On the Allocation of Resources in Developing East Asia and Pacific

Francesca de Nicola

Vera Kehayova

Ha Nguyen

WORLD BANK GROUP

East Asia and the Pacific Region

Office of the Chief Economist

October 2018

Abstract

Over the past decades, East Asia and Pacific's productivity has been gradually catching up with the frontier (the United States), with China leading the pack. Productivity growth has been driven by sustained within-sector productivity growth. Reallocation of labor to sectors with higher productivity, such as industry and services, also contributed to productivity improvements. Nevertheless, resource

misallocation remains. Firm-level evidence from four East Asia and Pacific countries (Indonesia, Malaysia, the Philippines, and Vietnam) suggests that resource misallocation across firms within a sector is large, albeit declining over time. Private domestic firms and firms with higher productivity face larger distortions.

This paper is a product of the Office of the Chief Economist, East Asia and the Pacific Region. It is part of a larger effort by the World Bank to provide open access to its research and make a contribution to development policy discussions around the world. Policy Research Working Papers are also posted on the Web at <http://www.worldbank.org/research>. The authors may be contacted at fdenicola@worldbank.org.

The Policy Research Working Paper Series disseminates the findings of work in progress to encourage the exchange of ideas about development issues. An objective of the series is to get the findings out quickly, even if the presentations are less than fully polished. The papers carry the names of the authors and should be cited accordingly. The findings, interpretations, and conclusions expressed in this paper are entirely those of the authors. They do not necessarily represent the views of the International Bank for Reconstruction and Development/World Bank and its affiliated organizations, or those of the Executive Directors of the World Bank or the governments they represent.

On the Allocation of Resources in Developing East Asia and Pacific

Francesca de Nicola, Vera Kehayova, Ha Nguyen¹

“Productivity isn't everything, but, in the long run, it is almost everything. A country's ability to improve its standard of living over time depends almost entirely on its ability to raise its output per worker.”

— [Paul Krugman](#)

JEL classification: D24, L11, O30, O47

Keywords: Productivity, Distortions, Resource Misallocation

¹ This is a background paper for the EAP Flagship Report: “A Resurgent East Asia: Navigating a Changing World”. We are grateful for comments and feedback from Sudhir Shetty, Andy Mason, Rong Qian, Norman Loayza, Lay Lian Chuah. All errors are our own.

1. Background

Productivity is at the foundation of the development of a country and the well-being of its people. Understanding the sources of growth is crucial to devise policies that efficiently and effectively promote economic development. Hence, for its importance historically, the topic has attracted substantial attention from policy makers and researchers alike. While initially physical and human capital accumulation were identified as main drivers of economic growth, more recent evidence indicates that productivity² accounts for most of the cross-country differences in income per capita (Easterly and Levine (2001)).

Productivity plays an important role towards the achievement of the twin goals of ending extreme poverty and boosting shared prosperity. First, cross-country evidence shows that countries with higher productivity display also lower poverty rates (Figure 1, Panel A). The negative correlation between labor productivity and poverty can be rationalized as follows. Productivity-enhancing policies encourage a more efficient allocation of factors of production and the adoption of new/better technologies. This in turn contributes to income growth and ultimately reduces poverty. An example is Asia's past experience where structural transformation enhanced growth, as labor moved from low to high productivity activities (McMillan and Rodrik (2011)). Second, higher productivity appears related to shared prosperity. In Figure 1 (Panel B), higher productivity is associated with a higher share of income held by the bottom 40% of the population, and a lower realization of the Gini index, a common proxy of income inequality. Cross-country evidence suggests that (i) growing differences between firms within sectors can account for most of the increase in individual wage inequality, and (ii) increased productivity dispersion tends to be associated with the heterogeneous diffusion of new technology across firms (Faggio et al. (2010)). Hence, removing barriers to the adoption of new technologies may narrow the productivity gap and reduce wage inequality.

Figure 1 Productivity and the twin goals

Panel A: Ending Poverty

² More precisely, it is physical productivity, TFPQ in the language of Section 4, a measure of the efficiency in transforming inputs into outputs.

Panel B: Boosting shared prosperity

Source: World Development Indicator, 2012

Note: Poverty headcount ratio at \$3.20 a day is the percentage of the population living on less than \$3.20 a day at 2011 international prices. Green scatter dots represent EAP countries; blue scatter dots represent countries from the rest of the world.

Despite its importance, measuring productivity is challenging. First, multiple definitions of productivity exist. Labor productivity or output per worker is commonly used. The measure does not impose extensive data requirement, and its simplicity allows for easy comparability over time and place (sectors and/or countries). However, it is an incomplete estimate of efficiency. Firms can raise labor productivity by investing in capital and acquiring more efficient machineries. Similarly, improving the business environment by promoting adequate and transparent regulations may free up resources and allows firms to operate more efficiently. Total factor productivity (TFP) is a more comprehensive, but harder to estimate measure. It provides an estimate of economic efficiency, accounting for the contributions from labor and capital. Empirically, labor productivity and TFP tend to be highly correlated. Difficulties arise in the measurement of capital, in the words of Hicks (1981) “the measurement of capital is one of the nastiest jobs that economists have set to statisticians”. Challenges are compounded when price

data are not available at the firm level. Differences in revenues per unit sold may reflect differences in productivity but also differences in quality. The problem may be more severe for tech companies, where product innovation frequently takes place. With these caveats in mind we set up our analysis.

Abstracting from entry and exit dynamics, there are two main sources of productivity growth. The first source is within-firm productivity growth, i.e., firms become more productive thanks to better technology or management practice. This more conventional understanding has been the subject of a long-standing literature and dominated much of policy discussions. However, recent views focus on the benefits of a second channel involving the 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. We focus on this source of productivity improvement, examining resource allocation across sectors, and across firms within a narrowly-defined industry.

This paper documents the evolution of productivity in developing EAP in the recent decades and identifies the sources of productivity growth. EAP's productivity has been gradually catching up with the frontier (United States), with China leading the pack. Productivity growth is driven by sustained within-sector productivity growth. Reallocation of labor to sectors with higher productivity, such as industry and services, also contributed to productivity improvements. Nevertheless, resource misallocation remains. Firm-level evidence from four EAP countries (Indonesia, Malaysia, Philippines and Vietnam) suggests that resource misallocation across firms within a sector is large, albeit declining over time. Private domestic firms and firms with higher productivity face larger distortions.

