directly links the extent of misallocation (the loss in productivity) with the sources of the misallocation, such as regulations, taxation, the cost of doing business, or preferential market access. However, in practice, sources of misallocation are not easy to identify. For example, lax enforcement of regulations—which is an important source of misallocation—is difficult to quantify objectively. Therefore, it may be challenging to adopt the direct approach if the nature of the regulation is highly specialized across specific industries. Furthermore, there is the question of whether findings related to the narrowly identified distortions, such as specific tax regulations, can be generalized for other sectors and economies.

While the direct approach allows us to directly link the extent to which specific distortionary regulations, institutional factors, and market imperfections affect TFP through misallocation of resources, the challenge remains in obtaining a broad quantifiable measure for resource misallocation.

### 3.2 The Indirect Measure of Misallocation

Recognizing the possibility that sources of misallocation are difficult to measure or very specialized and diffused, the indirect approach seeks to identify the extent of misallocation without identifying the underlying source of misallocation. Often it is not easy to isolate and disentangle a single factor that causes the misallocation of resources. Rather, there could be a combination of interrelated factors, which are difficult to separate.

Thus, studies adopting the indirect approach intuitively assume that any factors that generate a wedge in the profit maximization function of firms are distortions that eventually result in productivity loss. These studies focus on the wedges as a representation of distortions in the market, rather than specific sources causing the distortions.

While the indirect approach is intuitively powerful, it requires some structure in the measurement of misallocation. There are two main limitations to this approach. First, the wedges might not reflect distortions but misspecification of the production functions. Second, given that the wedges are estimated using actual data, they may also implicitly reflect measurement errors in the data.

Restuccia and Rogerson (2008) examine the conditions that could exacerbate the impact of distortions on aggregate TFP. They report two key findings. First, randomly taxing and subsidizing some firms shift inputs among these firms, leading to lower TFP. Second, when high-productivity firms are systematically taxed and low-productivity firms are systematically
subsidized, the adverse effects on overall aggregate TFP could be several times larger. The main take-away is that misallocation can have larger effects on productivity if high-productivity producers face systematic constraints.

Restuccia and Rogerson (2008) choose firm-specific taxes and subsidies to represent the many different types of distortions. While both were seen to have significant impact on aggregate TFP, they are hypothetical simulations. They do not use data to estimate the nature and size of misallocation that exists in actual economies. However, two subsequent papers, Hsieh and Klenow (2009) and Bartelsman, Haltiwanger, and Scarpetta (2013), address these limitations.

Hsieh and Klenow (2009) show that distortions can be measured quantitatively from firm data. Their estimation framework assumes that each producer behaves as a monopolistic competitor when choosing capital and labor and each produces a variety of products. The demand structure implied by the constant elasticity of substitution (CES) aggregator is important in allowing them to infer TFP when the dataset only contains information on total revenue and not physical output.

Hsieh and Klenow (2009) find large effects of misallocation on TFP. If the distortions that cause the misallocation are eliminated, TFP in the manufacturing sector will increase by 86–115% in China; 100–128% in India; and 30–43% in the United States. However, Hsieh and Klenow (2009) measure misallocation without identifying the specific sources of misallocation. Instead, they broadly classify the sources of distortions as capital market–and output market–related distortions. The essence of their findings is that resource misallocation affects productive firms’ access to sufficient resources (in terms of capital and labor) needed for expansion, resulting in lower aggregate productivity. Therefore, reallocation of resources through the elimination of distortions in the markets enhances productivity because this allows productive firms to grow and the less productive ones to either shrink in size or exit the sector.

The Hsieh and Klenow (2009) estimation approach has been widely applied by many studies, such as Busso, Madrigal, and Pagés (2013) for Latin American countries; Nguyen, Taskin, and Yılmaz (2016) for Turkey; and Cirera, Fattal Jaef, and Maemir (2017) for African countries. Specifically, Nguyen, Taskin, and Yılmaz (2016) estimate TFP gains of 78% in 2014 if resources were allocated efficiently across firms in the Turkish manufacturing sector. They identify the textile, transport, food, and leather sectors to suffer the most from distortions.

Although many studies have provided evidence on the effects of misallocation on TFP, there are still questions about the relative size of distortions within or across industries, and whether these misallocations reflect business cycles as well as distortions. The degree of misallocation could be affected by measurement errors and wedges or distortions could reflect adjustment costs and other misspecification errors. Hsieh and Klenow are aware of these issues. Hence, their estimate is meant to be a “baseline” that serves as a common start point for comparison. Therefore, in their study, they benchmark their estimates to the level of misallocation found in the United States.

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11 See Bils, Klenow and Ruane (2017).


4.0 Methodology and Data

4.1 Hsieh and Klenow (2009) Framework

This section provides a simplified discussion of Hsieh and Klenow’s (2009) estimation framework. Consider an economy with many sectors, denoted \( s \). Final output \( Y \) is produced in each country using a Cobb-Douglas production technology:

\[
Y = \Pi_{s=1}^{S} Y_{s}^{\theta_{s}} \tag{1}
\]

where \( \theta_{s} \) is the value added share of sector \( s \) and \( \Sigma_{s=1}^{S} \theta_{s} = 1 \).

Each sector's output \( Y_{s} \) is the aggregate of the individual firms’ output \( Y_{si} \), using the CES technology:

\[
Y_{s} = \left[ \Sigma_{i=1}^{M_{s}} Y_{si}^{\sigma} \right]^{\sigma-1}, \tag{2}
\]

where \( Y_{si} \) is the differentiated product by firm \( i \) in sector \( s \) and \( \sigma \) is the elasticity of substitution across firms within the sectors.

Each firm produces a differentiated product with the standard Cobb-Douglas production function:

\[
Y_{si} = A_{si} L_{si}^{1-\alpha_{s}} K_{si}^{\alpha_{s}} \tag{3}
\]

where \( A_{si} \) stands for firm-specific productivity; \( L_{si} \) is the firm’s labor; \( K_{si} \) is the firm’s capital; and \( \alpha_{s} \) is the industry-specific capital share. Note that the assumption in this framework is that firms in the same narrowly defined sector—that is, the 3-digit Malaysia Standard Industrial Classification (MSC)—have the same production function.

Each establishment maximizes current profits:

\[
\pi_{si} = (1 - \tau_{ys}) P_{si} Y_{si} - w_{si} L_{si} - (1 + \tau_{Ksi}) R K_{si}, \tag{4}
\]

where \( P_{si} Y_{si} \) is the firm's value added (which is the firm's revenue minus the cost of intermediate inputs); and \( w_{si} \) and \( R \) are the cost of one unit of labor and capital, respectively. The term \( \tau_{ys} \) denotes firm-specific output distortions that reduce firms' revenues. Many factors could contribute to output distortions, ranging from transportation costs to discriminatory tax regimes to subsidies. These factors could reduce output for a given set of inputs. The firm-specific "capital" distortions, which raise the cost of capital (relative to labor), are denoted as \( \tau_{Ksi} \). Credit market imperfections such as preferential access to finance and labor market frictions could contribute to different "capital" distortions \( \tau_{Ksi} \) across firms. Therefore, an increase in usage of capital is indicative of relative distortions in the labor markets.

