# How large is the productivity loss from misallocation?

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**Abstract**

Recent studies stipulate that large fraction of cross-country income differences could be accounted for by differences in productivity, which could be partially attributed to misallocation of resources across firms. Product market distortions, such large between-firm dispersion in markups, is considered as one of the main factors behind resource misallocation. In this paper, I quantify productivity loss from dispersion in markups and resource misallocation using firm level data from over 70 countries. Three main results emerge. First, productivity loss from misallocation is sizable, significantly varies across countries and is strongly negatively correlated with GDP per capita. Misallocation could explain about a quarter of cross-country variation in manufacturing productivity. Second, trade openness reduces the productivity loss from misallocation via reducing between-firm dispersion in markup (or revenue productivity). Third, the productivity loss from a counterfactual import ban significantly differs across countries, ranging from just under 5% in China to over 15% in a typical country with weak manufacturing sector, implying that the procompetitive effect of trade is more significant in countries with underdeveloped domestic manufacturing sector.

Keywords: Economic growth, Firm heterogeneity, International Trade, Misallocation, Markups, Productivity. JEL Codes: D43, F12, F14, L13, L60, O47

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# 1 Introduction

A number of studies in the past decade have documented large productivity dispersion among firms within narrowly defined industry.[1] Such productivity dispersion is considered as evidence of product and/or input (particularly capital) market distortion, and is believed to account for significant fraction of aggregate productivity differences across countries (Restuccia and Rogerson 2013; Restuccia and Rogerson 2017; Hsieh and Klenow 2009; Bartelsman et al. 2013). Aggregate productivity differences is a leading candidate in explaining why per capita income and living standards differ across countries.

This paper's main goal is to provide an empirical evidence on the link between misallocation of resources between firms in an industry, aggregate productivity and per capita income using firm-level data from over 70 countries. In particular, this paper aims at documenting how productivity loss from misallocation varies across countries and quantifying the effect of international trade. My main empirical exercises build on key theoretical insight from variable-markup heterogeneous-firm trade models such as (Melitz and Ottaviano 2008; Atkeson and Burstein 2008) that, if markups are increasing in firm productivity, more productive firms would have higher prices and lower output than they should have under monopolistic competition with constant markup/perfect competition environments. That is, when markups are increasing with firm productivity, output market is distorted, which leads to misallocation of resources. By increasing the competitiveness of the industry and forcing least productive firms exit, international trade decreases average markups and its dispersion among firms within industry (commonly known as the procompetitive effect of trade), thus decreasing misallocation.

I combine data from three main sources for my empirical analysis. The first dataset is World Bank Enterprise Survey (WBES). WBES provides firm-level data on revenue, employment, material input, capital, etc. from 149 countries. The key advantage of this data is that standardized methodology is used to collect data from all countries, which is crucial in minimizing discrepancies in definition and measurement of variables. The second data source is UNIDO-INDSTAT data which collects and distributes industry-level panel data on output, value-added, employment, number of firms, etc for over 150 countries. The third main data source is UN Commodity Trade data, which provides product-level bilateral trade data for virtually all countries in the world.

A number of interesting results emerge. First, there is large difference in the extent of within-industry dispersion in markups and revenue productivity across countries, which imply variation in the extent of resource misallocation across

[1] See Syverson 2011 and Restuccia and Rogerson 2017 for survey of literature.

countries. Second, the productivity loss from misallocation significantly varies across countries and decreases with GDP per capita (a correlation of -0.7), varying from about 15% in countries such as Sweden and Belgium to over 80% in some sub Sahara African countries and oil-based economies. Third, openness to import trade explains significant fraction of the variations in the extent of misallocation across countries and industries, consistent with the theoretical result of procompetitive effect of trade, while an industry's export orientation does not affect the extent of misallocation in the industry. A counterfactual import ban leads to different magnitude of productivity loss across countries. The productivity loss is significantly larger in countries where the manufacturing sector is less developed. That is, compared to countries where manufacturing sector is well developed, liberalization of import significantly improves the competitiveness of product markets in less industrialized countries thereby decreasing the extent of dispersion in markups and revenue productivity across firms within an industry by a larger magnitude. Lastly, misallocation could explain about a quarter of cross-country variation in aggregate manufacturing productivity and over a third of per-capita income differences.

The seminal paper by Hsieh and Klenow (2009) documents larger productivity dispersion among firms in India and China compared to their counterparts in the U.S., and interprets these results as reflecting poorer business environments in India and China.[2] In particular, they attribute the larger productivity dispersion in these countries to policies restricting firm size in India which limited the growth of more productive firms, and to state ownership in China which kept lower productive state-owned firms expand which otherwise may not have survived. The current paper explores whether the result of larger productivity dispersion in India and China, compared to USA, could be generalized to larger set of less developed and more developed countries, and explores how productivity loss from misallocation varies across countries.

This paper is closely related to Edmond et al. (2015) who use quantitative trade model to explore how trade liberalization increases competition, reduces markup and misallocation using Taiwanese data.[3] They show that, when domestic and foreign firms within a given sector are at similar level of productivity, opening to trade increases the level of effective head-to-head competition between home and foreign

[2] However, Ziebarth (2013) argues that higher productivity dispersion among Indian and Chinese firms, compared to US firms, is probably not caused by the factors hypothesized by Hsieh and Klenow (2009) by showing that US firms had similar TFP dispersion during the 19th century. Instead, he suggests that the underdevelopment of India and China is the likely reason for higher TFP dispersion compared to modern US. He emphasizes the role road network in explaining higher dispersion in TFP in modern India and China and 19th century US.

[3] See also Edmond et al. (2018) who quantify the welfare costs of markup in a dynamic model with heterogeneous firms and endogenously variable markups, and show that misallocation of resources is one of the main mechanism through which markups reduce welfare.

firms, which would lead to decrease in market power, markups and product market distortion. However, if, say, home country firms are substantially less productive than foreign firms, opening to trade would allow foreign firms to expand their market share, which would increase the dispersion in markups and TFPR. Contrary to Edmond et al. (2015), in this paper we find that the procompetitive effect of trade is larger for less industrialized countries than in countries where the domestic manufacturing sector is well developed. This could be attributed to the fact that in more industrialized countries, the domestic industry is already competitive enough so that the marginal gain from procompetitive effect of import is less significant. The exact opposite holds in countries with less developed manufacturing sector.

The current paper is also closely related to Epifani and Gancia (2011) who emphasize markup dispersion across sectors and how trade could potentially reduce welfare by increasing markup dispersion among sectors that are asymmetrically exposed to trade, particularly when entry is restricted. The current paper focuses on markup dispersion and misallocation among firms within industry, rather than misallocation between industries.

More recently, Peters (2020) studies how the distribution of markup is endogenously determined by firms' accumulation of market power by improving their productivity and creative destruction. In imperfectly competitive environment such as Bertrand competition, firms start with low markups because Bertrand competition forces the firm charge a limit price. Over time, a firm improves their productivity and increase their markups. Incumbent firm is replaced by a new firm with exogenous probability, which resets the markup. The author applies the model to firm-level data from Indonesia and shows that markups account for 15% of TFPR dispersion/misallocation. The current paper studies the role of trade in shaping the equilibrium distribution of markups among firms in an industry empirically in a reduced-form regression. Using a reduced-form analysis has the advantage that one need not take a stand on the specific channel through which trade openness affects the the distribution of markup. In the context of the model in Peters (2020), trade could affect the equilibrium distribution of markups by intensifying both the creative destruction and firms' investment on improving their productivity and accumulate market power.

A number of other studies have suggested why there could be larger productivity dispersion/misallocation among plants in developing countries compared to those in advanced economies, including: bad institutions and policies, such as corruption and direct government involvement (Restuccia and Rogerson 2017; Alfaro et al. 2009; Wu 2018); property rights and quality of legal system (Kalemli-Ozcan and Sørensen, 2014); credit market frictions (Gilchrist et al. 2013; Midrigan and Xu 2014); and quality of road infrastructure which limit growth of firms in some locations (Ziebarth

2013). A common feature of these studies is that they are based on plants in one country or a hand-full of countries with poorly comparable data. Comparing the levels of productivity loss from misallocation across countries and identifying the causes of its variation requires comparable firm-level data from many countries. In this paper, I use World Bank Enterprise Survey (WBES) data that covers plants in over 70 countries and provides comparable and consistent data across countries and over time.

This paper is also related to early studies that document the pro-competitive effects of trade including Levinsohn (1993) and Harrison (1994). Prominent theoretical papers include Melitz and Ottaviano (2008) and Atkeson and Burstein (2008). Chen et al. (2009) put the predictions in Melitz and Ottaviano (2008) to direct empirical test using industry-level data from EU and document that trade openness exerts competitive effect – industry prices and markup decrease and productivity increases in the short run following openness to trade.[4] A more recent paper, De Loecker et al. (2016), studies the pro-competitive effects of trade liberalization episode in India during early 1990s. They study the effect of both output and input trade liberalization and find that the net effect on markup is positive, i.e., though both output and input prices fall following the trade liberalization episode, input prices fall proportionately more, resulting in increase in markups. Feenstra and Weinstein (2017) structurally estimate the procompetitive effect (on markups) of globalization using a translog preference structure. The current paper complements these empirical studies by exploring the effect of trade openness on the second moments of markups and productivity distributions among firms within an industry, which has crucial implications for the effect of trade openness on resource misallocation and aggregate productivity.

The rest of the paper is organized as follows. Section 2 describes construction of dataset. Section 3 briefly describes the theoretical motivation while section 4 discusses measurement and estimation. Section 5 discusses the estimation results while Section 6 presents quantitative analysis of the aggregate productivity loss from misallocation and the effect of counterfactual import ban. Section 7 concludes the paper.

## 2 Data and sources

The data used in this paper comes from several sources.

[4]However, they find that the evidence on the pro-competitive effects of trade in the long run is more ambiguous.

**World Bank Enterprise Survey (WBES):** The WBES use standard survey instruments to collect firm-level data on revenue, labor, material and capital inputs, and several other firm performance measures as well as the business environment from business owners and top managers from about 150 countries.[5] World Bank offers the data in two formats: standardized and country survey. The standardized dataset follow the global standardized methodology -country data are matched to a standard set of questions. This format allows cross-country comparisons and analysis but sacrifices those country-specific survey questions which cannot be matched. This paper uses the standardized data. The standardized data includes over 90,000 firms from 149 countries.

The sampling methodology for Enterprise Surveys is stratified random sampling. The strata for Enterprise Surveys are firm size, business sector, and geographic region within a country. Firm size levels are 5-19 (small), 20-99 (medium), and 100+ employees (large-sized firms). Sector breakdown is usually manufacturing, retail, and other services. For larger economies, specific manufacturing sub-sectors are selected as additional strata on the basis of employment, value-added, and total number of establishments figures. Geographic regions within a country are selected based on which cities/regions collectively contain the majority of economic activity. Detail information about the survey methodology can be obtained following this link.[6]

The WBES is practically crossectional at country level. Some countries have multiple rounds of survey. When conducting a new Enterprise Survey in a country where data was previously collected, maximal effort is expended to re-interview as many firms from the prior survey as possible.

The most important advantage of WBES is that it uses standardized survey and methodology across countries, and is centrally administered by World Bank. This minimizes the concern of measurement errors that systematically vary across countries, due to say different methodologies or different definitions of variables across countries' statistics offices.

**UNIDO-INDUSTAT:** This dataset provides industry-level manufacturing data for over 150 countries, including historical data. We use the dataset at two-digit industrial classification (ISIC-3). For each two-digit industry classification, the data reports output, value-added, number of establishments, labor employment, wages and salaries, etc.[7] The latest data available if for the year 2018. The data goes back to 1960s for some countries.