The rest of the paper is organized as follows. Section 2 provides an overview of the aggregate trends for EAP productivity, using country-level data. Focusing on labor, one of the factors of production driving the results in Section 2. Section 3 employs newly available sector-level information and examines how labor movement is linked to labor productivity differential across sectors over the last ten years. This allows us to examine if labor has moved from sectors with low productivity to sectors with high productivity, i.e., better resource allocation across sectors. The allocation of resources within an industry has implications for aggregate productivity; Section 4 digs deeper into this using manufacturing data for four developing EAP countries (Malaysia, Philippines, Indonesia and Vietnam). It first presents evidence on misallocation and its dynamics and then explores possible determinants.

2. Aggregate trends for EAP's productivity

Notwithstanding significant volatility and heterogeneity, developing EAP total factor productivity (TFP) is gradually catching up to the frontier (the United States) since 2000 (Figure 2). In the aftermath of the 1997-1998 East Asian financial crisis, a sharp drop in aggregate productivity is observed in many EAP countries. Since then, the recovery process has been gradual and slow. Yet, there is heterogeneity in the speed of convergence across countries. On the one hand, China and Malaysia have fully recovered and high catch-up speed has increased since the crisis. On the other hand, relative TFP is below the pre-crisis levels in Indonesia and, to

a lower extent, the Philippines and the convergence is only marginally improving since late 1990s. Moreover, since 2010, there is a noticeable slowdown of TFP growth in many countries (e.g. China, Malaysia, Thailand).

Figure 2 Total factor productivity relative to the U.S. in selected developing EAP countries

Source: Penn World Table 9.0 and authors' calculation. TFP series are calculated by the Penn World Table, except for Vietnam and Indonesia. Vietnam's labor share is missing in the PWT 9.0. We assume labor share of Vietnam is 2/3 (consistent with Vietnam 2035 report) to calculate Vietnam's TFP. TFP series for Indonesia between 2011-2014 is recalculated based on extrapolated years of schooling for the country.

Conversely, output per worker is converging towards the U.S. level at higher and consistent speed across China and ASEAN-5 (Figure 3**Error! Reference source not found.**). Again, labor productivity is expressed relative to the U.S. level. Malaysia shows the highest labor productivity, while China has the highest speed of convergence.

Figure 3 Labor productivity relative to the U.S. in selected developing EAP countries

Source: Penn World Table 9.0

Similarly, China and other large developing EAP countries are moving toward convergence with the United States in capital intensity since 1997 (Figure 4). Capital intensity is measured as real capital stock divided by total employment; EAP country-levels are expressed in terms of the U.S. level of capital intensity.

Figure 4 Capital intensity relative to the U.S. in selected developing EAP countries

Source: Penn World Table 9.0

Developing EAP countries are closer to bridging the gap in human capital with the United States (Figure 5). Malaysia shows the strongest performance. Indonesia is the furthest from convergence with the United States, especially after the worsening in human capital accumulation in recent years.

Figure 5 Human capital relative to the U.S. in selected developing EAP countries

Source: Penn World Table 9.0

Note: Human Capital, H , in the Penn World Table 9.0 is assumed to take the form (based on Mincer equations): $H = \exp(.134 * \min(\text{yr_sch}, 4) + .101 * \max(0, \min(4, (\text{yr_sch} - 4))) + .068 * \max(0, \text{yr_sch} - 8))$ where yr_sch is country's average year of schooling. Years of schooling for Indonesia between 2011 and 2014 are extrapolated.

A breakdown of contributions by TFP, capital accumulation, growth in labor force and human capital reveals that capital accumulation plays a key role for convergence toward the U.S. level of output per capita (red bars in Figure 6). This is true across countries and periods.

TFP seemed to also play a key role between 2000-2007, but the role of TFP was clearly smaller for many countries (China, Thailand, Vietnam, Malaysia) between 2008 and 2014. Average TFP growth for these countries was sharply lower between 2008 and 2014. China's average TFP growth was 1.3%, Vietnam's was 1.1%, Malaysia's was -0.36%; and Thailand's was 0.24%.

Figure 6 Growth contribution of TFP, capital accumulation and growth in employment and human capital

Source: Penn World Table 9.0. Human capital H in the Penn World Table 9.0 is assumed to enter production as in the following production function $Y = AK^\alpha(HL)^{1-\alpha}$. Years of schooling for Indonesia between 2011 and 2014 are extrapolated. Output, capital and TFP are measured at constant national prices.

3. Labor allocation across sectors

In EAP, labor productivity improvement was driven largely by labor productivity growth within sectors (Figure 7).³ The three sectors we consider are agriculture, industry, and services. The reallocation of labor away from less-productive sectors to more productive sectors (“static reallocation”) also contributed to improving productivity, especially in Indonesia, Thailand and Vietnam. Limited evidence of faster productivity growth (“dynamic reallocation”) is available only for China.

Figure 7 Growth in labor productivity: contributions of intersectoral reallocation and within-sector productivity growth (annualized, percent)

³ This is consistent with the evidence from Foster-McGregor and Verspagen (2016). The authors note that within-sector productivity growth explains most of the productivity change for middle to high-income countries. Conversely, structural transformation plays a larger role as economies move from low- to middle-income status. This can be explained by the fact that high-income economies tend to display lower dispersion in productivity across sectors.

Source: World Development Indicators, and General Statistics Office of Vietnam for the period 1990-2011 when key variables are missing in WDI.

Note: Aggregate labor productivity growth is decomposed as follows:

$$\Delta P_t = \sum_{i=1}^n \theta_{i,t-k} \Delta p_{i,t} + \sum_{i=1}^n \Delta \theta_{i,t} p_{i,t-k} + \sum_{i=1}^n \Delta \theta_{i,t} \Delta p_{i,t}$$

where P_t and $p_{i,t}$ denote, respectively, economy-wide and sectoral labor productivity; $\theta_{i,t}$ denotes sectoral employment shares; the subscripts i and t refer, respectively, to the sector and year; and the Δ operator denotes changes over time. The first term on the right-hand side captures the impact of within-sector productivity growth; the second and third terms capture the impact of structural reallocation, that is, shifts toward sectors with higher initial productivity (“static reallocation,” the second term), or shifts toward sectors with higher productivity growth (“dynamic reallocation,” the third term) (de Vries et al. 2015).