Hsieh and Klenow (2009) differentiate the two productivity measures: TFPQ, which captures “physical productivity”; and TFPR, which captures “revenue productivity”:

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12 For details of the framework, see Hsieh and Klenow (2009).
13 We follow Hsieh and Klenow’s notation, where sector refers to industries within the manufacturing sector. However, readers should not be confused when, in the later part of this paper, we conform to the terminology of industries used by the Department of Statistics Malaysia, which refers to “sector” as the overall manufacturing sector.
\[
T_{FPQ_{si}} = \frac{Y_{si}}{L_{si}^{1-\alpha_s}K_{si}^{\alpha_s}}. \quad (5)
\]
\[
T_{FPR_{si}} = \frac{P_{si}Y_{si}}{L_{si}^{1-\alpha_s}K_{si}^{\alpha_s}}. \quad (6)
\]

In an absence of distortions, TFPR should not vary across firms within each sector. In other words, in the absence of distortions, more capital and labor should be allocated to firms with higher physical productivity (TFPQ) to the point where their higher output results in a lower price, \(P_{si}\), which also results in the \(T_{FPR_{si}}\) equalizing across firms \(i\). Any dispersions of TFPR across firms within a sector imply distortions. A firm with TFPR higher than the sector average suffers from the effects of distortions. On the contrary, it is common for TFPQ to vary across firms because different firms may have different productivity levels.

From the revenue data, we can also derive \(T_{FPQ_{si}}\) as:
\[
T_{FPQ_{si}} = A_{si} = \kappa \left( \frac{P_{si}Y_{si}}{K_{si}^{\alpha_s}(\omega L_{si})^{1-\alpha_s}} \right)^{\frac{\sigma}{\sigma-1}}. \quad (7)
\]

Equation (7) shows that TFPQ is calculated from \(P_{si}\), which contains elements of distortions, and \(\kappa\) is normalized to 1.\(^{14}\)
\[
P_{si} = \frac{\sigma}{\sigma-1} \frac{(1+\tau_{ksi})^{\alpha_s}}{A_{si}(1-\tau_{ysi})} \left( \frac{R}{\alpha_s} \right)^{\alpha_s} \left( \frac{\omega}{1-\alpha_s} \right)^{1-\alpha_s}. \quad (8)
\]

Hsieh and Klenow (2009) choose the elasticity of substitution, \(\sigma=3,^{15}\) and R=10, assuming a real interest rate of 5% and a depreciation rate of 5%. Capital share, \(\alpha_s\), and labor share, \((1-\alpha_s)\), are taken from the United States manufacturing sectors, where firms are assumed to operate in an environment of minimal distortions. Therefore, the shares of capital and labor of firms in the United States represent an efficient utilization of resources. Any deviations of the U.S. capital-labor shares suggest distortions.

Distortions represented by the output and capital wedges can be measured as follows:
\[
1-\tau_{ysi} = \frac{\sigma}{\sigma-1} \frac{w_{si}L_{si}}{(1-\alpha_s)P_{si}Y_{si}}. \quad (9)
\]
\[
1+\tau_{Ksi} = \frac{\alpha_s}{1-\alpha_s} \frac{w_{si}L_{si}}{R K_{si}}. \quad (10)
\]

Firm \(i\)'s wage bill is represented by \(w_{si}L_{si}\), and \(P_{si}Y_{si}\) represents the firm's value added. Both values are taken from the census data. Rewriting equation (10) to equation (11) shows that the relative utilization of factors will be affected by distortions in the capital market and \(\frac{1-\alpha_s}{\alpha_s}\), the labor-capital ratio in the less distorted (United States) environment.
\[
(1+\tau_{Ksi}) \frac{1-\alpha_s}{\alpha_s} = \frac{w_{si}L_{si}}{R K_{si}}. \quad (11)
\]

\(^{14}\) See Hsieh and Klenow (2009) for a detailed explanation.

\(^{15}\) Elasticity of substitution between products is related to the markups \(\frac{\alpha_s}{\alpha_s-1} = 1 + \mu_s\), where \(\mu_s\) is the markup. An elasticity substitution of 3 corresponds to a markup of 50%.
If firm $i$’s actual labor-capital ratio $\frac{w_{si}}{RK_{si}}$ is higher than the less distorted labor-capital ratio, this implies that firm $i$ may be facing difficulties in accessing capital (relative to hiring labor), and thus that firm $i$ uses less than the optimal level of capital. In other words, firm $i$ has a positive capital wedge $\tau_{ksi}$.

Hsieh and Klenow (2009) show that without distortions, $TFPR_{si}$ is proportional to the product of the marginal revenue product of labor and capital:

$$TFPR_{si} \propto (MRPK_{si})^{\alpha_s} (MRPL_{si})^{1-\alpha_s}, \quad (12)$$

where $MRPK_{si}$ is the marginal revenue product of capital for firm $i$ in sector $s$ and $MRPL_{si}$ is the marginal revenue product of labor for firm $i$ in sector $s$.

Rewriting equation (12):

$$TFPR_{si} = \frac{\sigma}{\sigma-1} \left( \frac{R}{a_s} \right)^{\alpha_s} \left( \frac{\omega}{1-\alpha_s} \right)^{1-\alpha_s} \frac{(1+\tau_{ksi})^{\alpha_s}}{1-\tau_{ysi}}, \quad (13)$$

Equation (13) implies that in the absence of distortions (that is, $\tau_{ksi}=0$ and $\tau_{ysi}=0$), $TFPR$ will be the same for all firms “$i$” within a sector “$s$.” Using this equation, we can deduce that a firm with higher $\tau_{ksi}$ and/or higher $\tau_{ysi}$ also has a higher $TFPR$.

The industry level $\overline{TFPR}_s$ is:

$$\overline{TFPR}_s = \left( \frac{\sigma}{\sigma-1} \right)^{\alpha_s} \left( \frac{R}{1+K_s} \frac{P_{sl} Y_{sl}}{P_{ys} Y_{ys}} \right)^{\alpha_s} \frac{w}{1-\alpha_s} \left( \frac{\sum_{i=1}^{M_s} (1-\tau_{ysi})^{\alpha_s}}{\tau_{ysi}} \right)^{1-\alpha_s}, \quad (14)$$

When there are no distortions (that is, $\tau_{ksi}=0$ and $\tau_{ysi}=0$) for all $i$, the right-hand side of equation (14) equals the right-hand side of equation (13), which also means that $TFPR$s are equalized for all $i$.

Rewriting equation (14):

$$lnTFP_s = \frac{1}{\sigma-1} \ln(\sum_{s=1}^{M_s} TFQP_{si}^{\sigma-1}) - \frac{\sigma}{2} var(lnTFPR_{si}), \quad (15)$$

where $M$ is the number of $s$ sectors, and distortions in allocation show up in the $var$ (variance) of revenue productivity $TFPR$ across firms, while $TFPQ$ is determined by technology.

The estimation of firm $i$’s productivity or $TFPQ_{si}$ exploits the market structure based on the CES aggregator. It takes the form:

$$A_{si} = \frac{(P_{si} Y_{si})^{\sigma}}{L_{si}^{1-\alpha_s K_{si} \alpha_s}}. \quad (16)$$

The efficient industry's productivity level (when all marginal products are equalized) is:

$$\overline{A}_s = \left( \sum_{i=1}^{M_s} A_{si}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}. \quad (17)$$

From equations (13), (14), (16), and (17), we can calculate the ratio of the actual TFP in the economy to the efficient level of TFP as:
\[
\frac{Y}{Y_{eff}} = \prod_{s=1}^{S} \left[ \sum_{i=1}^{M_s} \left( \frac{A_{si}}{A_s \mathcal{TFPR}_{st}} \right) \sigma^{-1} \right]^{\frac{\theta_s}{\sigma}}.
\] (18)

4.2 Data Description

A. Profile of Firms

For this study, we use firm-level data obtained from Malaysia’s manufacturing sector census in 2000, 2005, and 2010.\(^{16}\) The data encompass individual firms belonging to 59 industries classified according to the 3-digit Malaysia Standard Industrial Classification (MSIC) 2000. To standardize the classification of firms by industries across the three census periods, the census data in 2010, which are based on MSIC 2008 codes, are converted into MSIC 2000.

The firms in the census frame report data on gross output, percentages of export sales, material expenditures, energy expenditures, salaries, employees’ benefits, number of employees, investments, book values, and ownership structure.