[5] The surveys cover a broad range of topics including access to finance, corruption, infrastructure, crime, competition, labor, obstacles to growth, and performance measures.

[6] https://www.enterprisesurveys.org/en/methodology

[7] Detailed information about the data can be found here. https://stat.unido.org/

**Trade data:** Trade date comes from UN Commodity trade database. This dataset provides product-level annual bilateral trade (both import and export) data for over 200 countries. We use this data in combination with UNIDO's INDUSTAT data to construct measures of trade openness at industry-country-year level as discussed in section 4.

# 3 Theoretical framework

The theoretical discussion in this section builds on Atkeson and Burstein (2008) and Edmond et al. (2015). We assume a representative firm in a perfectly competitive market produces a homogeneous final good by combining outputs from $S$ sectors in a CES technology:

$$Y = \left( \sum_{s=1}^{S} Y_s^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}} \tag{1}$$

where $\rho$ is elasticity of substitution between outputs of different industries, and $Y_s$ is output from industry $s$, which is produced by a CES aggregate of differentiated intermediate goods within the industry:

$$Y_s = \left( \sum_{i=1}^{M_s} Y_{is}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \tag{2}$$

where intermediate good producing firms in an industry are indexed with $i = 1, ..., M_s$, and $\sigma > \rho$ is the elasticity of substitution among varieties within an industry.

Suppose the production function of firm $i$ is given as $Y_{is} = A_{is}F(K_{is}, L_{is})$, where $A_{is}$ is firm physical productivity (TFPQ), $K_{is}$ and $L_{is}$ are capital and labor inputs, and $Y_{is}$ is output. Later, we will make assumption about the functional form and introduce more inputs such as electricity. Note that the productivity level $A_{is}$ varies across firms.

**Demand for intermediate good:** The final good producer chooses quantities of intermediate inputs to maximize its profit given by:

$$\pi = PY - \sum_{s=1}^{S} \sum_{i=1}^{M_s} P_{is} Y_{is} \tag{3}$$

subject to equations 1 and 2. This gives the following expression of the demand for intermediate goods:

$$Y_{is} = \left(\frac{P_{is}}{P_s}\right)^{-\sigma}\left(\frac{P_s}{P}\right)^{-\rho} Y = P_{is}^{-\sigma} D_s, \quad \text{where} \quad D_s = P_s^{\sigma-\rho} P^{\rho} Y \tag{4}$$

where $P = \left(\sum_{s=1}^{S} P_s^{1-\rho}\right)^{\frac{1}{1-\rho}}$ is final good price, and $P_s = \left(\sum_{i=1}^{M_s} P_{is}^{1-\sigma}\right)^{\frac{1}{1-\sigma}}$ is intermediate good price index. Note that the nested CES structure implies that demand elasticity (and hence markup) varies across firms. For the case of Cournot competition, where each firm chooses its quantities taking the quantities of its competitors in the industry as given, Atkeson and Burstein (2008) and Edmond et al. (2015) show that the elasticity of demand can be given as a function of the firm's market share $z_{is}$:

$$\epsilon_{is} = \frac{1}{\frac{z_{is}}{\rho} + \frac{(1-z_{is})}{\sigma}} \tag{5}$$

where $z_{is} = \frac{P_{is} Y_{is}}{\sum_{i=1}^{M_s} P_{is} Y_{is} + \sum_{i'=1}^{M_s^F} P_{i's}^F Y_{i's}^F}$ is market share of a firm in domestic market, where the superscript $F$ represents foreign firms.

The intermediate good producing firm takes the above demand condition and maximizes the following profit:

$$\Pi_{is} = R(K_{is}, L_{is}, A_{is}, D_{is}) - \kappa K_{is} - w L_{is} - f \tag{6}$$

where $\kappa$ is rental rate of capital, $w$ is market wage rate and $f$ is fixed costs, both of which are assumed to be the same across firms. $R(.)$ is revenue function. $D_{is}$ captures the demand condition facing the firm, and it summarizes information about industry competitiveness. The only assumption we require to have within industry dispersion in productivity in equilibrium is that the revenue function $G(.)$ is twice differentiable and concave in $L$ and $K$. Specifically, we assume $\partial R/X > 0$, $\partial^2 R/\partial X^2 < 0$, $\partial R/\partial A > 0$, and $\partial R/\partial X \partial A > 0$, for $X \in L, K$. This, regardless of the form of competition in the product market gives us unique equilibrium capital $K_{is}^*$ and employment level $L_{is}^*$, which is increasing in firm productivity $A_{is}$.

Maximization of profit function in equation 6 subject to the demand condition in equation 4 implies that price is given as:

$$P_{is} = \mu_{is} \frac{c}{A_{is}}, \quad \textbf{where} \quad \mu_{is} = \frac{\epsilon_{is}}{\epsilon_{is} - 1} \tag{7}$$

where is $c$ is the cost of composite inputs common across firms (for a Cobb-Douglas technology and assuming only capital and labor as inputs it is given as $c = (\kappa/\alpha^k)^{\alpha^k}(w/\alpha^l)^{\alpha^l}$ where $\alpha^k$ and $alpha^l$ are output elasticities with respect to capital and labor, respectively) [8] and $\epsilon_{is}$ is firm-level demand elasticity defined in equation 5.

**Dispersion in A (TFPQ):** We define TFPQ as TFPQ $\equiv A_i = \frac{Y_i}{F(K_i,L_i)}$. We assume that a large pool of potential producers pay a sunk entry cost of $f_E$ to draw their productivity $A_i$ from a distribution with a density $g(A)$ and distribution function $G(A)$. There is a productivity cutoff $\underline{A}$ pined down by the free entry condition such that firms with a productivity draw above this cutoff make a positive profit and continue to produce, and those with productivity draw below this cutoff make negative profit and exit. The productivity distribution for the firms that decide to continue producing in equilibrium is the truncation of $g(A)$ above $\underline{A}$ and is non-degenerate because concavity of the revenue function ensures that more productive firms do not have the capacity to serve the entire market.

**Dispersion in TFPR:** Hsieh and Klenow (2009) present a special case where TFPR is constant across firms. This occurs with a constant returns to scale (CRS) Cobb-Douglas technology and isoelastic demand (constant markup across firms). In this particular case, high TFPQ ($\equiv A$) firms have an exactly offsetting lower price, so that there is no dispersion in TFPR across firms, unless there are distortions in the input markets.

However, in the case of variable markup (e.g., Melitz and Ottaviano 2008; Atkeson and Burstein 2008) higher TFPQ firms have higher markups, implying that firms do not pass on all their TFPQ advantage to consumers in the form of lower prices.[9] Such distortion in product market implies there would be dispersion of TFPR across firms. In other words, if higher TFPQ firms have higher markups (a condition that can be tested empirically), this restricts their size, ultimately leading to misallocation of inputs compared to allocation under competitive market or even imperfect competition with constant markup. The focus of this paper is this kind of misallocation in output market. Given the firm's production function $Y_i = A_i F(K_i, L_i)$, it's revenue is given by $R_i = P_i A_i F(K_i, L_i)$, and it's TFPR is defines as TFPR $\equiv P_i \times A_i = \frac{R_i}{F(K_i,L_i)}$. In logs and using equation 7 we can write:

$$\begin{aligned} \log\text{TFPR}_{is} &= \log P_{is} + \log A_{is} \\ &= \log \mu_{is} + \log c \end{aligned} \tag{8}$$

[8]To estimate misallocation within an industry, we do not require $c$ to be constant across firms in different industries, but we still require firms in the same industry face similar input costs.

[9]See Mary et al. 2019 for empirical evidences on how prices and markup vary with firm productivity and size. They show that the elasticity of firm price with respect to change in its marginal costs is 0.6 on average, and is declining in firm size. This implies that larger firms absorb significant fraction of the cost shocks in their markup while the pass-through of the cost shock to prices is almost complete for smaller firms.

If input costs are constant across firms within a country-industry cell, equation 8 shows that (i) TFPR and markups are positively related one-for-one in logs, for firms in the same country and industry, and (ii) dispersion in TFPR is proportional to dispersion in markups for firms in the same country and industry: $\text{var}(\log\text{TFPR}_{is}) \propto \text{var}(\log\mu_{is})$. We directly test whether these relationships hold empirically, as they are crucial tests of how well the theory fits the data. However, note that these results are direct implication of our assumption that the only source of misallocation is dispersion in markup. In section 6, we relax this assumption and entertain other sources of misallocation, distortion in the capital market.

**The effect of trade openness:** The misallocation due to product market distortion (variable markup) decreases with industries' competition from imports. This can be easily shown using equations 5, 7 and 8. From equation 5 we infer that elasticity of demand increases as market share decreases. Import competition decreases firm market share and hence increases the elasticity of demand that a firm faces and its markups.[10]

**Other potential channels:** One of the hypothesis regarding larger TFP dispersion among firms in a given industry in developing countries is slower technology/knowledge diffusion from frontier to laggard firms (Bahar 2018, Bessonova and Tsvetkova 2022). Opening to trade is also found to encourage technology adoption through improving the return on adoption of new technology (Bustos 2011, Lileeva and Trefler 2010). Hence, trade could reduce dispersion in $A_i$, and hence dispersion in markups, among firms within an industry via encouraging adoption of improved technology by lower productive surviving firms. However, if adoption of improved technology by laggard firms is the main operating channel of trade, we would also see that average

[10] In Melitz and Ottaviano (2008) – linear demand and Cobb-Douglas technology (without scale restriction)– using our notation, firm price and markup are given by $p_i = w/\underline{A} + w/A_i$ and $\mu_i = 1/2(w/\underline{A} - w/A_i)$, respectively. Thus, firms with higher $A_i$ have higher markups. This implies the following elasticity of firm price with respect to productivity.

$$\frac{dlog(p_i)}{dlogA_i} = -\frac{w/A_i}{w/\underline{A} + w/A_i} = -\frac{w/A_i}{2(\mu_i + w/A_i)} \tag{9}$$

(For comparison, in Hsieh and Klenow (2009) case of isoelatic demand, price is given by $p_i = \frac{\sigma}{\sigma-1}\frac{w}{A_i}$, which implies $\frac{dlogp_i}{dlogA_i} = -1$. That is, the correlation between $\log p_i$ and $\log A_i$ is perfectly negative.) Equation 9 shows that for higher markup (higher productive) firms, the correlation between $\log p_i$ and $\log A_i$ is weaker. That is, as $\mu_i \longrightarrow \infty$, $\frac{dlogp_i}{dlogA_i} \longrightarrow 0$. This implies that the correlation between firm productivity and firm size becomes weaker. In other words, more productive firms are undersized and are not employing as much resources as they should under constant/zero markup case.

Trade liberalization reduces distortion/misallocation through two channels. First, as low productive firms exit, market share and resources are reallocated towards more productive firms ($\underline{A}$ increases). Second, as the competitiveness of market increases (as reflected in increase in $\underline{A}$), markup of surviving firms decreases and hence distortion from high markups decreases.

industry markup would increase following openness to trade and improvement in productivity of firms. As we show below, this not the case – openness to trade decrease both the average level and dispersion of markups within an industry.

# 4 Measuring misallocation

Following the theoretical results above and previous studies (Hsieh and Klenow 2009; Foster et al. 2016; Foster et al. 2008), I use within industry-country-year variance in markups and TFPR as the main measure of product market distortion and resource misallocation. Below, I discuss the estimation of firm-level TFPR, TFPQ, and markup.