The analysis employs data on value added at U.S. constant prices, and on employment, for the following 3 sectors: agriculture, industry, and service.

Industry and services witness the largest within-sector labor productivity growth (Figure 8). Across countries, at least two-thirds of labor productivity growth within sectors is realized in either services or industry. The contribution of agriculture is much more limited. Potentially this is due to narrower margins of improvements that remain in the sector of the selected countries considered, as suggested by the structural transformation results discussed below.

Figure 8 Sectorial decomposition of within-sector labor productivity growth (annualized, percent)

Source: World Development Indicators, and General Statistics Office of Vietnam for the period 1990-2011 when key variables are missing in WDI.

Structural transformation contributed to higher productivity: labor moved from the less productive agricultural sector to the more productive industry and service sectors. Theoretically, structural transformation could improve productivity in two ways. First, it could raise total output by shifting resources away from less productive sectors towards more productive ones. Second, it could raise productivity within the relatively less productive sectors. The agricultural sector dynamics may be taken as an example of this second channel. The sector is typically characterized by low productivity and underemployment, so when workers move to other sectors, agriculture's labor marginal productivity increases, given that land, a key sectoral input, is largely fixed.

The intensity of this structural transformation varies across developing EAP countries. China went through more significant structural change than Indonesia or Thailand (Figure 9, Panel A). Chinese agricultural employment share dropped by more than 13 percentage points between 2000-2007 and 2008-2015. The corresponding change in Indonesia (Figure 9, Panel B) is 8pp and less than 6pp in Thailand (Figure 9, Panel C). Similarly, output per worker in agriculture increased by 1.34% in China, but only by 0.67% in Indonesia and 0.64% in Thailand. Labor reallocation to industry and services and correspondent increase in output per worker was also more pronounced in China than in either of the other two countries considered.

Figure 9 Structural transformation

Panel A: China

Source: World Development Indicators

Panel B: Indonesia

Source: World Development Indicators

Panel C: Thailand

Source: World Development Indicators

Broadening the focus to other developing EAP countries shows that also Myanmar, Cambodia and Mongolia witnessed significant structural transformation. Figure 10 summarizes structural transformation for developing EAP countries. The horizontal axis captures *change* in employment share between 2000-2007 and 2008-2016 (note that the change is not annualized). The vertical axis is *percentage change* in real output per worker over the same period (again, the change is not annualized). In the northeast (southwest) quadrant are country-sector pairs that have observed an increase (decline) in both productivity and employment. In the northwest quadrant are country-sector pairs where productivity has grown but the employment share has fallen. Comparing performances within country and across sectors informs about the structural transformation dynamics. Specifically, we find that across the region workers move out of agriculture towards more productive sectors. The employment shift towards services tends to be more pronounced. It is worth noting that the service sector encompasses activities that typically vary widely in terms of productivity, such as retail and IT. Whether workers move from agriculture towards more or less productive jobs in the service (and industry) sectors has important implications for future growth, as anticipated in the discussion about Figure 7 regarding the labor decomposition based on de Vries et al. (2015).

Figure 10 Structural transformation of all developing EAP countries

4. Misallocation across firms within a narrowly-defined industry

Productivity analyses based on resource misallocation provide a new framework for policy makers and researchers. More conventional discussions about productivity center on technology and require a different set of policy prescriptions. For example, 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 those that incentivize learning, upgrading of skills, and investment in education. However, a complimentary approach focuses 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 (see Box 1 for an example of power sector reform that disproportionately benefits firms and sectors with heavier electricity use).

What is resource misallocation in a narrowly-defined industry? 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, leading to an increase in the overall productivity of the sector. In an economy with high levels of distortion, however, unproductive firms have disproportionately large access to resources, hence dragging down the overall productivity of that sector. The literature proposes two different approaches to detect this resource misallocation. The *direct approach* method discussed in the box focuses on specific sources of misallocation and quantifies their impact on productivity, typically through structural models. The *indirect approach* discussed in the rest of the section provides a comprehensive measure of misallocation,

since it captures misallocation from multiple channels not being limited to pre-identified sources of misallocation. This method requires some structure as discussed below, but it does not involve specifying a full-fledged model as the direct method.

Hsieh and Klenow (2009) provide a prominent empirical framework to assess the extent of misallocation under the indirect approach (See Appendix A for detailed setup). Their basic idea is that allocative efficiency is maximized when two firms within a narrowly defined industry can access resources until their marginal revenue products are equalized. Under their framework, large dispersions in marginal revenue products among firms operating within a narrowly defined industry imply misallocation of resources in the industry. Specifically, Hsieh and Klenow (2009) consider an economy where each firm produces according to a standard Cobb Douglas function (with sector specific factor shares) and outputs can be aggregated through a CES function for each narrowly defined sector. The firm-specific output and capital may be subject to distortions (or wedges/taxes in the language of the authors). Bringing their framework to the data allows to compute two measures of aggregate productivity: the “actual” one where distortions are present and the “potential” one where these wedges are assumed away. Comparing these two measures allows to quantify the potential productivity gains from a more efficient allocation of resources. Note that this methodology does not identify the amount of misallocation deriving from specific sources but provides an all-encompassing measure (see the box for a discussion about the sources of misallocation).

Box 1 On the sources of misallocation

The background paper assesses the extent of misallocation based on Hsieh and Klenow (2009) or the indirect approach. This methodology does not identify the amount of misallocation deriving from specific sources but provides an all-encompassing measure. To complement this evidence, we turn to the literature where specific factors directly affecting misallocation are examined. Specific sources of misallocation may be more transparent such as the introduction of subsidies in favor of a given sector. Specific groups of firms may enjoy distortive interventions: state-owned enterprises may access finance at distorted/more favorable rates; large firms with substantial bargaining power may face preferential treatments through specific regulatory treatment and/or lower borrowing costs.