When examining the three periods of the census data, we noticed that there were significant shifts in the distribution of firms. In particular, there was a sharp increase in the number of small firms entering the second and third periods of the census. In our analysis, firm size is defined by the number of employees, where small firms are defined as ones that have 1–19 workers, medium-sized firms have 20–99 workers, and big firms have more than 99 workers.

The distribution of log of employees over the three census periods shows that it has become increasingly skewed toward small firms (skewness in 2000, 12.9; in 2005, 16.9; in 2010, 26.1). Figure 4 shows the number of small firms increased by a compound annual growth rate (CAGR) of 11% during the 10-year period.

Figure 3: Distributions of Log of Employment in the Three Census Periods

Figure 4: Firms Classified by Size Entering the Three Census Periods

Source: Department of Statistics Malaysia (DOSM)

\(^{16}\) The Department of Statistics Malaysia (DOSM) conducts a census on the manufacturing sector every five years.
The significant shifts in the distribution of firms have compelled us to truncate the census data to minimize measurement bias. We conducted several simulations to arrive at an “optimal” threshold according to which the distributions of firms across the three periods are similar. As we varied the threshold between 5 employees and 20 employees, we found the “optimal” threshold to be 10 employees (figures 5 and 6). The truncation implies a loss of about 2.4% of total value-added and 3% of total employment during the 3 census periods. Setting a threshold may be the “second-best” option because there is a trade-off between eliminating the bias from unexplained shifts in firm size distributions and losing information from small firms.

**Figure 5:** Distributions of Log of Employment at the Threshold of > 10 Employees

**Figure 6:** Firms Covered in the Census at the Threshold of > 10 Employees

**Figure 7:** Percent of Firms by Industry, 2000 and 2010

| Year | F&B | Textile | Wood | M&E&C | Transport equip | Others |
|------|-----|---------|------|-------|----------------|--------|
| 2000 | 1.3 | 23.3    | 6.4  | 10.4  | 17.8           | 20.7   |
| 2010 | 1.9 | 17.0    | 4.7  | 10.2  | 17.4           | 44.3   |

Source: Department of Statistics Malaysia (DOSM).

Note: F&B includes the food and beverage industries. Textile includes the textile, apparel and leather related industries. Wood includes the wood, paper products, and furniture industries. Petchem includes refined petroleum, basic chemical, other allied chemical products, rubber and plastic industries. Metal includes non-metallic mineral, basic metal and fabricated metal industries. M&E&C includes machinery and equipment, electrical, electronics and computer, and measuring equipment industries. Transport equip include motor vehicles, bodies for motor vehicles; trailers and semi-trailers and parts and accessories for motor vehicles industries. Others include jewelry, musical instruments, sporting goods, medical and dental instruments, other industries not elsewhere classified.

Based on our meeting with the Department of Statistics Malaysia (DOSM), the shifts were due to two reasons: an increased coverage of small and medium enterprises (SMEs) in 2003; and a change in the filtering process of identifying active firms during the 2010 census.
The setting of the threshold does not change the composition of firms by industry (figure 7). The textile, apparel and footwear industry still has the largest number of firms, increasing its share of total number of firms from 21% in 2000 to 44% in 2010. The second largest industry is the food and beverage (F&B) industry, which accounts for 17–18% of total number of firms in both 2000 and 2010.

In value added terms, the textile, apparel and leather industry accounted for only 2% of total value added in 2010, and the F&B industry, 13%. Both are smaller compared to the petroleum and chemical products industry (35%) and the machinery, electrical, electronics and computers (M&E&C) industry (27%) (table 1). Table 1 also shows that the relative shares of value added for the respective industries do not change significantly after “normalizing” the distribution of firms in the three census periods. This implies that the smaller firms that were truncated are possibly low–value added firms and therefore the overall value added across the three periods remained almost unchanged.

**Table 1: Firms Represented in the Census Data, by Numbers and Value Added, 2010**

| Industry | Number of firms belonging to the industries in the 2010 Census | Number of firms after setting the threshold of >10 employees in 2010 | Value-added of industries represented in the 2010 Census | Value-added of industries after setting the threshold of >10 employees in 2010 |
|----------|---------------------------------------------------------------|---------------------------------------------------------------|--------------------------------------------------|--------------------------------------------------|
| F&B      | 18.3                                                          | 17.4                                                          | 13.2                                             | 13.2                                             |
| Textile  | 30.9                                                          | 44.3                                                          | 2.2                                              | 2.1                                              |
| Wood     | 7.5                                                           | 4.7                                                           | 5.3                                              | 5.3                                              |
| Petrochemical | 9.9                                                        | 4.4                                                           | 34.5                                             | 34.6                                             |
| Metal    | 19.1                                                          | 17.0                                                          | 14.4                                             | 14.3                                             |
| M&E&C    | 4.9                                                           | 1.9                                                           | 27.3                                             | 26.8                                             |
| Transport| 0.2                                                           | 0.1                                                           | 0.8                                              | 0.8                                              |
| Others   | 9.3                                                           | 10.2                                                          | 3.1                                              | 2.9                                              |

Source: Department of Statistics Malaysia (DOSM).
Note: F&B includes the food and beverage industries. Textile includes the textile, apparel and leather related industries. Wood includes the wood, paper products and furniture industries. Petchem includes refined petroleum, basic chemicals and other allied chemical products industries. Metal includes non-metallic mineral, basic metal and fabricated metal industries. M&E&C includes machinery, and equipment, electrical, electronics and computer industries. Transport equip include motor vehicles, bodies for motor vehicles; trailers and semi-trailers and parts and accessories for motor vehicles industries. Others include jewelry, musical instruments, sporting goods, medical and dental instruments, other industries not elsewhere classified.

Authors’ calculations based on the census data, where value added=gross output minus gross inputs. The value added of industries in 2000 and 2005 remained almost the same as in 2010, with the Petrochemical, Metal, and M&E&C industries remaining the top three industries.
Figure 8: Percent of Firms by Age, 2000 and 2010

a. 2000

b. 2010

Source: Department of Statistics Malaysia (DOSM).

Note: Firms that reported an inconsistent age over the three census waves are excluded from the age analysis. About 9.5% of firms are removed from this analysis.

Likewise, the truncation does not imply that the age distribution of firms shifts towards older firms (figure 8, panels a and b). In the truncated sample, the percentage of firms younger than 5 years increased from 21.6% to 29.1%, and that for firms between 6 and 15 years of age decreased from 43.9% to 38.4%. This pattern is quite similar in the truncated sample, as can be observed in figure 8.

Figure 9: Share of Firms that Are Locally, Foreign, and Jointly Owned, 2000 and 2010 (percent)

Source: Department of Statistics Malaysia (DOSM).

A large proportion of firms (86–90%) in all the three censuses are locally owned (figure 9). The truncation of data does not change the ownership profile of firms, where locally owned firms still represent the majority.

B. Treatment of Data

(i) Construction of the Capital Stock

We analyze the patterns of investment across the three census periods to derive a reasonable measure for the growth rate of investment, \( g \). Our analysis focuses on investment made by
surviving and new firms. In doing so, we attempt to understand the dynamics of investment to derive a reasonable growth rate that can be applied in the construction of capital stocks for the manufacturing sector.

Surviving firms accounted for 65% of total flows of investment in 2010, while new firms accounted for the remaining 35%. Young firms that entered the census frame accounted for about 40% of total investment of new firms in 2010, while the remaining 60% is comprised of firms that entered through the expanded coverage of active firms in the census (figure 10, panel a). From the profile of surviving firms, old firms contributed 63% of gross investment flows. Investments of new and surviving firms increased by an average rate of 11% and 3.6%, respectively, during 2005–10. However, overall investments of firms grew at a rate close to zero during 2000–10, thereby providing guidance for our assumption, $g$. In other words, the average investment growth rate within a firm, $g$, is found to be constant across the three census periods.