**Estimation of firm-level TFPR:** We now make functional form assumption for the production of intermediate goods. Each of the differentiated product in an industry are produced in the following Cobb-Douglas production function:

$$Y_{is} = A_{is} K_{is}^{\alpha_s^k} L_{is}^{\alpha_s^l} E_{is}^{\alpha_s^e} \tag{10}$$

where $i$ indexes firms/differentiated products within an industry $s$. $Y$ is measure of (value-added) physical output, $L$ is labor (number of workers), $k$ is value of capital (replacement value), and $E$ is spending on electricity. $\alpha_s^k$, $\alpha_s^l$ and $\alpha_s^e$ are the output elasticities with respect to capital, labor and electricity, respectively, and are allowed to vary across industries.

Given the intermediate good production function in equation 10, we define TFPQ and TFPR as follows:

$$\begin{aligned} \text{TFPQ}_{is} \equiv A_{is} &= \frac{Y_{is}}{K_{is}^{\alpha_s^k} L_{is}^{\alpha_s^l} E_{is}^{\alpha_s^e}} \\ \text{TFPR}_{is} \equiv P_{is} A_{is} &= \frac{P_{is} Y_{is}}{K_{is}^{\alpha_s^k} L_{is}^{\alpha_s^l} E_{is}^{\alpha_s^e}} \end{aligned} \tag{11}$$

Combining equations 10 and 4, we can write the revenue function of the intermediate good producing firm as follows:

$$R_{is} = \tilde{A}_{is} K_{is}^{\theta_k} L_{is}^{\theta_l} E_{is}^{\theta_s^e} \tag{12}$$

where $R_{is} = P_{is} Y_{is}$ is revenue, $\tilde{A}_{is} = D_s^{\frac{1}{\sigma}} A_{is}^{\frac{\sigma-1}{\sigma}} \equiv \text{TFPR}_{is}$, and $\theta_n = \alpha_n \frac{\sigma-1}{\sigma}$ for $n \in l, k, e$ are the elasticity of revenue with respect to capital, labor and electricity.

There are two widely employed production function specifications in the literature: the value-added production function and gross production function (which includes material expenditure as one of the inputs). The TFPQ and TFPR definitions for gross production function specification are straightforward modifications of those definitions given in equation 11 for value-added production function. Gandhi et al. (2017) document that the value-added and gross production function approaches imply different level of dispersion in TFP. To see whether the choice of specification for the production function has any effect on the results in this paper, I estimate TFPR following both value-added and gross production functions.

I obtain firm-level TFPR from a residual in either of the following regressions:

$$\begin{aligned}\text{Value-added:} \quad & v_{isct} = \theta^l_{sc} l_{isct} + \theta^k_{sc} k_{isct} + \theta^e_{sc} e_{isct} + \omega^v_{isct} + \varepsilon_{isct} \\ \text{Gross:} \quad & r_{isct} = \theta^l_{sc} l_{isct} + \theta^k_{sc} k_{isct} + \theta^m_{sc} m_{isct} + \theta^e_{sc} e_{isct} + \omega^r_{isct} + \varepsilon_{isct} \end{aligned} \tag{13}$$

where $r$ is log revenue, $v$ is log value-added i.e., log(revenue - material cost), $m$ is log material expenditure, $\omega^v$ and $\omega^r$ are unobserved value-added and revenue productivity,respectively, and $\varepsilon$ is a mean-zero random error. $i$, $s$, $c$, and $t$ index firm, industry(sector), country and year, respectively.[11]

The revenue elasticity parameters ($\theta$s) are separately estimated for firms in each industry-country cells. That is, the production technology is allowed to vary across countries and industries (sectors). To have enough degree of freedom in estimation of the production function parameters, I confine my estimation to industry-country cells that include at least 50 firms. But for quantitative analysis in section 6 I relax this restriction to industries with at least 30 firms.

There is a well know endogeneity concern in the estimation of the production function parameters and TFPR in equation 13. Unfortunately, due to the cross-sectional nature of our dataset, we cannot directly address this issue by employing the popular approaches to consistently estimate the production function such as the control-function approach of Olley and Pakes (1996) or Levinsohn and Petrin (2003). Instead, I check whether my results are robust by estimating the production function parameters and the TFPR non-parametrically using the index-method. However, because we are interested in within industry summary statistics and second moments of TFPR, the endogeneity problem in estimating production function parameters and TFPR might not matter as much as they usually do when one is interested in firm-level measures of TFPR.

**Estimation of TFPQ:** Because we do not observe firm level prices and quantities separately, estimation of TFPQ ($A_{is}$) is not straightforward. As a result, we rely on our theoretical model to obtain a measure for physical output $Y_{is}$. Given demand function $Y_{is} \propto P^{\sigma}_{is}$, we can write revenue $R_{is} = P_{is} Y_{is} \propto Y_{is}^{\frac{\sigma-1}{\sigma}}$, which implies

[11]Note that the value-added specification is consistent with a production function with the following structural specification: $R = L^{\theta^l} K^{\theta^k} E^{\theta^e} e^{\omega+\varepsilon} + M$. Subtracting $M$ from both sides and taking log gives the value-added regression equation in 13.

$Y_{is} \propto R_{is}^{\frac{\sigma}{\sigma-1}}$. We follow the trade literature and use a value of 5 for $\sigma$. Given a measure of $Y_{is}$, we can estimate the production function in equation 10 to recover the output elaticities with respect to capital, labor, electricity, and recover TFPQ (=A).

**Estimation of markups:** The theoretical discussion shows that dispersion in markup is a sign of product market distortion and would cause misallocation of resources, and that trade has a potential to reduce the within-industry dispersion in markup across firms. To test this hypothesis, we first estimate firm-level markups and construct a measure of within-industry dispersion in markup. We follow De Loecker and Warzynski (2012) to estimate firm-level markup. Their method is derived from cost-minimization problem of firms and does not assume a specific market structure in which the firm is competing. They show that a firm's markup $\mu$ can be estimated as follows:

$$\mu_{isct} = \frac{\theta_{sc}^X}{\alpha_{isct}^X} \tag{14}$$

where $\theta^X$ is the elasticity of value-added output with respect to variable input $X$ in the case of value-added production function or the elasticity of revenue with respect to variable input $X$ in the case of gross production function specification.[12] I use the value-added production function specification and labor as a variable input in my main specification. However, I show that the result is robust to markup estimates obtained from revenue elasticities estimated from gross production function. $\alpha_{isct}^X$ is the share of expenditure on input $X$ in firm value-added or revenue. Again, I restrict my estimation to industry-country cells that include at least 50 firms.

**Measures of openness:** We construct measures of openness for import and export trades at industry-country-year level. We combine UNIDO-INDUSTAT and the UN Commodity Trade datasets to construct these measures of openness. UNIDO-INDUSTAT data provides industry-level data on number of firms, output, value-added, employment, etc., for over 100 countries and from 1960s to 2018.[13] UN Commodity Trade dataset provides product-level bilateral trade flow between countries. We convert this dataset to industry-level by using concordance table provided by the Worldbank's WITS database.

The import and export openness measures are constructed as follows:

[12]Although it is possible to have firm-level variation in this elasticity by using a translog specification where interaction terms of the inputs are added in equation 13, this approach yields markup estimates that are implausible (too large or negative markup estimates) for a significant fraction of firms. So I stick to Cobb-Douglas specification of production function and estimate $\theta$ for each industry-country cells separately.

[13]Unfortunately, the dataset is not regularly updated for some countries though more and more countries are included over time.

$$\text{Import Openness} = \frac{\text{Industry Import}}{\text{Industry output}} \times 100 \tag{15}$$

$$\text{Export Openness} = \frac{\text{Industry Export}}{\text{Industry output}} \times 100 \tag{16}$$

While Import Openness measure can be any number greater or equal to zero, Export Openness measure should, in principle, range from 0 to 100. However, due to measurement and aggregation issues, and because some of the exports are re-exports, significant number of observations have export openness measure higher than 100. Thus, one should be cautious when interpreting the results about the effect of Export Openness.

**Openness and dispersion in markups:** We estimate the effect of trade openness on second moments of markups within industry-county-year cell in the following regression:

$$\begin{aligned}\text{Var(LogMarkup)}_{sct} = {} & \beta_0 + \beta_1 \text{Log(ImportOpenness)}_{sct} \\ & + \beta_2 \text{Log(ExportOpenness)}_{sct} + \gamma_s + \gamma_c + \gamma_t + \varepsilon_{sct}\end{aligned} \tag{17}$$

where $\text{Var(LogMarkup)}_{sct}$ is the variance of log markup within industry-country-year cell. The reason why we use variance of log markup (instead of variance of markup) will become clear when we talk about the quantitative analysis in section 6. We also use the ratio of 90th percentile to 10th percentile as an alternative measure of dispersion. The latter measure has the advantage that it is not sensitive to extreme values of TFPR. The $\gamma_s$, $\gamma_c$ and $\gamma_t$ are industry, country and year fixed effects. We estimate standard errors using bootstrap method to account for the fact the markups are estimated with error. The bootstrapping is conducted at country level to account for potential correlation of the error term among industries within a country.

**Openness and dispersion in productivity:** We estimate the effect of trade openness on second moments of productivity within industry-county-year cell in the following regression:

$$\begin{aligned}\text{Var(LogTFPR)}_{sct} = {} & \beta_0 + \beta_1 \text{Log(ImportOpenness)}_{sct} \\ & + \beta_2 \text{Log(ExportOpenness)}_{sct} + \gamma_s + \gamma_c + \gamma_t + \varepsilon_{sct}\end{aligned} \tag{18}$$

where $\text{Var(LogTFPR)}_{sct}$ is the variance of log TFPR within industry-country-year cell. The $\gamma_s$, $\gamma_c$ and $\gamma_t$ are industry, country and year fixed effects. We estimate standard errors using bootstrap method to account for the fact the dependent variable is estimated with error. The bootstrapping is at country level to account for potential correlation of the error term among industries within a country.

# 5 Results

## 5.1 Main results

This section presents the main results. I first test the crucial assumption behind how markups could serve as product market distortion by testing monotonicity of markups with firm productivity. I then present the results for the effect of openness on within-industry dispersion in markups and TFPR.

### 5.1.1 Monotonicity of markups with productivity

The key assumption behind markups as source of product market distortion and misallocation of inputs is that more productive firms (firms with higher TFPQ) have higher markups. As a result, they have higher prices and smaller size, and consequently aggregate productivity will be lower, than the first-best allocation where markups are uniform across firms. This assumption can easily be tested given firm-level estimates of markups and TFPQ. We estimate the following regression:

$$\text{Log}\mu_{isct} = \gamma_0 + \gamma_1 \text{Log(TFPQ)}_{isct} + \gamma_2 \text{X} + \delta_{sc} + \delta_t + \varepsilon_{isct} \tag{19}$$

where $X$ is a vector of firm size dummies: small ($< 20$ employees), medium (20-99 employees) and large (100 and more employees); $\delta_{sc}$ is country-sector(industry) fixed effect, and $\delta_t$ year fixed effect.

Table 3 presents the regression results. To check sensitivity of the results, we test monotonicity of markups with firm productivity using all the alternative markup estimations and the alternative productivity estimations discussed above. In panel A, the regressor is TFPQ estimated from value-added production function. All the four columns show that the elasticity of markups with respect to TFPQ is positive and statistically significant regardless of the methods used to estimate markups. Panel B uses TFPQ estimated from gross productions function as a regressor. Again, the results across the four columns show a positive and statistically significant elasticity of markups with respect to firm productivity. Note also that the elaticities of markups with respect to TFPQ are close to one in most specifications.

In our model, TFPR and markup are proportionate (at least within an industry), up to a positive constant that captures input costs (see equation 8). If this is also true empirically, it suggests that markups are the sole factor behind within-industry dispersion in TFPR and misallocation. We test this prediction by running the following regression:

$$\text{Log}(\text{TFPR})_{isct} = \gamma_0 + \gamma_1 \text{Log}\mu_{isct} + \gamma_2 \text{X} + \delta_{sc} + \delta_t + \varepsilon_{isct} \tag{20}$$

where $X$ is a vector of firm size dummies: small ($<$ 20 employees), medium (20-99 employees) and large (100 and more employees); $\delta_{sc}$ is country-sector(industry) fixed effect, and $\delta_t$ year fixed effect.