Interestingly, although not surprisingly, none of the individual channels by itself is able to explain the magnitude of misallocation estimated using the indirect approach. A given economy may suffer from multiple sources of misallocation at once. Alternatively, or additionally, the indirect method may overestimate the extent of misallocation, in the presence of measurement error and/or departures from the assumed market structure. This box builds on Hopenhayn (2014) and Restuccia and Rogerson (2017) and reports the evidence emerging from EAP countries regarding specific sources of misallocation.

Regulation. A wide range of policy instruments have been considered in the literature to assess the extent to which regulatory interventions contribute to misallocation and thereby lower aggregate productivity. The focus has moved from adjustment costs, such as firing costs, to the broader category of “size-dependent policies”, e.g., higher taxes that become effective

beyond a certain employment threshold, yet any of these measures tends to explain only a small fraction of misallocation.

Conversely, regulatory restrictions to movements across space appear to play a more important role. Tombe and Zhu (2015) study the impact of goods- and labor-market frictions using a general equilibrium model calibrated with Chinese data. Overall the reduction in trade and migration frictions explain almost 50% of productivity growth in 2000-2005, and the fall in internal trade and migration costs contributed about 20%.

Other studies of China examine also state-owned enterprises, their preferential access to resources, and the related productivity losses (e.g., Song, Storesletten and Zilibotti (2011)). Brandt, Tombe, and Zhu (2013) study the period 1985-2007 and find that within-province misallocation of capital between state and nonstate sectors reduced the nonagricultural TFP growth rate by 0.5% per year. The costs of misallocation appear to have sharply increased during the latest period analyzed, 1997-2007.

Property rights. Property rights affect resource allocation and therefore productivity, by limiting expropriation and facilitating market transactions (Besley and Ghatak (2010)). Adamopoulos and Restuccia (2014) assess the impact of the Comprehensive Agrarian Reform Program (CARP) on agricultural productivity by calibrating a model with data from the Philippines.⁴ In 1988, the reform introduced ceilings on existing land holdings, promoted transfer of above-ceiling land to landless and smallholders, and restricted the transferability of the redistributed land. Between 1989 and 1993, agricultural productivity fell by more than 10%. According to the model, this decline is the result of distortions in farm size and occupational choices, as land is transferred from more to less productive holders.

Trade and competition. Trade policy influences the allocation of resources across heterogeneous producers and consequently impacts aggregate productivity. Two approaches are used to quantitatively assess the impact of tariffs and/or other distortionary forms of protection. On the one hand, evidence comes from model-based estimates. For example, building on Arkolakis, Costinot, and Rodríguez-Clare (2012), Edmond, Midrigan, and Xu (2015) study the impact of moving from autarky to free trade by calibrating a model to Taiwanese manufacturing data. Opening to trade leads to greater competitive pressure and substantially reduces markup distortions. Consequently, it reduces misallocation and improves total factor productivity by more than 12%.

On the other hand, specific trade policy changes are examined for causal inference. Khandelwal, Schott, and Wei (2013) study the elimination of externally imposed quotas on Chinese textile and clothing exports. Interestingly, the distortionary effects of the quotas imposed by the United States, Canada and European Union were compounded by the effects of government-imposed quotas allocated in favor of (less productive) state-owned enterprises. The authors find that 71% of the productivity gains derived from the empirical analysis are

⁴ Incidentally, it is interesting noting that models tend to explain a larger share of the changes in agricultural rather than manufacturing productivity.

due to the elimination of misallocated quota licenses; while the remaining 29% is explained by the removal of misallocation due to the quota itself.

Credit constraints and informational frictions. There is an established literature on the positive correlation between financial market development and growth (See Buera, Kaboski and Shin (2015) for an overview). Credit constraints may lead to misallocation, potentially magnifying the persistency of low productivity, as more productive firms take longer time to overcome financial constraints. This empirical question has been tested in multiple frameworks and the resulting estimates tend to vary substantially across studies. On the conservative side are the results by Midrigan and Xu (2014). They calibrate a model with Korean plant-level data and find that losses from misallocation in an environment with borrowing constraints amount to 4.7% of the TFP decline (accounting for over 27% of the change). Borrowing constraints harm growth more through the selection (into a sector) channel rather than through the misallocation (within the sector) channel.

A complimentary analysis is proposed by David, Hopenhayn, and Venkateswaran (2016) who focus on informational frictions. Under their framework, firms have limited knowledge about the demand conditions in their own markets when choosing inputs. The authors estimate a structural model with 2012 data on firm-level production variables and stock returns for three countries: China, India, and the United States. Informational frictions for investment but not labor decisions lead to losses in productivity (of 4, 7, and 10%) and output (5, 10, 14%) (for the United States, China and India, respectively). The authors show that financial markets have limited ability to overcome these frictions given the high level of noise in market prices. Conversely, valuable information can be inferred from private (internal to the firm) sources.

As acknowledged by Hsieh and Klenow (2009), their approach relies on restrictive assumptions such as (i) CES aggregation of differentiated products within a narrowly defined sector (allowing to derive TFPQ in the absence of information on input and output quantities), and (ii) constant mark-ups within the same sectors. Under these conditions, any variation in TFPR is attributable to resource misallocation. However, heterogeneous mark-ups reflecting differences in demand and/or quality within the sector or measurement errors could also explain variations in TFPR.

Bils et al. (2017) propose a methodology that exploits the panel structure of the data to correct for potential measurement errors (see Appendix B). The authors build on the Hsieh and Klenow (2009) approach and allow for additive⁵ measurement error in revenues and intermediate inputs. We apply Bils et al.'s (2017) framework to firm-level data available from four ASEAN countries: Indonesia, Malaysia, the Philippines and Vietnam. Table 1 provides an overview of the data sources used. For robustness, we exclude from the sample 4-digit sectors with fewer than 5 firms.

⁵ Assuming additive rather than multiplicative measurement error yields more conservative estimates.