However, the main limitation in deriving $g$ from these census periods is that it effectively excludes investments by firms during the noncensus periods. This could potentially contribute to mismeasurement of the “actual” $g$ because the overall investment rate in the manufacturing sector is much larger than the $g$ that we derived from the census data (2005, 3.2%; 2010, 18.4%).

**Figure 10:** Investment of New and Surviving Firms

| Year | New Firms | Surviving Firms |
|------|-----------|-----------------|
| 2005 | 25.7%     | 49.5%           |
| 2010 | 44.8%     | 63.1%           |

Source:
Note: Young firms are ≤6 years in operations; middle-aged firms are 6–15 years in operations; old firms are ≥16 years in operations. Ave I are average investments of young, middle-aged, and old firms respectively for every census period.

Based on our analysis, the average investments of surviving firms were between two and four times higher than that of new firms during the 2005 and 2010 census periods. This provides support for our hypothesis that a large proportion of the book values reported by firms in the census may be “undervalued” because surviving firms that were middle-aged and old were the main capital accumulators. Net investments, measured as gross investments after accounting for depreciation and disposals, were slightly positive for census years 2000 and 2010 but negative for census year 2005 (figure 11).
**Figure 11:** Investments, Depreciation, Disposals, and Net Investments in the Three Periods

![Bar chart showing Investments, Depreciation, Disposals, and Net Investments in the Three Periods]

Source: Department of Statistics Malaysia (DOSM)

Note: Investments take into account all firms in the three census periods, including ones that have reported an inconsistent year of starting operations. Total I = total investment during a particular census period; dep = depreciation of assets during the particular census period; disp = assets disposed during a particular census period; net I = total investment – depreciation of assets – disposed assets.

Therefore, initial investment $I_o$ is:

$$I_o = \frac{\bar{I}}{\bar{p}_{y_t}} \cdot p_{y_t}, \quad (19)$$

where $\bar{I}$ is the average investment of firm $i$ during the three census years; and $\bar{p}_{y_t}$ is the average value-add of firm $i$ at the initial year.

Initial capital stock $K_0$ is calculated as:

$$K_0 = \frac{I_o}{(d + g)}, \quad (20)$$

where $d$ is the depreciation rate, which is assumed to be at 5%. The growth rate of investment, $g$ is calculated to be zero: that is, within the firm, the investment rate is constant across the census periods.

The initial capital stock $K_0$ will be at the period in which a non-zero investment value is first observed for a firm, and the capital stock for the other periods will either be iterated forward or backward. Specifically, the capital stock iterated forward is constructed by depreciating the capital stock in the previous period and adding the flows of extrapolated average investments:

$$K_{t+5} = K_{t+4}(1 - \delta) + I_{t+5} \quad . \quad (21)$$

Equation (20) is iterated forward through repeated substitution of $K_{t+5}$ in equation (21):

$$K_{t+5} = K_0(1 - \delta)^5 + \bar{I}(1 + g)(1 - \delta)^4 + \cdots \quad (22)$$

Capital stock observed in the later census period is iterated backward:

$$K_{t-5} = \frac{K_0}{(1 - \delta)^5} - \frac{\bar{I}(1+g)}{1-\delta} - \frac{\bar{I}(1+g)^2}{(1-\delta)^2} - \cdots \quad (23)$$

The advantage of building the capital stock using this approach is that it allows us to use the investment values that may better reflect the current market values. However, we also consider
Hsieh and Klenow’s (2009) method in using the average book values to construct the capital stock. The limitations of using this approach are discussed in appendix A.

While constructing the capital stock from investment flows is viewed to be more representative of current values, there are three main complications arising from this approach. First, the censuses are five years apart; thus, we do not observe investments outside the census periods. We observe that many firms drop out from the estimation because of zero investment during the three census periods. Second, the prices of capital stock for each industry are not available to adjust the values to the base year 2010. Third, the depreciation rate of 5% may not be representative of all industries. For example, technologically advanced industries may depreciate their capital at a faster rate. In addition, the adjustment of capital stock for depreciation accounts for normal wear and tear of the capital stock and has limited implications for productive capacity. The implication for production is different if a firm decides to retire, depreciate, or dispose of capital with the intention of adopting new or advanced technologies.

(ii) Trimming of Data

The data cleaning process is similar to that used by Nguyen, Taskin, and Yilmaz (2016). First, firms with zero capital stock, investment, and compensation are removed from the census because we assume that firms cannot operate without any capital or labor. Second, industries that are represented by fewer or equal to 20 firms are also removed. Thirdly, to “normalize” the distribution of firms, only firms above the 10-employee threshold are included in the estimation framework. Finally, 1% tails of $\log \left( \frac{TFPR_{si}}{TFPR_s} \right)$, $\log \left( \frac{A_{si}}{A_s} \right)$, and capital-to-value added ratios across industries were trimmed when calculating the productivity gains derived from the hypothetical elimination of distortions. After the data cleaning and trimming process, the original dataset, which consists of 78,845 observations, was trimmed to 24,621 observations. The main trimming occurred at the normalization of the distribution of firms stage, where more than half of the observations (43,292) dropped out from the estimation framework.

5.0 Findings

5.1 Measuring Allocative Distortions

Table 2 shows the manufacturing sector’s hypothetical TFP gains derived from a reduction of misallocations either through a complete elimination of distortions or a partial elimination to that of levels experienced by the United States, the benchmark economy in this study.

The larger the hypothetical gain (table 2), the further the manufacturing sector is from the allocative efficiency frontier, which implies the more severe the resource misallocation is across firms within the sector of a country. Gain 1, which is the hypothetical efficiency gain derived from a complete elimination of distortions, is estimated to be between 60% and 95%. Had resources been allocated “perfectly” across firms, the hypothetical productivity gain is calculated to be an average of 79% for the three census periods. The estimated productivity gains across the three periods show that the productivity gaps not only persisted but allocative efficiency across firms in the manufacturing sector appears to have worsened over time.
The lack of visible improvements in allocative efficiencies could be potentially due to the
disruptions to economic growth during the global financial crisis (GFC).\textsuperscript{18} However, further
investigation is needed to identify the distortions and channels through which they have
operated. The other limitation is related to measurement issues.\textsuperscript{19} These arise from the
inaccurate measurement of the market value of physically capital stock, as well as the estimated
growth rate of investments. The five-year gap between each census period could result in the
underestimation of investments. Failure to account for the change in prices that reflect
differences in product quality could also contribute to the mismeasurement of TFP gains.

Following Hsieh and Klenow (2009), we measure how much TFP in the manufacturing sector
could increase had capital and labor been reallocated to equalize marginal products across firms
within each 3-digit industry to the level experienced by the United States, in 1997.\textsuperscript{20} The United
States is used as the benchmark economy. More importantly, should measurement errors exist,
benchmarking the results would help mitigate some of the bias arising from such errors. In
other words, if results in the United States and Malaysia are exposed to the same degree of
bias, the benchmarking approach will cancel out the errors. The results show that had
Malaysia’s resource misallocation problem matched the relatively smaller level of the United
States in 1997, Malaysia’s manufacturing TFP could hypothetically have increased by 36\% in
2010.