The result is reported in Table 4. The first panel uses TFPR estimated from value-added production function as dependent variable whereas panel B uses TFPR estimated from gross production function. In both panels, the elasticity of TFPR with respect to markup is high but not equal to unity. The only exception is the last column where the measure of markup used is the ratio of revenue to costs. These results suggest that, at least at firm level, TFPR is not proportional to markup. Figure 6 plots within-industry variances in logTFPR and logMarkups. While the two are strongly positively correlated, the correlation is significantly lower than unity. The figure also shows that the within-industry variance in markup is slightly higher than the variance of TFPR. These results suggest that markups are not the only source of TFP variation. In the next section, we will revisit how our baseline model could be extended to allow for other sources of TFPR dispersion and misallocation, in addition to markups.

#### 5.1.2 Markup level and dispersion

Before we present the results for the effect of trade openness on the within-industry average and dispersion of markup, we present the summary statistics of within industry-country-year median markups constructed following different methodologies in Table 1 . The first column reports the summary statistics for markup constructed from the value-added production function. Columns 2 and 3 present the summary statistics for markups constructed using revenue elasticities from gross production function, and the last column presents revenue-cost margin (revenue per cost). While all the markup measures are strongly correlated, the different measures imply different levels of markup.

Table 5 shows how markup levels vary with openness measures. Column 1 shows that average markup significantly decreases with import openness while Column 2 shows that export openness is not significantly correlated with average markup. Column 3 includes both import and export openness measures, and shows that average markup is still significantly negatively related to import openness. Using the summary statistics in Table 1, moving from the least open to the most open industry-country-year cells decreases industry markup by 25% relative to average.

The central point of this paper is that markups cause distortion in output market and may account for significant fraction of dispersion in TFPR. The larger the level of markups and the higher its dispersion, the higher the extent of product market distortion and TFPR dispersion. One would thus expect trade openness would decrease not only markup levels but also its dispersion across firms within an industry through increasing industry competitiveness. Table 6 presents the effect of trade on within-industry dispersion in markups. Panel A uses the within industry-country-year variance of log markup as a measure of dispersion. In column 1, we see that the variance of markup is significantly negatively related to import openness. Column 2 regresses the dispersion in markup on export openness and shows that there is no statistically significant relationship. Column 3 includes both import and export openness as regressors. The result shows that import openness continues to have a strong negative effect on markup dispersion. The point estimate implies that moving from the least open to the most open observation decreases the variance of logmarkup by about 50% relative to the mean.

Panel B replicates the same analysis as panel A using the within industry-country-year ratio of 90th percentile to 10th percentile markup as a measure of dispersion. The results in columns 1 and 3 clearly show that import openness significantly decreases the dispersion in markup.

#### 5.1.3 Dispersion in TFPR

First, we present how our estimated TFPR dispersion compare across the value-added and gross production function specifications. Table 2 reports summary statistics of the TFPR dispersion and measures of openness. Columns 1 and 2 report summary statistics for dispersion of TFPR obtained from value-added production function. In both columns, we observe that there is massive variation across countries and industries in the extent of within industry-country-year TFPR dispersion across firms: TFPR dispersion in the highest dispersion country is forty times the dispersion level in the lowest dispersion level. Columns 3 and 4 report similar summary statistics about dispersion in the TFPR obtained from gross production function. While the level of within industry dispersion in TFPR obtained from gross production function is smaller on average, compared to those obtained from value-added production function (as shown in figure 1), it still shows significant variation across countries and industries. Gandhi et al. (2017) show that the value-added and gross production function specifications yield systematically different level of within industry TFPR dispersion using firm-level data from and Colombia, with value-added specification yielding larger dispersion.

Table 7 shows the result for the effect of trade openness on TFPR dispersion within country-industry-year cells.[14] Panel A is based on TFPR estimated from value-added production function while Panel B uses TFPR estimated from gross production function. The results in Table 7 clearly shows that there is significant negative relationship between within industry dispersion in TFPR and openness (import penetration). This result is robust regardless of measure of TFP dispersion used. Focusing on panel A, the first column shows that import openness has a significant negative effect on the variance of logTFPR. Moving from the least open to the most open industry-country-year cell results in 0.44 decrease in the variance of logTFPR, which is nearly 60% of the average variance of logTFPR. On the contrary, export openness has no significant effect on the dispersion of TFPR as shown in column 2. Column 3 includes both import penetration and export openness as regressors and we see that the coefficient of import openness continues to be statistically significant and is of the same magnitude as under column 1. Panel B of Table 7 reports similar results using TFPR obtained from estimation of gross production function given in equation 13. Again, import penetration has statistically significant negative effect on dispersion of TFPR. However, the magnitude of the estimates is smaller. This is because TFPR estimated from gross production function shows less dispersion compared to the one estimated from value-added production function.

## 5.2 Robustness exercises

In the main result, we estimate the production function parameters and TFPR without addressing the potential endogeneity in the choice of inputs, due to data limitation. As a robustness exercise we estimate the production function parameters and TFPR using alternative approach, index-method.[15] According to this method revenue/value-added elaticities of factors are estimated as the share of factor costs in the firm revenue/value-added, and by taking the median or average across firms within industry-country. Because it is difficult to calculate the cost of capital services, this approach is often combined with constant returns-to-scale CRS assumption. Hsieh and Klenow (2009) employ this approach to estimate TFP in their analysis. Table A.1 presents the effect of openness on dispersion in TFPR estimated using index method and value-added production function. The results show that openness to import significantly decreases the dispersion of TFPR.

[14]There are 19 two-digit ISIC Revision 3 industries in the WBES data.

[15]Productivity estimates obtained following this approach are equivalent to TFPQ, assuming that firms' objective is cost minimization and production technology is constant returns to scale (see Blackwood et al. (2021) for more discussion).

# 6 Quantifying the aggregate productivity loss from misallocation

In this section, we quantify the extent of productivity loss from dispersion in markup and the potential gain from trade. The approach we take is simple, and closely connects with our empirical exercises in the previous section. First, we consider our baseline model where markup dispersion is the only source of TFPR dispersion and misallocation, and quantify the productivity loss from markup dispersion and the gain from trade. Next, we allow for other sources of dispersion in TFPR and quantify the productivity loss and the gain from trade.

When markup dispersion is the only source of TFPR dispersion, following Hsieh and Klenow (2009), it can be shown that when $A_{is}$ and $\mu_{is}$ are jointly log-normally distributed, the following closed-form expression for industry productivity can be written:

$$\begin{aligned}\log\text{TFP}_s &= \frac{1}{\sigma-1}\log\Big(\sum_{i=1}^{M_s} A_{is}^{\sigma-1}\Big) - \frac{\sigma}{2}\text{Var}\Big(\log\text{TFPR}_{is}\Big)\\ &= \frac{1}{\sigma-1}\log\Big(\sum_{i=1}^{M_s} A_{is}^{\sigma-1}\Big) - \frac{\sigma}{2}\text{Var}\Big(\log\mu_{is}\Big) \qquad (21)\end{aligned}$$

where the first term in this equation is industry productivity under efficient allocation and the second term captures how dispersion in markup across firms within an industry decreases the industry productivity. Equation equation 21 can be used to estimate the productivity gain from efficient reallocation (elimination of markup dispersion) at industry level:

$$\text{TFP}_s^{gain} = \frac{\log\text{TFP}_s}{\frac{1}{\sigma-1}\log\Big(\sum_{i=1}^{M_s} A_{is}^{\sigma-1}\Big)} \qquad (22)$$

Because our empirical exercises in the previous section enable us to directly estimate how openness to trade affects within-industry dispersion in markup (the second term in equation 21), it allows us to quantify the effect on aggregate industry TFP. We can use equation 22 to quantify the gain in industry productivity from increases in trade and the resulting decreases in markup dispersion – the so-called procompetitive effect of trade. Once we have industry productivity, the aggregate productivity gain is calculated as:[16]

$$\text{TFP}^{gain} = \left[ \frac{\sum_s \text{TFP}_s^{\rho-1}}{\sum_s \text{A}_s^{\rho-1}} \right]^{\frac{1}{\rho-1}} \tag{23}$$

where $\text{TFP}_s$ is obtained from equation 21 and $A_s = \left( \sum_{i=1}^{M_s} A_{is}^{\sigma-1} \right)^{\frac{1}{\sigma-1}}$ is industry TFP under first-best allocation. We use $\rho = 1.8$ (though we find that the result is very similar for different values of $\rho \in [1.1, 3]$. Theoretically, the only requirement on $\rho$ is that it should be less than $\sigma$.

## 6.1 Productivity loss from dispersion in markup and the procompetitive gain from trade

Before we present the productivity gain from trade, we present the loss in productivity from within-industry dispersion in markup and how it varies across countries at different stages of economic development. Figure 2 presents TFP loss from markup dispersion (TFP as a percent of TFP under first-best allocation, i.e., with zero dispersion in markup) and how it varies with GDP per capital across countries. The figure shows a strong positive correlation of 0.544 between TFP loss and GDP per capita. The TFP loss from markup dispersion in high-income countries such as Belgium, Denmark, Finland, Sweden, and Netherlands is around 5%, whereas the TFP loss in some countries in Sub Saharan Africa, South Asia and East Europe is above 50%. Notably, oil-based economies such as Azerbaijan, Iraq and Kazakhstan seem to have high TFP loss from misallocation. Figure 3 shows the flip-side of the figure where the TFP gain from efficient reallocation is plotted against GDP per capital. The productivity gains from efficient reallocation in countries such as Azerbaijan, Afghanistan, Albania, Pakistan and Uruguay are above 50%. The efficiency gain in emerging economies also seems sizable but heterogeneous: e.g., China (21%), India (24%), Mexico (21%), Turkey (23%), South Africa (22%), Poland (34%), Thailand (38%), and Brazil (45%).

Now we explore the productivity effect of a counterfactual import ban. First, we estimate by how much industry markup dispersion increases from a counterfactual import ban based on our reduced form estimation from the previous section. The estimation results in panel A of Table 6 show that the elasticity of the variance of log markup with respect to import openness is about 0.061. We use this estimate to calculate the resulting increases in markup dispersion following a complete import

[16]This aggregation assumes there is no between-industry misallocation. We make this simplification mainly due to data limitation. In our data, significant number of the countries do not have multiple manufacturing sectors with more than 30 firms (our threshold for including in the analysis).

ban for each industry, and quantify its effect on industry productivity using equations 21 and 22. In Figure 4, we present TFP loss from a counterfactual import ban aggregated across industries for each country for the most recent year with available data. The figure shows that the procompetitive gain from trade significantly varies across countries, from just under 5% in China to about 45% in Azerbaijan, with the median and average of about 11%.

A closer look at figure 4 reveals that countries that experience larger productivity loss from import ban are less industrialized countries or oil-dependent countries (such as Azerbaijan and Iraq). Import ban is likely to worsen product market distortion more seriously in countries such as Afghanistan, Democratic Republic of Congo, Ethiopia and Madagascar where the domestic manufacturing sectors is less developed than in countries where domestic manufacturing sector is well developed such as China, Indonesia, Ireland, Turkey and Italy. This is confirmed in figure 5 which plots TFP loss from import ban against manufacturing value-added as a percentage of GDP. This is because the procompetitive effects of imports is significant in less industrialized countries than it is in more industrialized countries, implying that efficiency loss from a counterfactual import ban is larger in less industrialized countries. In other words, less industrialized countries have higher import to domestic production ratio across many industries implying that the procompetitive benefit from trade is likely to be larger whereas in countries where the domestic manufacturing sector is well developed, the procompetitive gain from import is marginal.