Table 1 Data sources

Indonesia	<p>The sample includes information from the Manufacturing Survey of Large and Medium-Sized Firms (Statistik Industri). It provides plant-level data from 2000 to 2015.</p> <p>The sample focuses on a subset of Indonesian enterprises. The 2016 economic census indicates that 98.3% of enterprises are micro and small business with less than 20 employees. However, the remaining 1.7% of firms, the ones interviewed for the Statistik Industri, employ a non-negligible amount (23.7%) of workers.</p>
Malaysia	<p>2000, 2005 and 2010 census of manufacturing firms with at least 10 workers. There are 37,211 firms across the three waves of census.</p> <p>In the 2010 manufacturing census, 36.7% of firms have at least 10 workers. They account for 66.4% of employment in the manufacturing census.</p>
Philippines	<p>The sample includes data from 2001 to 2014 surveys on manufacturing firms with at least 10 workers.</p> <p>The economic census data is not disaggregated by firm size, so we refer to the latest Enterprise Survey which indicates that firms with 5-19 workers account for 52% of the sample. Firms with less than 20 workers employ almost 12% of the labor force.</p>
Vietnam	<p>The sample includes data from 2009 to 2014 on manufacturing firms with at least 1 worker. There are 259,721 manufacturing firms between 2009 and 2014.</p>

The potential gains from reallocation are large, even after accounting for measurement error (Table 2). We present three different measures of the potential productivity gains that can be achieved from reallocation. First, consistently with Hsieh and Klenow (2009), Panel A provides the estimates of potential gains if distortions (taxes) to revenue and labor are removed and factors of production (labor, capital and intermediate inputs) are reallocated towards their most productive uses. Panel B accounts for the presence of measurement error. Accounting for measurement error significantly reduces the magnitude of the potential gains from reallocation, these changes are as low as 6 percentage points in the Philippines and up to as high as 72 percentage points in Indonesia. Yet, even after accounting for measurement error, the estimates indicate that productivity can substantially increase where distortions are removed.

Table 2 Potential gains from reallocation

	Malaysia	Indonesia	Philippines	Vietnam
	<i>Panel A: without correction</i>			
2000-2007	95.9	169.9	98.0	-
2008-2015	96.0	176.3	103.5	98.4
	<i>Panel B: with correction for measurement error</i>			
2000-2007	109.7	107.5	91.9	-
2008-2015	75.0	104.4	82.8	25.8

Source: Country data as detailed in Table 1 and authors' calculation.

The potential productivity gains appear to decline over time. The result is encouraging as it suggests that economies have undertaken steps to reduce misallocation. This is consistent with the evidence from the Global Competitiveness Index (GCI) (**Error! Reference source not found.**). The GCI provides a summary measure of competitiveness based on three dimensions: basic requirements (i.e., institutions, infrastructure, macroeconomic environment, health and primary education), efficiency enhancers (i.e., higher education and training, goods market efficiency, labor market efficiency, financial market development, technological readiness, market size), and innovation and sophistication factors (i.e., business sophistication and innovation). Higher values are associated with more competitive economies.⁶

Figure 11 Evolution of Global Competitiveness Index

Source: Global Competitiveness Report 2017-2018

Within a narrow industry, highly productive firms are facing higher distortions (or “taxes”). In this framework, distortions are measured by TFPR (revenue TFP), while productivity is measured by TFPQ (quantity TFP). Figure 12 plots $\log \frac{TFPR_i}{\overline{TFPR}}$ against $\log \frac{TFPQ_i}{\overline{TFPQ}}$, where $\overline{TFPR}$ and $\overline{TFPQ}$ are the sector averages. In a frictionless world, firms with higher (lower) TFPR would grow (shrink) up to the point where TFPR are equalized ($TFPR_i = \overline{TFPR}$). For all ASEAN countries studied, we observe a positive relationship between revenue and physical productivity. The result is consistent with the evidence emerging from other developed and developing countries. It suggests that more productive firms (i.e. those that have larger TFPQ) face larger idiosyncratic distortions (i.e. larger TFPR). In other words, more productive firms are “taxed” at a higher rate (either explicitly or implicitly), hence capital and output wedges or taxes absorb

⁶ In 2018, the GCI ranged from 5.7 for the U.S. to 2.8 for Chad. The average for the 17 East Asia and Pacific economies considered by the GCI was 4.8, with Singapore and Mongolia on opposite sides of the spectrum.

resources that would have otherwise been used to expand production. This results in lower productivity for the overall economy.

Figure 12 TFPR and TFPQ growth

Indonesia

Malaysia

Philippines

Vietnam

Note: Results based on authors' calculation. For each country, the latest available data are plotted (2010 in Malaysia, 2014 in Philippines and Vietnam, 2015 in Indonesia).

In addition, foreign firms (in Indonesia, Vietnam, and the Philippines) and SOEs (in Vietnam and the Philippines) have lower distortions (or “taxes”), which reflects their relative privileges in the economies. Figure 13 plots the coefficients (scatter dots) and the related 90% confidence interval (horizontal line) when regressing log of TFPR on firms' characteristics selected based on data availability. Controlling for sector-year fixed effects and firms' characteristics, revenue (TFPR) and physical (TFPQ) productivity are positively correlated. Like the evidence from **Error! Reference source not found.** Figure 13, this suggests that more productive firms face larger distortions. We find some evidence that firm size (small or medium firms) and firm ownership (foreign or state-owned) significantly correlate with distortions (TFPR), indicating that regulatory restrictions that affect these dimensions hamper achieving an efficient allocation of capital and labor.

Figure 13 TFP and firms' characteristics

While Bils et al.'s (2017) framework offers interesting insights on the dynamics of misallocation, it remains mute on the forces behind these changes. To address this, we combine it with the insights from standard TFP decomposition. Specifically, we compute the changes in the median and dispersion of productivity at the country- and sector-level (see Appendix C for details). Under this approach, an increase in median TFP may be interpreted as a sign that incumbent firms have become more productive by: (i) innovating, (ii) adopting new technologies, and (iii)

applying best managerial practices (“within” component). A decline in TFP dispersion⁷ may indicate reallocation of factors of production, economic activity, and market shares towards more efficient firms (“between” component).