While the size of the TFP gain gives a sense of the magnitude of distortions in the economy,
oberving the trends of these gains across time is equally important. The trends suggest that the
productivity gaps appear to have worsened over the 10-year period, implying that Malaysia
faces difficulties in “catching-up” with the more advanced countries.

\begin{table}[h]
\centering
\begin{tabular}{|c|c|c|c|c|c|c|c|c|}
\hline
Year & No. of obs. & TFPQ & TFPR & Wedge & P.H. & P.H.
\hline
 & SD & 75–25 & 90–10 & SD & 75–25 & 90–10 & Capital
 & SD & Output
 & Gain 1 & Gain 2 & SD
\hline
2000 & 7,698 & 1.0537 & 1.5096 & 2.7399 & 0.7564 & 0.9414 & 1.8666 & 1.6637 & 0.5713 & 61.22 & 12.82
\hline
2005 & 9,511 & 1.0738 & 1.4774 & 2.7769 & 0.7813 & 0.9685 & 1.9440 & 1.6427 & 0.5681 & 80.81 & 26.53
\hline
2010 & 7,412 & 1.1385 & 1.5394 & 2.9679 & 0.7843 & 1.0017 & 1.9591 & 1.6220 & 0.6002 & 93.95 & 35.72
\hline
\end{tabular}
\caption{TFP Dispersions and Gains in 2000, 2005, and 2010}
\end{table}

Source: Authors’ calculations.
Note: Potential Hypothetical (P.H.) Gain 1 is measured as TFP gains derived from a complete elimination of distortions in the
economy. Potential Hypothetical (P.H.) Gain 2 is measured as TFP gains derived from a removal of distortions to that of the
level of the United States in 1997. TFPQ, TFPR, Wedge, and Gains 1 and 2 are estimated based on census data for firms that
exceed the threshold of 10 employees. No. of obs. = number of observations; P. H. = potential hypothetical; TFPQ = physical
productivity; TFPR = revenue productivity; SD = standard deviation.

\textsuperscript{18} Benkovskis (2015) observes growing misallocation of resources before and during the global financial crisis (2007–08) and
improvement in the allocation of resources afterward. The improvement in allocation of resources made a positive contribution
to economic growth in 2011–13.

\textsuperscript{19} The issue arising from mismeasurement and suggestions to address the problem are discussed in Bils, Klenow, and Ruane
(2017).

\textsuperscript{20} We follow Hsieh and Klenow (2009) in choosing the United States as the benchmark economy because it is assumed to be
an economy that had the least distortions and the year 1997 was when the United States registered the largest productivity
gains.
Because misallocation is potentially related to distortions arising from the limited competition in the domestic economy, we juxtapose the results with Malaysia’s global competitiveness ranking in areas related to domestic competition. The World Economic Forum’s countries ranking for goods market efficiency and intensity of competition in local markets provide some anecdotal evidence of the business conditions in which firms operate (WEF 2009 and 2010). The modest improvement in the intensity of local competition in 2010 (to a ranking of 38, from a ranking of 42 in 2009) is negated by the deterioration of the efficiency of the goods market (from 20 in 2009 to 27 in 2010). Anecdotal evidence suggests that the subsequent recovery from the economic downturn in 2009 was not induced by any discernable improvements in resource allocation efficiencies.

A comparison among the upper-middle-income countries shows that Malaysia has similar levels of resource misallocation as China (figure 12, panel a). The upper-middle income countries are estimated to have higher allocation efficiencies than India, where TFP gains are estimated to be around 128%. This means that Turkey, China, and Malaysia are closer to the frontier of resource allocation efficiency than India. In the case of China, Hsieh and Klenow (2009) find evidence of a more rapid reallocation as less efficient state-owned enterprises are being weeded out of the economy, while the reallocation process appears to be slower in India.

**Figure 12: TFP Gains**

a. Obtained from An Efficient Allocation of Resources

b. Moving to the Level of Efficiency of the United States in 1997

Source: Authors’ calculations; Ciera, Fattal Jaf, and Maemir (2017); Nguyen, Taskin, and Yilmaz; and Hsieh and Klenow (2009).

Note: CHN = China; IND = ; KEN = Kenya; MYS = Malaysia; TUR = Turkey; US = United States.

### 5.2 Productivity Dispersion

Figure 13, panel a, shows the distributions of log TFPQ, \( \log \left( \frac{A_{gi}}{A_g} \right) \) for 2000, 2005, and 2010. TFPQ represents the physical productivity of firms. The panel shows that distributions have a longer left tail, and over time, the dispersions appear to widen. The standard deviations (SD)

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21 Note that the comparisons of TFP gains are made across different time periods. China’s gains are estimated for 2005, while India’s are estimated for 1994. See Hsieh and Klenow (2009) for explanations on the differences in TFP gains for China and India.
for TFPQ increased from 1.05 in 2000 to 1.07 in 2005 and 1.14 in 2010. The widening dispersions suggest that less efficient firms continue to operate instead of exiting the industry. The Kolmogorov-Smirnov (ksmirnov) test for equality of distribution functions shows that the log TFPQ distributions across the three censuses are significantly different.\textsuperscript{22}

Our focus is on TFPR, the revenue productivity, since the dispersions in TFPR are indicative of resource misallocation. It is important to reiterate that in this framework, in the absence of distortions, TFPR should equalize across firms in narrowly defined industries. Firms with higher TFPQ should have access to more capital and labor. Hence, these firms should have a higher output, and therefore charge a lower price. As such, they will register a TFPR similar to the smaller and less productive firms that would have compensated for their low TFPQ by charging higher prices. Panel b shows that the left tail of the log TFPR, $\log \left( \frac{\text{TFPR}_{si}}{\text{TFPR}_{s}} \right)$, distributions are also getting wider, suggesting that an increasing number of unproductive firms are compensating for their lower productivity through higher prices.

**Figure 13:** TFPQ and TFPR Dispersions in Three Census Periods

| a. TFPQ dispersions | b. TFPR dispersions |
|---------------------|---------------------|
| ![TFPQ distribution](image1) | ![TFPR distribution](image2) |

Source: Authors’ own calculation

Note: TFPQ = physical productivity; TFPR = revenue productivity.

The standard deviation of TFPQ for Malaysia (2010, 1.14) is almost similar to that of Turkey (1.11 in 2014,) (figure 14). However, it is higher than that of the United States (0.84 in 1997) and China (0.95 in 2005), but lower than that of India (1.23 in 1994). The estimated productivity gap among firms shows that firms in the 75\textsuperscript{th} percentile are 4.7 times more productive than firms in the 25\textsuperscript{th} percentile. The productivity gap increases to 19.5 times between firms in the 90\textsuperscript{th} and 10\textsuperscript{th} percentile. The productivity gap for Malaysian manufacturing firms in the 75\textsuperscript{th} and 25\textsuperscript{th} percentile is similar to Turkey’s, but lies between China’s (3.6 times) and India’s (5.0 times).

\textsuperscript{22} The two-sample Kolmogorov-Smirnov test for equality of distribution functions shows that log TFPQ distributions in 2000 and 2005, 2005 and 2010, and 2000 and 2010 reject the null hypothesis of the two sample distributions being equal, at a p-value of 0.0000.
Malaysia’s TFPR dispersion (0.78), as measured by the standard deviation (SD), is higher than Turkey’s (0.76 in 2014), China’s (0.63 in 2005), and India’s (0.67 in 1994) (figure 14). The difference between TFPR of 25th percentile and 75th percentile firms in Malaysia is estimated to be 2.7 times, compared to 2.6 times for Turkey, 2.3 times for China, and 2.2 times for India.

The size of TFPR dispersions not only suggest an inefficient allocation of resources across firms but are also indicative of the magnitude of productivity gains. Countries that show higher dispersions should reap higher hypothetical productivity gains when distortionary elements are reduced or removed from their markets. Our estimates show Malaysia’s TFPR dispersions to be higher than China’s and India’s, yet the hypothetical productivity gains are estimated to be lower than India’s but close to China’s. One possible explanation for such inconsistencies is the differences in the economic structure of these countries. The TFP gains are a weighted sum of each industry’s specific gains. Misallocation of resources in an industry that is insignificant and accounts for a smaller weight in the overall manufacturing sector will result in smaller hypothetical productivity gains. In contrast, the hypothetical productivity gain will be larger if misallocation occurs in an important industry that carries a larger weight in the sector.