Our results are very similar to the estimated gain from trade in Edmond et al. (2015), who find about 13% productivity loss from a counterfactual move to autarky using manufacturing data from Thailand. Our estimates show similar level of productivity loss for countries at similar level of manufacturing development, despite our different approach in quantifying the effect of trade restriction.

## 6.2 Extension: capital misallocation

Our analysis in the previous subsection assumes that markups are the only source of misallocation. Though our model predicts that markup and TFPR are proportional up to a constant factor (see equation 8) and hence should have equal dispersion, empirically this is not exactly true. Figure 6 plots the dispersion in logTFPR against the dispersion in logMarkup at industry level, which shows that the dispersion in TFPR is larger than that of markup for most industries. The dispersion in TFPR is strongly correlated with dispersion in markup but the correlation between the two is not perfect. Table 4 shows that the correlation between log markup and log TFPR is less than one, though it is clearly close to one.

Equation 8 implies that another potential source of dispersion in TFPR is variation in the cost of inputs across firms. While our empirical approach still allows for variation in factor prices across industries/sectors, so far we assumed firms within an industry faced the same prices of labor, capital and electricity. However, a growing literature documents that firms face different costs of capital (Wu 2018; David and Venkateswaran 2019; Hsieh and Klenow 2009; Midrigan and Xu 2014; Gilchrist et al. 2013). This could be due to financial frictions or due to outright government favoritism or political connection in favor of some firms. Regardless of the underlying cause, if firms within the same industry face different costs of capital, this would lead to dispersion in TFPR among firms within an industry even in the absence of product market distortion. Let $\kappa_{it}$ denote the firm specific cost of capital. This modifies equation 8 as follows:

$$\log\mathrm{TFPR}_{is} = \log\mu_{is} + \alpha_s^k \log\kappa_{is} + c \tag{24}$$

where $\kappa_{is}$ is the cost of capital faced by firm $i$, $c = (w/\alpha_s^l)^{\alpha_s^l}(p_e/\alpha_s^e)^{\alpha_s^e}$ captures the composite cost of labor and electricity, whose prices $w$ and $p_e$ are assumed to be the same across firms within an industry. Because the firm employs capital at a point where the marginal revenue product of capital (MRPK) equals the cost of capital, in equilibrium $\kappa_{is} = \mathrm{MRPK}_{is} = \theta_s^k \frac{R_{is}}{K_{is}}$.

Substituting the expression for the variance of $\log\mathrm{TFPR}_{is}$ from equation 24 in equation 21, we can write the aggregate industry productivity in the following closed form:

$$\begin{aligned}\log\mathrm{TFP}_s = \frac{1}{\sigma-1}\log\Big(\sum_{i=1}^{M_s} A_{is}^{\sigma-1}\Big) - \frac{\sigma}{2}\mathrm{Var}\Big(\log\mu_{is}\Big) - \frac{\sigma(\alpha_s^k)^2}{2}\mathrm{Var}\Big(\log\kappa_{is}\Big) \\ - \sigma\alpha_s^k \mathrm{Cov}\Big(\log\mu_{is}, \log\kappa_{is}\Big)\end{aligned} \tag{25}$$

Figures 7 and 8 show the scatter plots of the ratio of actual TFP to TFP under efficient allocation (i.e., TFP under zero within-industry dispersion in TFPR) and TFP gain from efficient reallocation against Log GDP per capita. Two key results emerge. First, the TFP gain from setting within-industry TFPR dispersion to zero is significantly larger compared to TFP gain from reducing within-industry markup dispersion to zero. This implies that misallocation in the factor (capital) market is sizable. The TFP gain ranges from about 20% in high-income countries such as Belgium, Denmark, Finland, Ireland, Netherlands, and Sweden to over 90% in Democratic Republic of Congo, Ivory Coast, Malawi, and Indonesia. The efficiency gain in emerging economies also seems sizable: e.g., Brazil (65%), China (34%), India (40%), Mexico (32%), Poland (39%), South Africa (46%), and Thailand (50%). Second, the figures show a strong correlation of productivity loss from misallocation with level of economic development. The correlations are 0.64 in figure 7 and -0.64 in 8. This is consistent with the result based on markup dispersion in figure 2. However, unlike the TFP loss from markup dispersion, we do not observe higher TFP loss in oil-based economies.

There are some notable anomalies in the results reported in figure 8. Italy and Turkey show over 90% gain from reallocation. Italy also shows higher misallocation due to markup dispersion (see figure 3). However, Turkey shows modest misallocation from markup dispersion but is among the highest in capital misallocation.

To quantify the gain from import openness, we conduct a counterfactual analysis where each industry import is set to zero (i.e., complete import ban). We proceed as follows. We follow similar procedure as our counterfactual experiment using dispersion in markup. First, we use our estimates in the first column of table 7 to map the import ban to increase in TFPR dispersion. Second, we recalculate industry TFP using equation 25. Note that TFPR dispersion includes markup dispersion, the MRPK dispersion and their covariance. Thus, the productivity loss from increase in TFPR dispersion due to import ban is larger than the loss from increased markup dispersion (the procompetitive effect) alone.

The results are reported in figure 9. A number of interesting results emerge. First, there is significant variation in the extent of productivity loss from import ban. The aggregate productivity loss from import ban ranges from about 8% in Ireland to over 80% in DRC. Compared to the exercise based on markup dispersion in Figure 4, the TFP loss calculated based on increase in TFPR dispersion are slightly larger.

Comparison of figures 4 and 9 reveals that the rankings of the countries in terms of TFP loss from import ban is not necessarily consistent across the two figures. This is because figure 4 captures only the procompetitive effect of trade while figure 9 captures both the procompetitive effect of trade and the effect on dispersion of MRPK. Some countries such as Indonesia and Turkey have relatively large MRPK dispersion but a modest markup dispersion. As a result, the procompetitive gain from trade is smaller but the gain from decrease in dispersion of MRPK is large.

Finally, figure 11 plots comparison of productivity gain from from efficient reallocation across gross and value added production function specifications. The figure clearly shows that the value-added production function implies larger productivity gain from efficient reallocation than the gross production function. This is a direct consequence of figure 1, which shows that TFPR estimated from value-added production function shows larger dispersion than the TFPR estimated from gross production function. However, productivity gains across the two specifications are strongly positively correlated (a correlation of 0.85).

## 6.3 How much of cross-country productivity and per capita income gaps are explained by misallocation?

Next we try to answer two interrelated questions. First, how much of cross-country variation in manufacturing productivity is attributed to misallocation? Second, how much of cross-country gap in GDP per capita is attributed to misallocation?

To answer these questions, we use a simple variance decomposition. First, given our measures of aggregate manufacturing TFP and misallocation at country level, from the law of total variance (LTV), we can write the following equation:

$$\text{Var(TFP)} = \text{Var}\Big(\text{E[TFP/Misallocation]}\Big) + E\Big[\text{Var(TFP/Misallocation)}\Big] \tag{26}$$

where $E$ is expectation sign. The first term captures the variance of TFP explained by misallocation whereas the second term captures the variance of TFP that is not explained by misallocation. We are interested in the quantity $\frac{\text{Var}\left(\text{E[TFP/Misallocation]}\right)}{\text{Var(TFP)}}$, which is the fraction of variation in TFP that is explained by misallocation. Assuming that the conditional expectation of TFP is linear, it can be shown that $\frac{\text{Var}\left(\text{E[TFP/Misallocation]}\right)}{\text{Var(TFP)}} = \text{corr(TFP, Misallocation)}^2$. The correlation between log TFP and misallocation measure is -0.52. This implies that about 27% of variation in log TFP across countries is explained by variation in the level of misallocation across countries.

Next, we follow similar logic to answer how much of variation in log GDP per capita across nations could be attributed to misallocation $\frac{\text{Var}\left(\text{E[logGDPPC/Misallocation]}\right)}{\text{Var(logGDPPC)}} = \text{corr(logGDPPC, Misallocation)}^2$. The correlation between log GDP per capita and and misallocation is -0.64, which implies that the up to 40% of cross-country per capita income gap could be explained by differences in the level of resource misallocation across countries.

# 7 Conclusions

This paper quantifies the productivity loss from product market distortions (markups) and capital market distortions. The productivity loss from both product and capital market distortions are sizable and vary systematically across countries. In particular, the productivity loss from these distortions are significantly larger in developing countries compared to developed countries. A simple analysis of variance shows that productivity loss from missallocation could account for about a quarter of of cross-country differences in aggregate productivity.

This paper also presents strong evidence that product market distortion due to variation of markups across firm within industry strongly responds to import competition – the so-called procompetitive effect of trade. Previous studies have shown that import competition could decrease the average industry markups by improving the competitive environment. The current paper shows that import openness decreases not only the average but also the dispersion of markups across firms within an industry. The decrease in markup dispersion in turn implies lower resource misallocation and higher industry productivity. Such procompetitive effect of trade is stronger in countries where the domestic manufacturing sector is underdeveloped and less competitive (such as sub Saharan countries) compared to countries with a vibrant domestic manufacturing such as China.

# Figures and tables

Figure 1: Kernel density of dispersion in TFPR

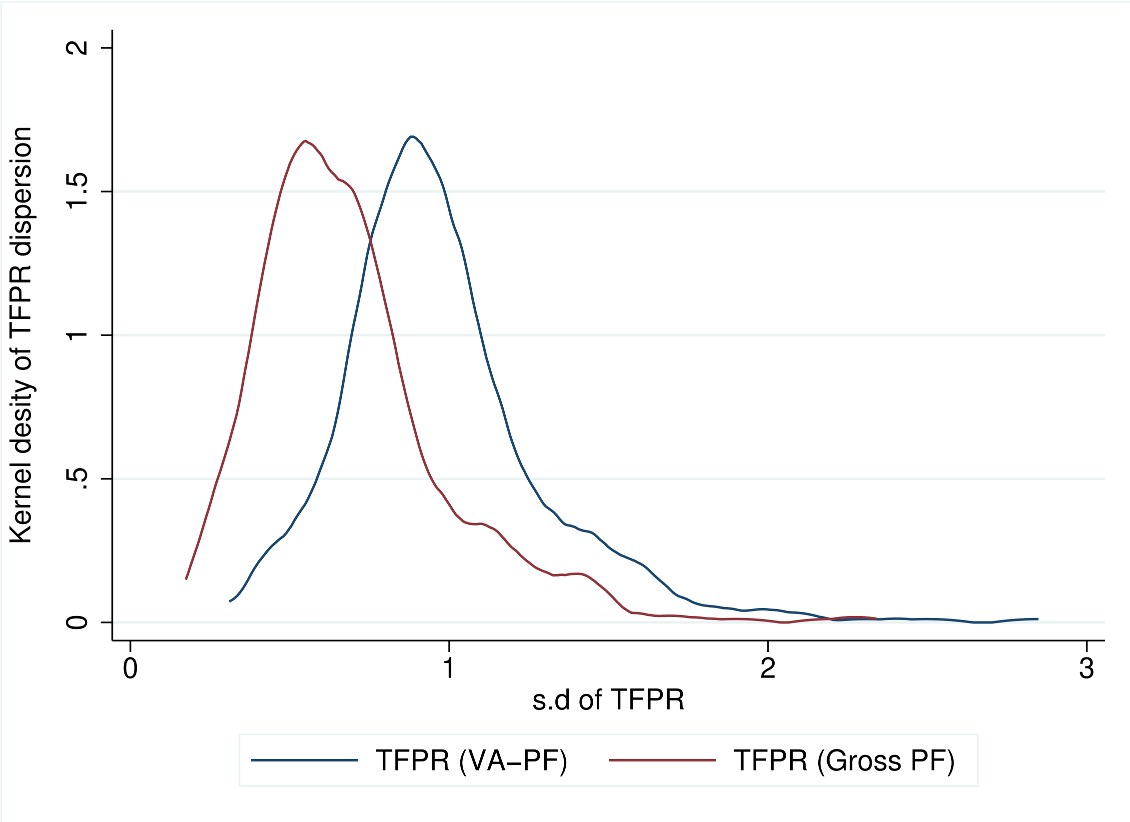


Figure 2: TFP as a percent of TFP under efficient allocation and log GDP per capita