The positive increase in aggregate productivity tends to be accompanied by higher TFP dispersion (Figure 14).⁸ This points to an improvement of the "within component" accompanied by a worsening of the "between component". Put differently, the analysis suggests that productivity has risen within firms because of improved capabilities (“within component”), but capital adjustment costs or other allocative distortions prevented productivity improvements across sectors (“between component”). Yet, there is heterogeneity within countries at the sector level. For example, the food, beverage and tobacco industry in the Philippines has witnessed a decline in median productivity in parallel with an increase in dispersion. This suggests a worsening of both the within and the between components. Distortions in the factor allocation within the firm and across sectors have prevented the materializing of productivity improvements. Over time, the economy has become less efficient, and the market share of less productive firms seems to have increased.

Figure 14 Evolution of TFP in Indonesia: Median and Dispersion

⁷ Two definitions of dispersion are considered: (i) the standard deviation of TFP which summarizes the entire distribution, and (ii) the interquartile difference (75th-25th) which focuses on half of the distribution and is less sensitive to extreme values. The results tend to be qualitatively similar.

⁸ We present the aggregate and sectoral breakdown of productivity evolution.

Source: Country data as detailed in Table 1 and authors' calculation

5. Conclusion

This paper documents the evolution of productivity in developing EAP since 1990. It examines labor productivity and total factor productivity. EAP's productivity has been gradually catching up with the frontier (the United States), with China having the fastest growth. The paper identifies and discusses the sources of the countries' productivity growth. Productivity growth is driven by sustained within-sector productivity growth. Reallocation of labor to sectors with higher productivity, such as industry and services, also contributed to productivity improvements. Nevertheless, resource misallocation remains. Firm-level evidence from four EAP countries (Indonesia, Malaysia, the Philippines and Vietnam) suggests that resource

misallocation across firms within a sector is large, albeit declining over time. Private domestic firms and firms with higher productivity face larger distortions.

6. References

- Adamopoulos, T., & Restuccia, D. (2014). Land reform and productivity: A quantitative analysis with micro data. *Unpublished manuscript, University of Toronto, December*, 1667-97.
- Arkolakis, C., Costinot, A., & Rodriguez-Clare, A. (2012). New trade models, same old gains? *American Economic Review*, 102(1), 94-130.
- Asker, J., Collard-Wexler, A. and Jan De Loecker (2014). Dynamic Inputs and Resource Misallocation. *Journal of Political Economy*, 122 (5), 1013-1063.
- Barro, R and Lee JW (1993) "International comparisons of education attainment" *Journal of Monetary Economics*, pp 363-394
- Besley, T., & Ghatak, M. (2010). Property rights and economic development. In *Handbook of development economics* (Vol. 5, pp. 4525-4595). Elsevier.
- Bils, M., Klenow, P. J., & Ruane, C. (2017, March). Misallocation or Mismeasurement? In *2017 Meeting Papers* (No. 715). Society for Economic Dynamics.
- Brandt, L., Tombe, T., & Zhu, X. (2013). Factor market distortions across time, space and sectors in China. *Review of Economic Dynamics*, 16(1), 39-58.
- Buera, F. J., Kaboski, J. P., & Shin, Y. (2015). Entrepreneurship and Financial Frictions: A Macroeconomic Perspective. *Annual Review of Economics*, 7(1), 409-436.
- Caselli, F (2005) "Accounting for Cross-Country Income Differences" Chapter 9, *Handbook of Economic Growth*, pages 679-741
- David, J. M., Hopenhayn, H. A., & Venkateswaran, V. (2016). Information, misallocation, and aggregate productivity. *The Quarterly Journal of Economics*, 131(2), 943-1005.
- De Vries, G., Timmer, M., & De Vries, K. (2015). Structural transformation in Africa: Static gains, dynamic losses. *The Journal of Development Studies*, 51(6), 674-688.
- Easterly, W., & Levine, R. (2001). What have we learned from a decade of empirical research on growth? It's Not Factor Accumulation: Stylized Facts and Growth Models. *the world bank economic review*, 15(2), 177-219.
- Edmond, C., Midrigan, V., & Xu, D. Y. (2015). Competition, markups, and the gains from international trade. *American Economic Review*, 105(10), 3183-3221.
- Faggio, G., Salvanes, K. G., & Van Reenen, J. (2010). The evolution of inequality in productivity and wages: panel data evidence. *Industrial and Corporate Change*, 19(6), 1919-1951.
- Foster-McGregor, N., & Verspagen, B. (2016). The Role of Structural Change in the Economic Development of Asian Economies. *Asian Development Review*, 33(2), 74-93.

- Hicks, J. (1981) *Wealth and Welfare: Collected Essays in Economic Theory*, Cambridge, Mass.: Harvard University Press.
- Hopenhayn, H. A. (2014). Firms, misallocation, and aggregate productivity: A review. *Annu. Rev. Econ.*, 6(1), 735-770.
- Hopenhayn, H., & Rogerson, R. (1993). Job turnover and policy evaluation: A general equilibrium analysis. *Journal of political Economy*, 101(5), 915-938.
- Hsieh, C. T., & Klenow, P. J. (2009). Misallocation and manufacturing TFP in China and India. *The Quarterly journal of economics*, 124(4), 1403-1448.
- Khandelwal, A. K., Schott, P. K., & Wei, S. J. (2013). Trade liberalization and embedded institutional reform: evidence from Chinese exporters. *American Economic Review*, 103(6), 2169-95.
- Klenow, P.J., and Andrés Rodríguez-Clare (1997). "The Neoclassical Revival in Growth Economics: Has It Gone Too Far?" *NBER Macroeconomics Annual* 12 (1997): 73-103.
- Melitz, M., & Polanec, S. (2015). Dynamic Olley-Pakes productivity decomposition with entry and exit. *The RAND Journal of Economics*, 46(2), 362-375.
- Midrigan, V., & Xu, D. Y. (2014). Finance and misallocation: Evidence from plant-level data. *American economic review*, 104(2), 422-58.
- Olley, S., & Pakes, A. The Dynamics of Productivity in the Telecommunications Industry. *Econometrica*, Vol. 64 (1996), pp. 1263–1298.
- Petrin, A. and Jagadeesh Sivadasan (2013). Estimating Lost Output from Allocative Inefficiency, with an Application to Chile and Firing Costs. *Review of Economics and Statistics*, 95 (1), 286-301.
- Restuccia, D., & Rogerson, R. (2017). The causes and costs of misallocation. *Journal of Economic Perspectives*, 31(3), 151-74.
- McMillan, M. S., & Rodrik, D. (2011). *Globalization, structural change and productivity growth* (No. w17143). National Bureau of Economic Research.
- Song, Z., Storesletten, K., & Zilibotti, F. (2011). Growing like china. *American Economic Review*, 101(1), 196-233.
- Tombe, T., & Zhu, X. (2015). Trade, migration and productivity: A quantitative analysis of china. *Manuscript, University of Toronto*

Appendixes

Appendix A: Hsieh and Klenow (2009) Framework

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

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

where θ_s is the value added share of sector s and $\sum_{s=1}^S \theta_s = 1$.