**Figure 14:** Dispersions of TFPR and TFPQ in Selected Countries

![Graph showing dispersions of TFPR and TFPQ in Selected Countries]

Source: Authors’ calculations; Nguyen, Taskin, and Yilmaz (2016); Hsieh and Klenow (2009).
Note: Number of firms: Malaysia (7,412); Turkey (22,148); China (211,304); India (41,006).

Restuccia and Rogerson (2008) argue that productivity losses due to misallocation would be even more significant if distortions are correlated positively with firms’ productivity. Figure 15 shows a positive relationship between log TFPR and log TFPQ, suggesting that productive firms appear to face larger idiosyncratic distortions. This shows that productive firms are “taxed” at a higher rate, and therefore could have expanded their production had they acquired more resources for their production. The constraints face by productive firms will ultimately worsen the overall productivity of the economy.
**Figure 15:** The Relationship between Productivity (log TFPQ) and Distortions (log TFPR)

At higher productivity levels, the capital wedge is also higher, suggesting a systematic link between the capital wedge and productivity (figure 16). The positive correlation of 0.1951, which is significant at the 99% level, supports the conjecture that productive firms appear to face higher capital distortions compared to less productive ones.

The log output wedge has a positive and significant correlation with physical productivity (correlation =0.5224, p-value=0.001), suggesting that the more productive firms also appear to face higher output distortions (figure 17). Examples of output distortions include preferential market access or preferential income tax incentives given to certain firms. Such market distortions will result in productive firms producing below their optimal level, while allowing unproductive ones to continue operating and consuming resources. This could also happen if the unproductive firms are subsidized.

**Figure 16:** Physical Productivity and Capital Wedge

**Figure 17:** Physical Productivity and Output Wedge

Source: Authors’ calculations.
5.3 Measuring Allocative Distortions in Selected Industries

The results presented so far are for the manufacturing sector weighted by the industry value added shares. While the broader picture provides an overview of the extent of the misallocation of resources, it might mask subtle but important differences between industries. An industry-level analysis will provide a sharper focus on the extent of misallocation in each industry and would be more informative for policy prescriptions.

In terms of productivity gains by industry, the petroleum and chemical products industry and the food and beverage industry are estimated to gain the most if distortions are removed and resources are allocated more efficiently to the more productive firms. The lowest productivity gains are estimated for the textile and apparel industries (figure 18). The export-oriented industries, such as the textile, wood products, and electrical and electronics industries, appear to be more efficient in the allocation of resources. Their efficiencies could be induced by the need to compete, interact with, and respond to global forces and trends. While average productivity gains for the transport equipment industry appear to be low, the estimated gains are derived from a small sample of 499 firms in the three census periods. In comparison, other industries are represented by at least three times the number of firms.

The F&B (food and beverage) industry, which produces mainly for the domestic market, appears to be the worst in terms of allocative efficiency, with an estimated average productivity gain of 196%. The large estimated productivity gain could also be partially attributed to the large varieties of output in the food manufacturing industry, which is made up of 8 sub-industries, ranging from firms in the processing and preserving of meat to producing dairy products and grain mill products. However, the large hypothetical productivity gains may also reflect the large subsidies received by the food industry. Basic food items such as rice, sugar, flour, and cooking oil are highly subsidized by the government. Government expenditure on various subsidies, including food, increased by a compound annual growth rate of 17% from 2000 to 2010 and accounted for an average share of 11% of the federal government’s total expenditure between 2006 and 2010. Subsidies, which artificially depress prices, can distort not only prices but consumption and production decisions, resulting in misallocation of resources. Therefore, subsidy reforms started in 2010 as the government gradually reduced the subsidies for some key commodities such as sugar, cooking oil, and flour, and replaced them with targeted cash transfers for poor households. The subsidy rationalization program was part of the broader agenda to remove distortions in the economy, improve competitiveness and market efficiency, and ensure a more optimal usage of resources in the economy.

The petrochemical industry, which is mainly an export-oriented industry, appears to have performed badly compared to the other export-oriented industries. Its performance could be influenced by the volatile prices of its inputs, which could in turn have implications for the efficiency of the allocation of resources. Furthermore, production decisions could also be

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23 For simplicity, our industry estimates are based on the 2-digit Standard Industrial Classification Code (SIC), which includes beverages in the estimation. The less narrowly defined industry classifications may result in larger TFPR differences.

24 The rationalization of subsidies for fuel and sugar resulted in an estimated savings of RM750 million in 2010 (IMF Article IV Consultation 2010, 2015, and 2016).
distorted by the subsidies provided for retail fuel prices, which were eliminated in 2014 and replaced by a targeted cash transfer program.\textsuperscript{25}

The average standard deviation (SD) of the output wedge for the F&B (0.98), metal (0.86), and petrochemical (0.82) industries are higher than the average for the manufacturing sector (0.58) (table 3). This shows that the allocation of resources in these industries is more affected by the distortions in the output market compared to other industries. As for distortions in the capital market, the SD in capital wedge for the textile industry (1.90) is higher than the manufacturing sector average (1.64). Identifying the distortionary factors would be useful for policy, but requires further investigation. At this point, anecdotal evidence associates price subsidies with distortions in the output market and misallocation of resources, particularly in the F&B industry.

**Figure 18:** Average Productivity Gains for Selected Industries in Malaysia during the Census 2000, 2005, and 2010

| Industry   | Average TFP gains |
|------------|-------------------|
| F&B        | 250               |
| M&E&C      | 200               |
| Textile    | 150               |
| Petchem    | 100               |
| Wood       | 50                |
| Metal      | 20                |
| Manufacturing | 5         |
| Transport  | 0                 |

Source: Authors’ calculations.

Note: F&B includes the food and beverage industries. Textile includes the textile and apparel industries. Wood includes the wood, paper products and furniture industries. Petchem includes refined petroleum, basic chemicals, and other allied chemical products industries. Metal includes non-metallic mineral, basic metal, and fabricated metal industries. M&E&C includes machinery, equipment, electronics, and electrical industries.

*The productivity gains estimated for the transport industry is derived from 499 firms, while the other industries are represented by more than 1500 firms in the three census periods.*

\textsuperscript{25} The blanket fuel subsidies mainly benefited the 20% richest households, which received 42% of the subsidies, while the bottom 20% of the households received only 4% of the fuel subsidies in 2009 (Bank Negara Annual Report 2014).
Table 3: Capital and Output Wedges, by Industry

| Industries  | Capital wedge (SD) | Output wedge (SD) |
|------------|--------------------|-------------------|
|            | 2000               | 2005              | 2010              | 2000               | 2005              | 2010              |
| F&B        | 1.8047             | 1.7409            | 1.7122            | 1.0335             | 0.9270            | 0.9885            |
| Textile    | 2.0199             | 1.9072            | 1.7702            | 0.8802             | 0.7103            | 0.6719            |
| Wood       | 1.8587             | 1.7357            | 1.6652            | 0.7642             | 0.6344            | 0.6117            |
| Petchem    | 1.5496             | 1.5263            | 1.4786            | 0.7837             | 0.8311            | 0.8421            |
| Metal      | 1.9438             | 1.7983            | 1.7493            | 0.9733             | 0.8169            | 0.7952            |
| M&E&C      | 1.8374             | 1.7878            | 1.8456            | 0.8266             | 0.7981            | 0.8076            |
| Transport  | 1.6753             | 1.7523            | 1.7061            | 0.8350             | 0.7967            | 0.7682            |
| Manufacturing | 1.6637          | 1.6427            | 1.6220            | 0.5713             | 0.5681            | 0.6002            |

Source: Authors’ calculations.
Note: F&B includes the food and beverage industries. Textile includes the textile and apparel industries. Wood includes the wood, paper products, and furniture industries. Petchem includes refined petroleum, basic chemicals, and other allied chemical products industries. Metal includes non-metallic mineral, basic metal, and fabricated metal industries. M&E&C includes machinery, and equipment, electronics, and electrical industries. Transport industry includes motor vehicles, parts and accessories, ships and boats, railway locomotives, air and space machinery, and military fighting vehicles. SD = standard deviation.