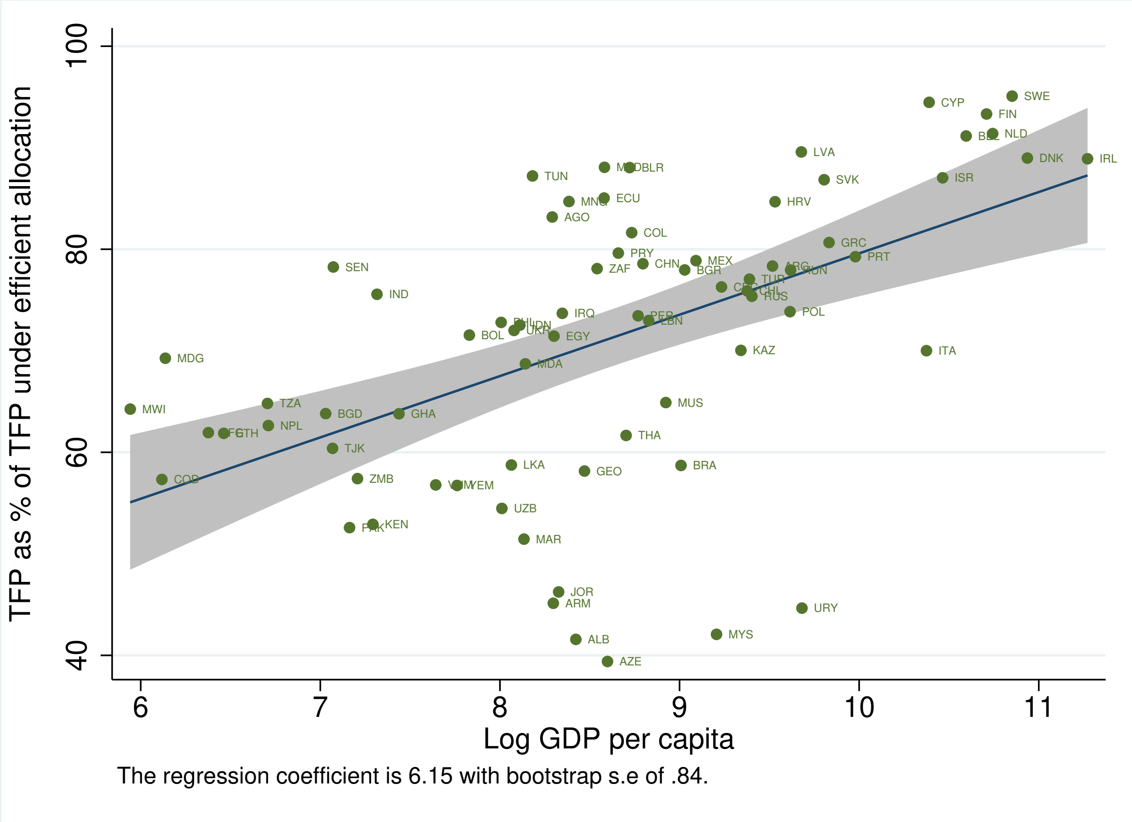



Figure 3: TFP gain from efficient reallocation

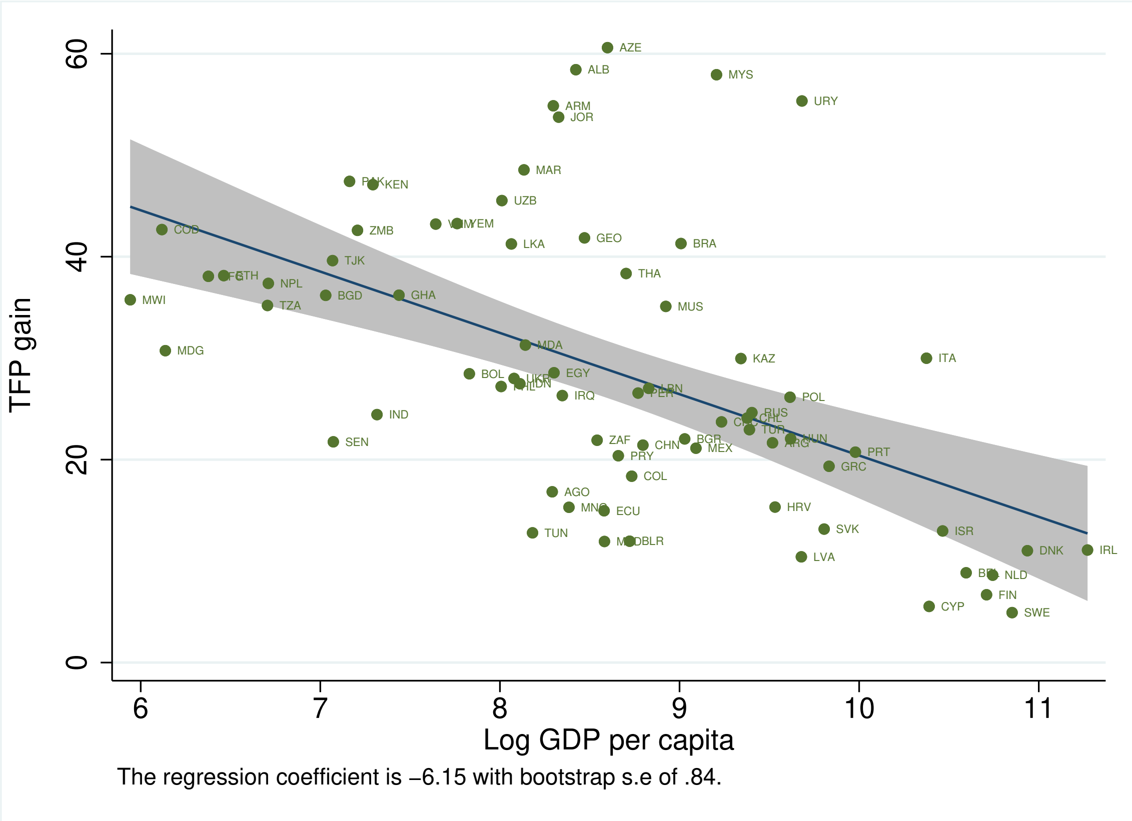


Figure 4: TFP loss from import ban

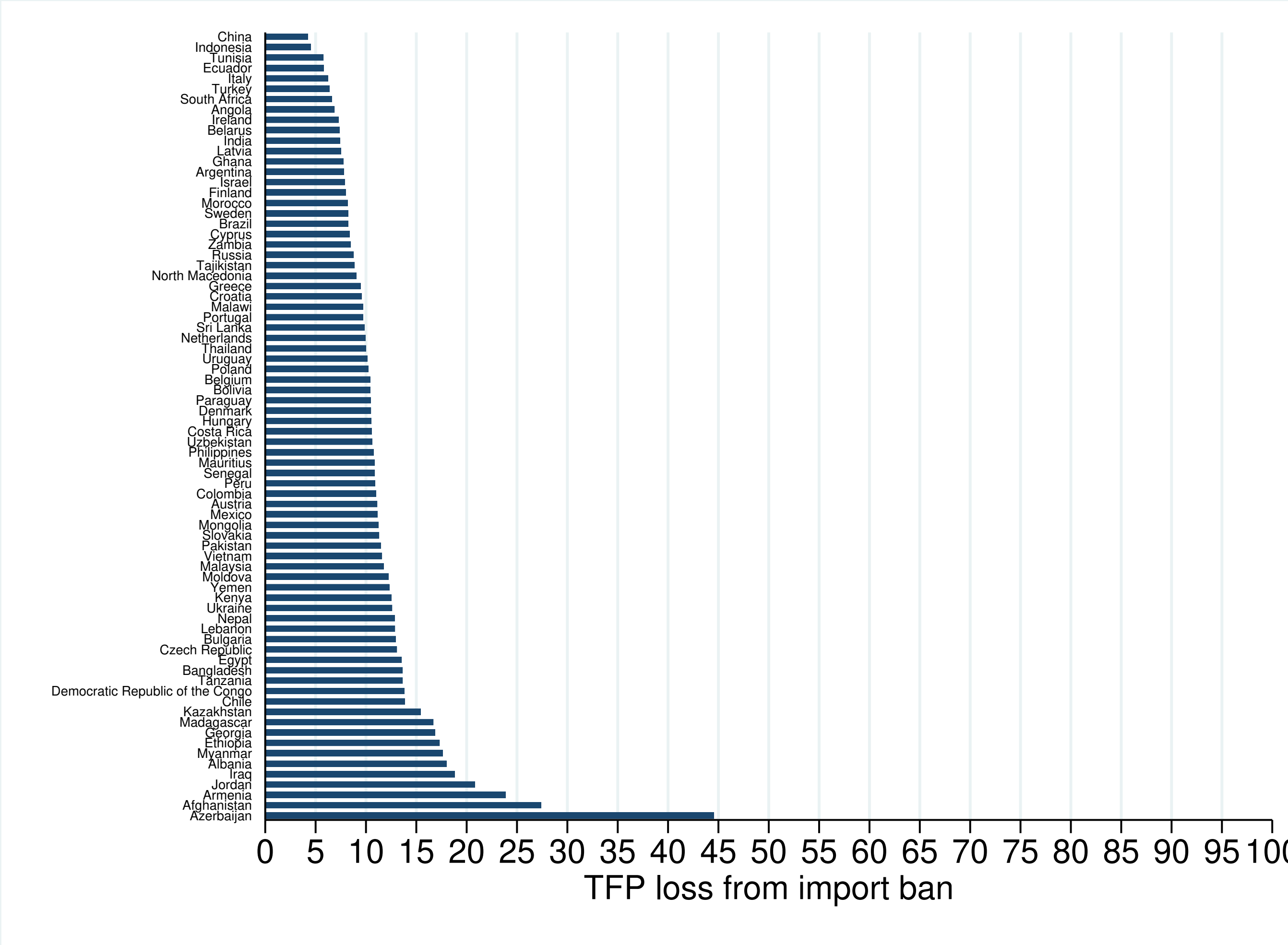
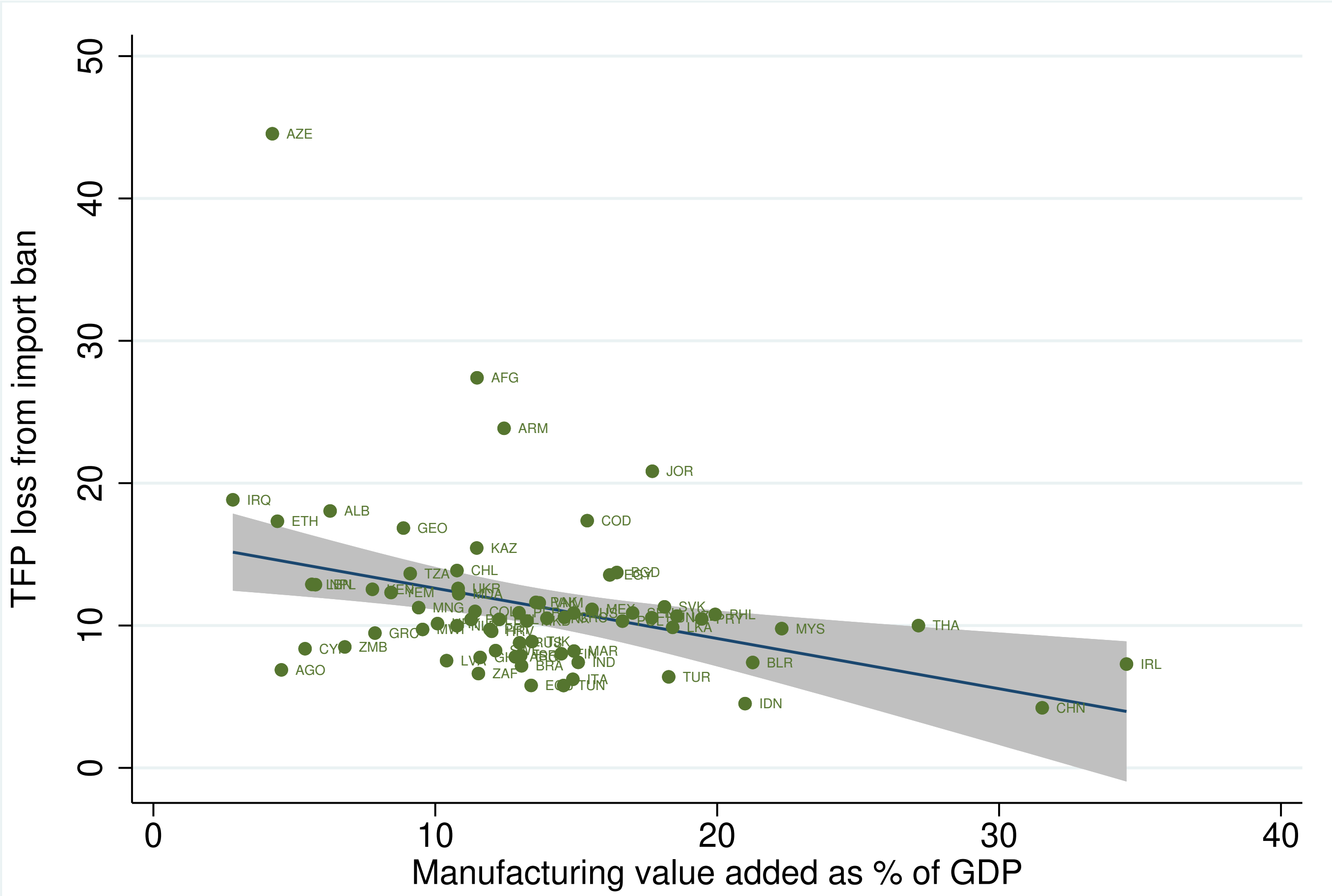
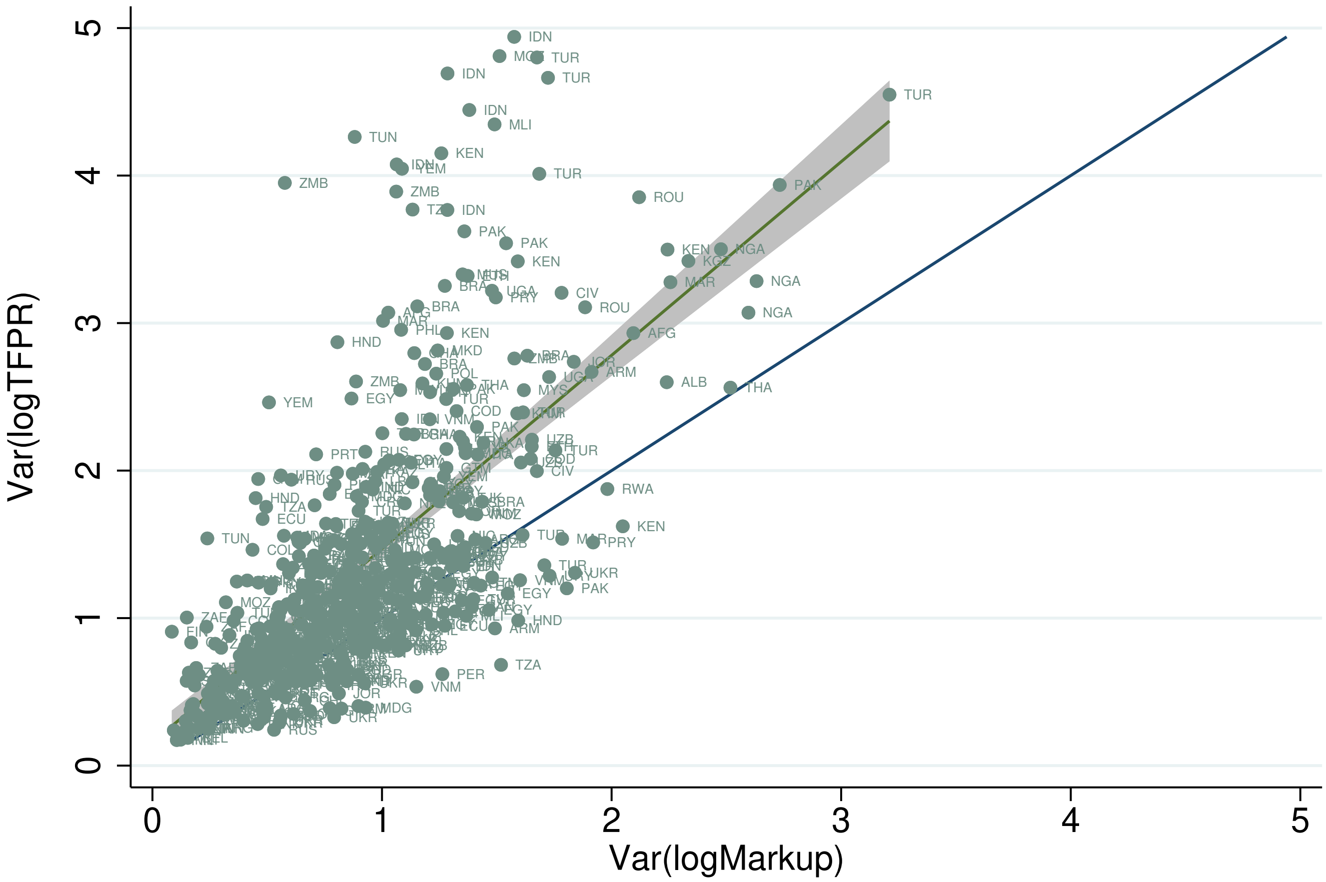


Figure 5: TFP loss from import ban and manufacturing sector development