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

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

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

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

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

where A_{si} stands for firm-specific productivity; L_{si} is the firm's labor; K_{si} is the firm's capital, and α_s is the industry-specific capital share. Note that the assumption in this framework is that firms in the same narrowly defined sector have the same production function.

Each establishment maximizes current profits:

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

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 τ_{Ysi} 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 τ_{Ksi} . Credit market imperfections such as preferential access to finance and labor market frictions could contribute to different "capital" distortions τ_{Ksi} across firms. Therefore, an increase usage of capital is indicative of relative distortions in the labor markets.

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

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

$$TFPR_{si} = \frac{P_{si} Y_{si}}{L_{si}^{1-\alpha_s} K_{si}^{\alpha_s}}$$

In the absence of distortions, TFPR should not vary across firms within each sector. In other words, in a frictionless environment, more capital and labor should be allocated to firms with higher physical productivity (TFPQ) up to the point where their higher output results in a lower price, P_{si} , which translates in the $TFPR_{si}$ equalizing across firms i . As such, any dispersions of TFPR across firms within a sector imply distortions. A firm with TFPR higher than the sector average suffers disproportionately more 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 $TFPQ_{si}$ as:

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

This shows that TFPQ is calculated from P_{si} , which contains elements of distortions, and κ is normalized to 1.⁹

$$P_{si} = \frac{\sigma}{\sigma-1} \frac{(1+\tau_{k_{si}})^{\alpha_s}}{A_{si}(1-\tau_{y_{si}})} \left(\frac{R}{\alpha_s}\right)^{\alpha_s} \left(\frac{\omega}{1-\alpha_s}\right)^{1-\alpha_s}.$$

Hsieh and Klenow (2009) choose the elasticity of substitution, $\sigma=3$,¹⁰ and $R=10$, assuming a real interest rate of 5% and a depreciation rate of 5%. Capital share, α_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 deviation from the US capital-labor shares suggests distortions.

Distortions represented by the output and capital wedges can be measured by:

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

$$1+\tau_{K_{si}} = \frac{\alpha_s}{1-\alpha_s} \frac{w_{si}L_{si}}{RK_{si}}$$

where 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 data. Rewriting this equation 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.

$$(1+\tau_{K_{si}})\frac{1-\alpha_s}{\alpha_s} = \frac{w_{si}L_{si}}{RK_{si}}.$$

If firm i 's actual labor-capital ratio $\frac{w_{si}L_{si}}{RK_{si}}$ 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

⁹ See Hsieh and Klenow (2009) for a detailed explanation.

¹⁰ Elasticity of substitution between products is related to the markups $\frac{\sigma_s}{\sigma_s-1} = 1 + \mu_s$, where μ_s is the markup. An elasticity of substitution of 3 corresponds to a markup of 50%.

that firm i uses less than the optimal level of capital. In other words, firm i has a positive capital wedge τ_{ksi} .

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

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

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 (B12) yields:

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

This 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 τ_{ksi} and/or higher τ_{ysi} also has a higher $TFPR$.

The industry average level $\overline{TFPR}_s$ corresponds to:

$$\overline{TFPR}_s = \left(\frac{\sigma}{\sigma-1} \frac{R}{\alpha_s \sum_{i=1}^{M_s} \left(\frac{1-\tau_{ysi}}{1+K_{si}} \right) \left(\frac{P_{si}Y_{si}}{P_sY_s} \right)} \right)^{\alpha_s} \left(\frac{w}{1-\alpha_s \sum_{i=1}^{M_s} (1-\tau_{ysi}) \left(\frac{P_{si}Y_{si}}{P_sY_s} \right)} \right)^{1-\alpha_s}$$

When there are no distortions (that is, $\tau_{ksi}=0$ and $\tau_{ysi}=0$) for all i , $TFPR$ s are equalized for all i .

Rewriting the latter equation:

$$\ln TFPR_s = \frac{1}{\sigma-1} \ln \left(\sum_{s=1}^{M_s} TFPQ_{si}^{\sigma-1} \right) - \frac{\sigma}{2} \text{var}(\ln TFPR_{si})$$

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 of:

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

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

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

Combining all elements together, we can calculate the ratio of the actual TFP in the economy to the efficient level of TFP as:

$$\frac{Y}{Y_{eff}} = \prod_{s=1}^S \left[\sum_{i=1}^{M_s} \left(\frac{A_{si}}{\overline{A}_s} \frac{TFPR_s}{TFPR_{si}} \right)^{\sigma-1} \right]^{\frac{\theta_s}{\sigma-1}}. \quad (\text{B18})$$

Appendix B. Bils, Klenow and Ruane (2017)

Hsieh and Klenow (2009) have attracted large attention, relying on model assumptions that allow to easily implement their framework across several countries. With increasing attention however has come also stronger scrutiny of the robustness of their distortion metrics. A key issue concerns measurement error, as acknowledge even by Hsieh and Klenow in their original paper. Bils, Klenow and Ruane (2017) develop a new methodology adapted from Hsieh and Klenow (2009) to address concerns of measurement error.

Bils, Klenow and Ruane (2017) propose estimating:

$$\Delta Ri = \Psi \Delta Ii + \Phi f(\ln(TFPRi)) - \Psi(1 - \lambda) g(\ln(TFPRi)\Delta Ii) + Ds + \xi i$$

Where Ri and Ii are firm-specific revenue and inputs (labor, capital and intermediate), $\ln(TFPRi)$ is the Tornqvist average for current and previous year, $f(\cdot)$ and $g(\cdot)$ are polynomials, and Ds are sector-year fixed effects.¹¹ The parameter of interest is λ which is defined as the ratio of the variances of true distortions and revenue productivity, i.e. $\lambda \equiv \frac{\sigma_{\ln \tau}^2}{\sigma_{\ln TFPR}^2}$, where τ is the firm-level distortion. If the elasticity of measured revenue with respect to inputs varies with the level of TFPR, then λ is different from one and measurement error is implied. Indeed, the presence of additive measurement error in either or both revenue and inputs can explain observing a marginal change in inputs but not a corresponding change in revenue.