5.4 Hypothetical Productivity Gains from Better Allocation of Resources and Implications on Malaysia’s Growth Prospects

Section 5.1 presented the estimates of hypothetical gains obtained by moving to the level of allocative efficiency in the United States in 1997. These hypothetical productivity gains of 13% to 36% estimated for the manufacturing sector could potentially translate into higher TFP growth, and ultimately higher gross domestic product (GDP) growth for the country. To assess the impact of the efficiency gains on GDP growth, we simulate three possible growth paths (under moderate reforms, more purposeful reforms, and aggressive reforms), based on the magnitude of the realization of productivity gains (table 4).
### Table 4: Scenarios and Assumptions

| Scenarios | Realization of hypothetical productivity gains (%) | Assumptions |
|-----------|-----------------------------------------------|-------------|
| Scenario 1 (S1)  (moderate reforms) | 10% | • The baseline growth projections for 2011–16 are obtained from the Eleventh Malaysia Plan (11MP). While the projections may have already included some assumptions about raising domestic competitiveness, we assumed that further improvements in allocative efficiency come from an increased effort and purposeful implementation of structural reforms. We also assume a quicker removal of non-performance–based incentives. We also simulated growth scenarios using a more realistic GDP baseline. |
| Scenario 2 (S2)  (more purposeful reforms) | 20% | • Capital and labor contributions to GDP growth remain the same as in the baseline. |
| Scenario 3 (S3)  (aggressive reforms) | 30% | • Productivity gains from better allocation of resources mainly flow through the productivity channel, and have limited implications on capital and labor. |
| | | • The share of the manufacturing sector to the overall economy remains at 23.4%, like its share in 2010. |

The first scenario assumes a realization of 10% productivity gains, which requires moderate reforms, particularly removing non-performance–based incentives (Eleventh Malaysia Plan, 2016–2020). The 10% realization of productivity gains is assumed to occur in five years, equivalent to an average productivity gain of 1.9% per year, a rate that is close to the U.S. pace of productivity gains between 1997 and 1987. The second and the third scenarios assume an additional 10% linear increase each, amounting to 20% for scenario 2 and 30% for scenario 3. The optimistic scenario of a 30% realization of productivity gains is close to China’s 4.7ppt CAGR during the 2001–05 period.

For the three scenarios, we also consider two baseline GDP growth trajectories. The first baseline adopts the official growth projections published in the Eleventh Malaysia Plan, 2016–2020 (11MP), which projects economic growth to increase an average of 5.8% during the 2016–20 period. The choice of this baseline raises concerns on two fronts. First, the growth forecast appears to be slightly optimistic. Second, the baseline in the 11MP already implicitly assumes some improvements in domestic competitiveness.

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26 Hsieh and Klenow (2009) estimate TFP gains from equalizing TFPR within industries in the United States to be 36.1% in 1977 and 30.7% in 1987. The decrease in the percentage of TFP gains represents a compounded average growth rate (CAGR) of 1.6ppt improvement in allocative efficiency during the 10-year period.

27 Hsieh and Klenow (2009) estimate China’s hypothetical TFP gains when moving toward the United States level of efficiency in 1997 to improve from 37% in 2001 to 30.5% in 2005.
On the first concern, we note that the average GDP growth registered during 2016–17 is 4.9%. To reach the target of 5.8% forecast in the five-year plan, the economy must grow at the rate of 6.3% for the remaining years, a growth rate that Malaysia achieved in the 1980s and 1990s. We take cognizance of the limitations in using the official forecast as our baseline, but we contend that our simulations focus on deviations, and less so on the actual growth rates. Furthermore, reaping productivity gains from a higher allocative efficiency is still possible in Malaysia’s case as it is still some distance away from the efficiency frontier. A more focused and purposeful removal of distortions in the domestic economy should allow the economy to reach a higher level of efficiency.

To address the concern about the optimistic baseline, we have also used a simple moving average model (ARMA) \([\text{MA}(q)]\) to project a second baseline GDP growth.\(^{29}\) Our ARMA \((0,3)\) model with a dummy to represent the periods in recession and growth trend produces an average growth of 5% during the 11MP period. This forecast growth is assumed to be the baseline growth for the second set of simulations (equation 24). Apart from the change in baseline growth, the other assumptions in table 4 apply.

\[
GDP = c + \alpha_1 \text{dummy} + \alpha_2 t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \theta_3 \varepsilon_{t-3} \quad |\theta| < 1, \quad (24)
\]

where GDP represents GDP growth rate; the dummy represents recession years in 1998 and 2009; and \(t\) represents trend.

Our assumption on the unchanged contribution of capital and labor to overall GDP growth in the three scenarios may be slightly conservative because a higher TFP often leads to a higher demand for capital. In other words, we are not accounting for the possible productivity spillovers that could result in a higher, and perhaps permanent, increase in growth. This could happen if such gains result in investments in production-enhancing technologies by firms in the manufacturing sector and its supporting sectors.

The simulation of the three scenarios based on a 10% incremental realization of productivity gains show an additional increase of GDP growth of between 0.4ppt and 1.3ppt (figure 19). With improvements in allocative efficiencies, the TFP component becomes the single most dominant component in growth, accounting for as much as 50% of the contribution to GDP growth (table 5). The simulations also show that TFP will reach its highest growth, comparable to the Republic of Korea’s average productivity growth of 3.4% from 1990 to 2011 (figure 20).\(^{30}\)

\(^{28}\) Based on a simple average of the official GDP growth rates from the first quarter 2016 to the third quarter 2017.

\(^{29}\) We used the Box Jenkins method to identify a suitable ARMA\((p,q)\) model, and found ARMA to be \((0,3)\). In other words, a simple MA\((3)\) that yields the lowest Akaike Information Criterion (AIC) appears to be the best model for GDP growth.

\(^{30}\) OECD estimates. Data are available on the OECD website: //data.oecd.org/lprdty/multifactor-productivity.
Figure 19: GDP Estimates for the Three Scenarios Using Two Baselines

a. Using 11MP Projections as the baseline  
b. Using MA(3) model projections as the baseline

Source: Authors’ calculations and the various Malaysia Plans.
Note: 6MP, 7MP, 8 MP, 9MP, 10MP, and 11MP = Sixth, Seventh, Eighth, Ninth, Tenth, and Eleventh Malaysia Plan, respectively; S1, S2, and S3 = Scenarios 1, 2, and 3, respectively.

The simulations using GDP growth lend support to the notion that the overall GDP projection of 5.8% may be too optimistic. Therefore, the 2.4ppt increase from the baseline of 5% GDP growth in scenario 1 appears more plausible, although this is conditional on structural reforms that increase the competitiveness of domestic markets.

Figure 20: Total Factor Productivity Growth Rates, 1971—2020

Source: Authors’ calculations and Eleventh Malaysia Plan (11 MP).
Note: 6MP, 7MP, 8 MP, 9MP, 10MP, and 11MP = Sixth, Seventh, Eighth, Ninth, Tenth, and Eleventh Malaysia Plan, respectively; ARMA = moving average model; S1, S2, and S3 = Scenarios 1, 2, and 3, respectively; TFP = total factor productivity.