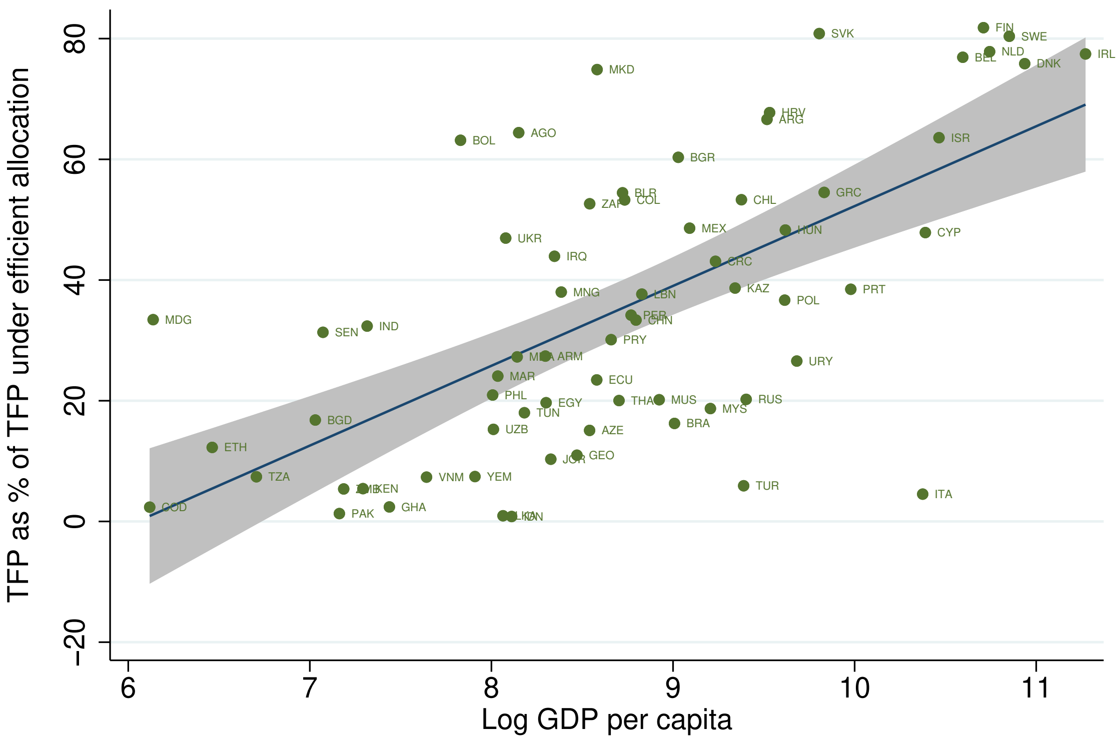

The regression coefficient is −0.35 with bootstrap s.e of 0.15.

Figure 6: Correlation between Var(LogTFPR) and Var(LogMarkup)




The regression coefficient is 1.85 with bootstrap s.e of 0.19.

Figure 7: TFP as a percent of TFP under efficient allocation and log GDP per capita: VA PF




The regression coefficient is 13.23 with bootstrap se of 1.91.