We can then build a measure of revenue productivity that explicitly accounts for measurement error, $\widehat{TFPR}_i = \exp(\hat{\lambda} \ln(TFPR_i) + \epsilon_i)$ where $\epsilon_i \sim N(0, (\hat{\lambda} - \lambda^2)\sigma_{\ln(TFPR)})$.

The authors then resume Hsieh and Klenow's (2009) machinery to assess misallocation by comparing revenue and physical productivity. Specifically, gains are measured in terms of allocative efficiency. Allocative efficiency is sector s at time t is given by:

$$AE_{st} = \left[\sum_i \left(\frac{TFPQ_{sit}}{TFPQ_{st}} \right)^{\epsilon-1} \left(\frac{TFPR_{sit}}{TFPR_{st}} \right)^{1-\epsilon} \right]^{\frac{1}{\epsilon-1}}$$

Where $TFPQ_{sit} = \frac{R_{sit}^{\frac{\epsilon}{\epsilon-1}}}{(K^{\alpha} L^{1-\alpha})^{\gamma} X^{1-\gamma}}$; $TFPQ_{st} = [\sum_i TFPQ_{sit}^{\epsilon-1}]^{\frac{1}{\epsilon-1}}$; $TFPR_{st} =$

$\frac{\epsilon}{\epsilon-1} \left[\frac{MRPL_{st}}{(1-\alpha)\gamma} \right]^{(1-\alpha)\gamma} \left[\frac{MRPK_{st}}{(\alpha)\gamma} \right]^{(\alpha)\gamma} \left[\frac{MRPX_{st}}{1-\gamma} \right]^{1-\gamma}$; and the elasticity of substitution, ϵ , is assumed to be 4. $MRPL_{st}$, $MRPK_{st}$ and $MRPX_{st}$ are the revenue-weighted harmonic mean values of the marginal products of labor, capital and intermediates.

Aggregating across sectors we obtain inferred aggregate allocative efficiency, which is equal to true allocative efficiency when there is no measurement error $\widehat{AE}_t = \prod_{s=1}^S \widehat{AE}_{st}^{\frac{\theta_{st}}{\sum_{s=1}^S \gamma_s \theta_{st}}}$ where γ

¹¹ The subscript t for time is omitted, to simplify the notation.

is the output elasticity and θ is the sectoral share of manufacturing output. The gains from reallocation are then simply $\left(1/\widehat{AE}_t - 1\right) 100$.

Appendix C. Explaining possible sources of TFP variation

This section provides the theoretical arguments behind the evidence presented in Part 4. Part 3 provides evidence of misallocation but remains mute regarding the sources of misallocation. Part 4 provides a framework to fill this gap, keeping the focus on aggregate productivity estimated at the firm level, and relying on a methodology that can be used for cross country comparisons. Specifically, it combines two approaches as documented below.

I. Identifying sources of change in productivity

Melitz and Polanec (2015) propose an extension of the Olley and Pakes (1996) productivity decomposition which improves the measurement of the contributions to aggregate productivity changes from surviving, entering and exiting firms. Under their framework, aggregate productivity changes are expressed as follows:

$$\Delta TPF = \Delta TFP_S^{\text{Average}} + \Delta \text{Cov}_S + SH_{E2}(TFP_{E2} - TFP_{S2}) + SH_{X1}(TFP_{S1} - TFP_{X1})$$

where $\Delta TFP_S^{\text{Average}}$ is the unweighted mean change in the productivity of surviving firms, ΔCov_S is the covariance change between productivity for surviving firms and market share, $SH_{E2}(TFP_{E2} - TFP_{S2})$ is the difference in aggregate productivity between entrant and surviving firms weighted by the share of entrants, and $SH_{X1}(TFP_{S1} - TFP_{X1})$ is the difference in productivity between surviving and exiting firms weighted by the share of exiting firms.

To put things differently, Melitz and Polanec (2015) decompose movements in productivity into: the contribution of surviving firms (“within” component, first term), the allocative efficiency (“between” component, second term), the changes in productivity due to selection either in (entrants) or out (exiting) of the market (third and fourth terms).

II. Identifying sources of productivity dispersion

Under a restrictive set of assumptions, Hsieh and Klenow (2009) and by extension Bils et al. (2017) argue that productivity dispersion can be associated with misallocation, thus reducing aggregate TFP.¹²

III. Combining the approaches to infer potential sources of productivity growth

We compute the median (less sensitive to extreme values) and dispersion (we consider both standard deviation and interquartile differences) of aggregate productivity and show how changes

¹² It is worth noting that the literature acknowledges that TFP dispersion may be explained by other factors besides economic distortions or misallocation. For example, Asker, Collard-Wexler and De Loecker (2014) show that a standard investment model with adjustment costs can account for 80-90% of the cross-industry and cross-country variation in dispersion.

in these statistics can be mapped into the within and between components as shown in the table below.

		TFP MEDIAN	
		UP	DOWN
TFP DISPERSION	UP	<ul style="list-style-type: none"> • Upgrading firms' capabilities • Allocative inefficiencies/Distortions • Adjustment costs in capital • Uncertainty and volatility in sales (+within) (-between)	<ul style="list-style-type: none"> • Lack of upgrading of firms' capabilities • Allocative inefficiencies/Misallocation of capital • Adjustment costs in capital • Uncertainty & volatility in sales (-within) (-between)
	DOWN	<ul style="list-style-type: none"> • Upgrading firm's capabilities • Allocative efficiencies • Reduced uncertainty and volatility in sales • Higher flexibility to adjust capital (+within) (+ between)	<ul style="list-style-type: none"> • Lack of upgrading firm capabilities • Allocative efficiencies • Reduced uncertainty and volatility in sales • Higher flexibility to adjust capital (-within) (+between)