The higher productivity growth in scenario 2 and scenario 3 will require even more purposeful and aggressive reforms to reduce restrictions and increase the intensity of domestic competition.
Table 5: Hypothetical Contribution of the Different Factors of Growth with a Partial Elimination of Distortions

|                      | Baseline projections | Baseline using 11MP | Baseline using MA(3) |
|----------------------|----------------------|---------------------|----------------------|
|                      | 11MP (2016–20)       | ARMA(p,q) (2016–20) | S1  | S2  | S3  | S1  | S2  | S3  |
| Capital              | 2.6 (44.8)           | 2.2 (44.8)          | 2.6 | 2.6 | 2.6 | 2.2 | 2.2 | 2.2 |
| Labor                | 0.9 (15.5)           | 0.8 (15.5)          | 0.9 | 0.9 | 0.9 | 0.8 | 0.8 | 0.8 |
| Total factor         | 2.3 (39.7)           | 2.0 (39.7)          | 2.7 | 3.2 | 3.6 | 2.4 | 2.9 | 3.3 |
| productivity (%)     |                      |                    |     |     |     |     |     |     |
| Gross domestic       | 5.8                  | 5.0                 | 6.2 | 6.7 | 7.1 | 5.5 | 5.9 | 6.3 |
| Additional growth    |                      |                     |     |     |     |     |     |     |

Source: Authors’ calculations and Eleventh Malaysia Plan (11MP).
Note: Top row = percentage point contribution to growth. Bottom row in brackets = percent contribution. 11MP = Eleventh Malaysia Plan; MA(3) = moving average 3; S1, S2, and S3 = Scenarios 1, 2, and 3, respectively; TFP = total factor productivity.
The assumption is that the manufacturing sector’s share of approximately 25% of the economy is also reflected in its share contribution to the aggregate TFP.
a. Calculated from the baseline growth of 5.8%.
b. Calculated from the baseline growth of 5%.

6.0 Conclusion

The current state of the debate is such that TFP explains a big part of the per capita income differences across countries. According to Hsieh and Klenow (2010), human capital accounts for 10%–30% of differences in country income, physical capital accounts for about 20%, and residual TFP explains the largest portion, 50%–70%.

As economic growth becomes increasingly dependent on improvements in productivity, it is important for Malaysia to harness the sources of productivity growth in the manufacturing sector, which accounts for 25% of the economy. Conventionally, TFP is often linked to innovation, technology, and human capital. However, Restuccia and Rogerson (2008) and Hsieh and Klenow (2009) put forth an idea that the misallocation of resources across heterogeneous firms could also hamper productivity. They argue that allocative efficiency is maximized when two firms identical in technologies can allocate the inputs to the point where they have the same marginal revenue product. Shifting resources to productive firms enhances productivity because it allows productive firms to grow, and less productive ones to shrink or eventually exit from the industry.

Our results show that market distortions exist. We find large revenue productivity (TFPR) differences between firms in the 90th and 10th percentiles, and 75th and 25th percentiles, with estimated ratios of 7:1 and 2:1, respectively. These differences are caused by an inefficient allocation of resources. They can be reduced by removing the distortions in the capital and output markets. A counterfactual analysis suggests that a complete removal of distortions or partial removal to the level of efficiency of the United States in 1997 will raise aggregate TFP.
by 94% and 36%, respectively in 2010. For the three census periods (2000, 2005, and 2010), the averages are 79% and 25%, respectively).

More crucially, our results show that there is a positive relationship between the measure of distortion (TFPR) and the measure of productivity (TFPQ). The positive relationship suggests that productive firms are systematically “taxed,” potentially resulting in larger drags on overall aggregate TFP. The decomposition of the sources of productivity shows that both the distortions in the output and capital market harm productive firms.

We simulate three different GDP growth trajectories based on different magnitudes (or speed) of the realization of hypothetical productivity gains. With modest reforms, a realization of a 10% TFP gains is expected to lift growth by 0.4ppt. This result suggests that increasing the intensity of market reforms will increase the realization of productivity gains and hence lift growth by as much as 1.3ppt per year over five years. This additional growth is especially crucial considering that the Malaysian authorities have identified TFP to be the most important source of future economic growth.

This paper provides evidence on the extent and the implications of misallocation of resources on Malaysia’s manufacturing sector and the overall economy. While we do not systematically identify the underlying sources of distortions, we provide insights that suggest that distortions in the output markets appear to matter more than distortions in the capital or labor markets. For policy makers, this may not be sufficient information for specific policy actions. One broad policy suggestion is to increase domestic competition, including lowering market barriers and reducing non-performance-based incentives. This is particularly evident for the food and beverage industry, which has received significant subsidies from the government.

Reducing barriers to labor mobility can also contribute positively to growth going forward. It is argued that Malaysia faces a shortage of skills and talent (World Bank, 2014). Thus, policies that address the misallocation of resources should also support a better use and allocation of human capital. For instance, barriers to inflows of talents into the country should be reduced. This, in turn, will strengthen learning from the global frontier.

In summary, the paper provides evidence to support the notion that productivity gains derived from a more efficient allocation of resources can be an important source of economic growth. The debates on whether the productivity gains estimates are dominated by measurement errors notwithstanding, we believe that the effects of misallocation on overall growth could be even higher than our estimates suggest because the manufacturing sector has significant linkages with other sectors in the domestic economy. Therefore, there may be potential spillovers of productivity loss into other sectors, particularly the services sector.

On the other hand, the Hsieh and Klenow framework makes simplifying assumptions such as constant elasticity of substitution (CES) aggregation and constant markup across firms in the same sector. Because of these assumptions, what we attribute to misallocation could be partly due to different markups, which in turn could be driven by differential quality and/or demand for firms’ products. In future research, we will try to disentangle improvements in physical efficiency (TFPQ) from other quality and demand factors, thanks to newly obtained data on outputs and material inputs for Malaysian manufacturing firms.
Appendix A

Limitations of Using Book Values as Capital Stock

The underestimation of the value of capital stocks may be even more critical for firms that have been operating for many years. Figure A.1 illustrates the relationship between the book value to value-added ratios of firms and their age. The scatter plots indicate that ratios are smaller for older firms, particularly those more than 50 years old (figure A.2). This suggests that either firms were indeed investing less compared to their younger counterparts or the value of their capital stock is in fact “undervalued.”

Figure A.1: Relationship between Ratio of Book Value to Value-Added and Firm Age

Source: Authors’ calculations.

Figure A.2: Relationship between Ratio of Book Value to Value-Added and Firms <50 Years

Source: Authors’ calculations.
Appendix B:
Entry and Exit of Firms

Over the course of three census periods (2000, 2005, and 2010), we tracked the entry and exit of firms using their unique identification number. This entry and exit analysis uses the nontruncated census data because the truncation removes not only small firms but young ones that might have entered during the census periods. We must contend with the trade-off between using complete but perhaps “noisier” information for this analysis.

About 48% of firms exited between the census periods 2000 and 2005, but they are replaced by a larger number of new firms. This resulted in a positive net addition of 6,775 firms. New firms in this analysis include firms that have just started operations and ones that enter the dataset through Department of Statistics Malaysia’s expanded coverage of active firms in the subsequent census. In the third census period, the number of firms that exited was slightly higher (7,959), but the net entry of firms was also higher because an even higher number of firms entered during the period (figure B.1).

Figure B.1: Entry, Exit, Survival, and Net Entry of Firms, Malaysian Census 2005 and 2010

Source: Authors’ calculations.
Note: Firms that reported an inconsistent year of starting operations over the three census periods are removed from the age analysis. They account for 9.5% of total firms. “New firms” are firms that enter the dataset in the following census period. “Surviving firms” are firms that survive for two consecutive census periods. “Net entry” refers to new firms minus firms that exited the dataset during the census period.

Firms that exited between the second and third census periods were mainly small firms (1–19 employees), accounting for 67% of total exits. Of the remaining firms, 24% were medium-sized firms (20–99 employees) and less than 9% were big firms (> 99 employees). A large proportion of firms (68%) that exited were middle-aged (6–15 years) and old (> 15 years) firms. About 32% of young firms (< 6 years) exited during the same period. Thus, the rejuvenation of the manufacturing sector took place as middle-aged and old firms exited from the sector. Half (50%) of the new firms that entered were new or young firms and half (50%) were older firms that entered the census frame through the expanded coverage of active firms.
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