Figure 8: TFP gain from efficient reallocation: VA PF

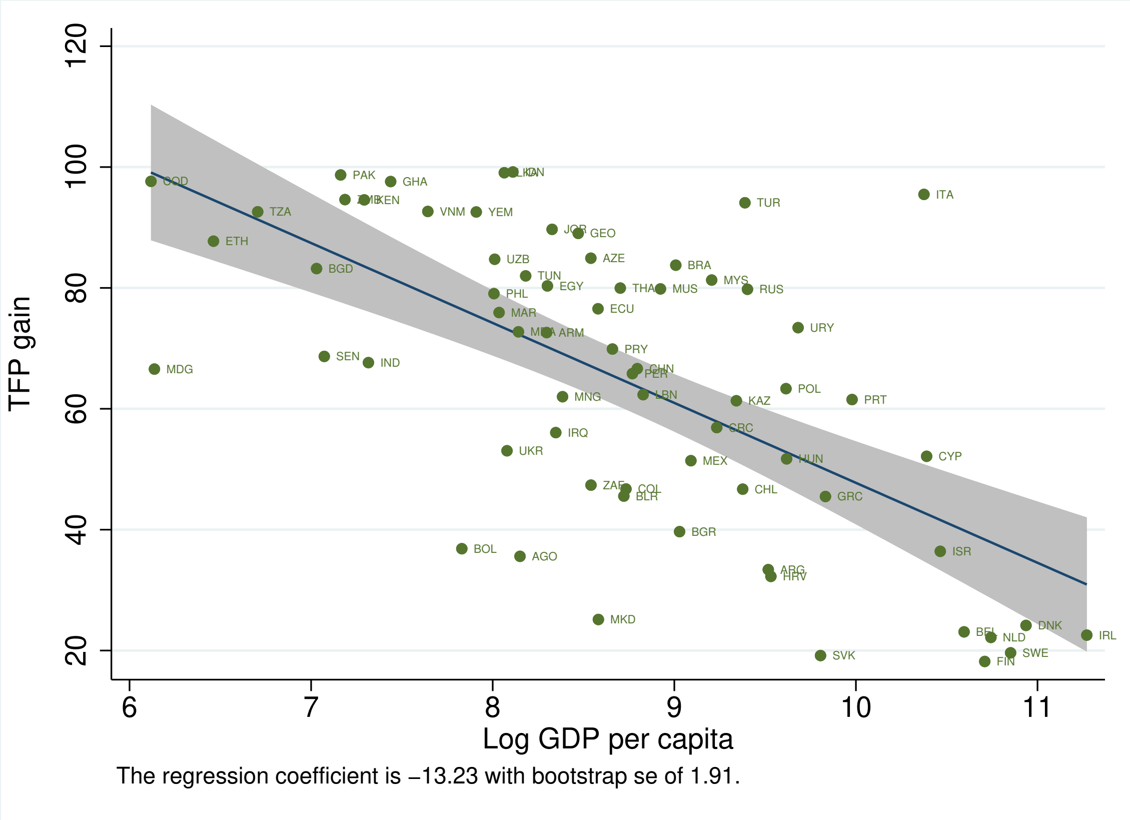



Figure 9: TFP loss from import ban

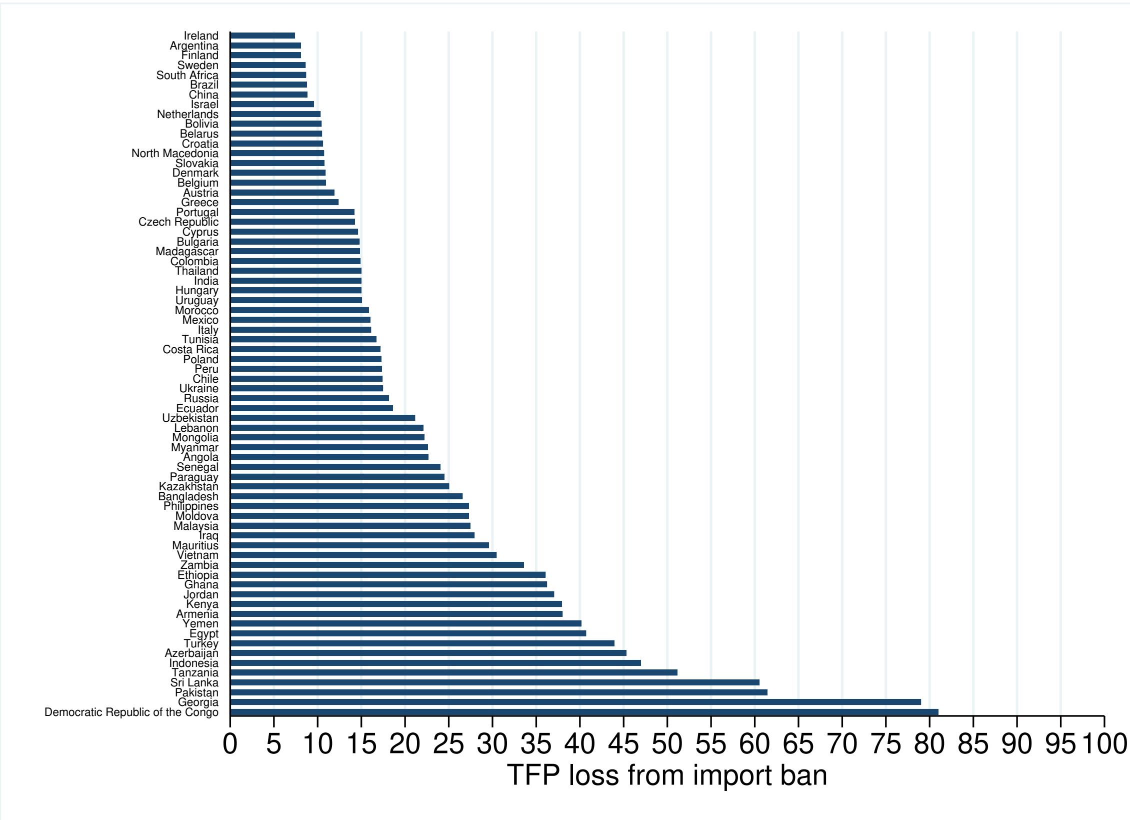


Figure 10: TFP gain from efficient reallocation: gross PF

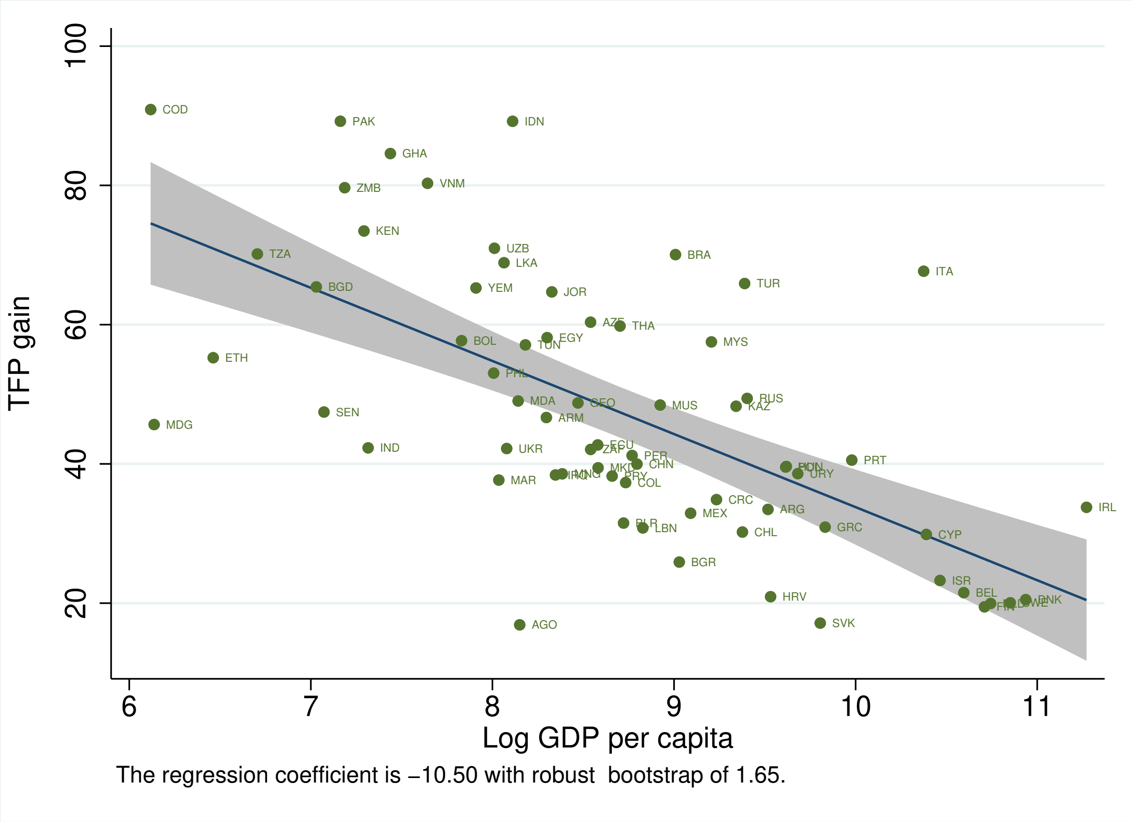



Figure 11: TFP loss from import ban and manufacturing sector development

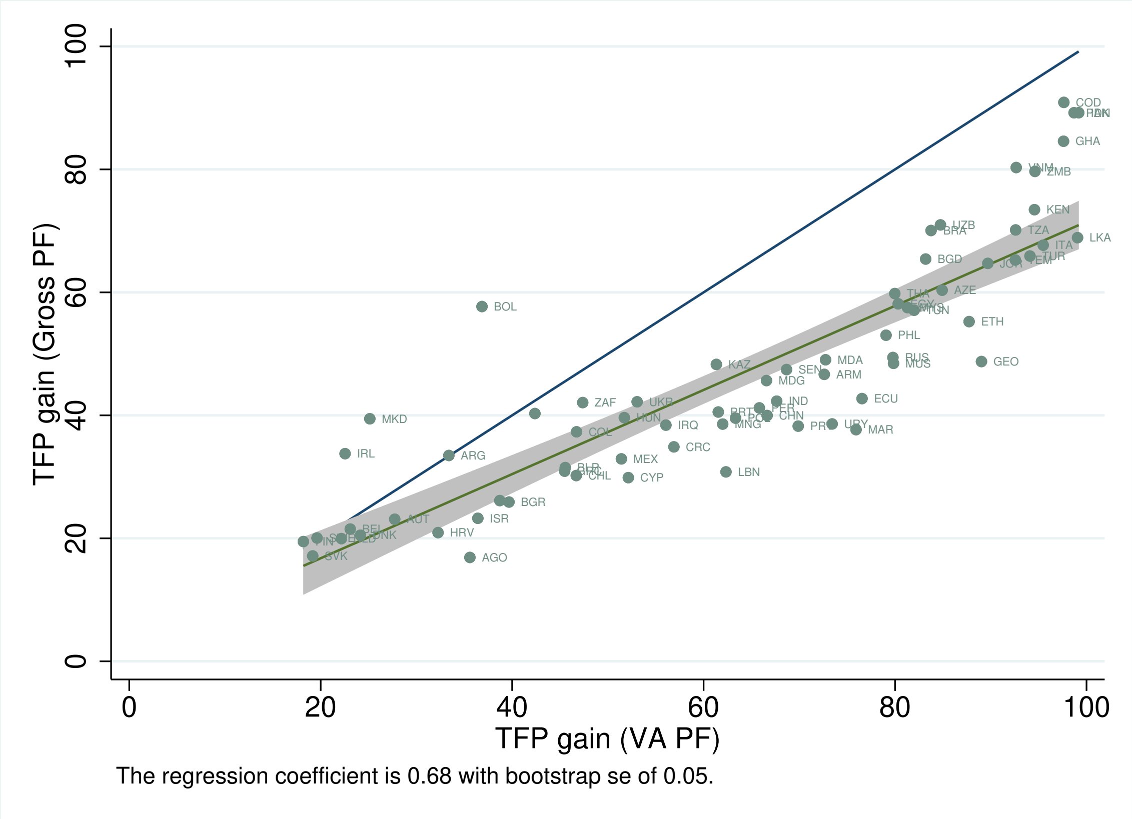


Table 1: Summary statistics of median (within industry-country-year) markups across countries and industries

| | Value-added PF | Gross PF | | Revenue-cost approach |
|---|---|---|---|---|
| | $\frac{\theta^l_{isct}}{\alpha^l_{isct}}$ | $\frac{\theta^l_{isct}}{\alpha^l_{isct}}$ | $\frac{\theta^m_{isct}}{\alpha^m_{isct}}$ | $\frac{\text{Revenue}}{\text{Total costs}}$ |
| P1 | 0.544 | 0.224 | 0.353 | 0.525 |
| P10 | 1.588 | 1.190 | 0.789 | 1.082 |
| P25 | 1.981 | 1.688 | 1.022 | 1.181 |
| P50 | 2.464 | 2.244 | 1.262 | 1.259 |
| Mean | 2.755 | 2.520 | 1.505 | 1.306 |
| P75 | 3.171 | 2.997 | 1.534 | 1.382 |
| P90 | 4.111 | 4.086 | 2.042 | 1.556 |
| P99 | 8.464 | 7.161 | 8.824 | 2.258 |
| SD | 1.354 | 1.449 | 1.541 | 0.306 |

Notes: P1, P10, P25, P50, P75, P90, and P99 represent the 1, 10, 25, 50, 75, 90, and 99 percentile values of the statistics. $\theta^X$ is revenue elasticity with respect to variable input $X$. In column 1, $\theta^X$ is estimated from a value-added production function. In columns 2 and 3, it is estimated from Gross production function as output elasticity with respect to labor and material inputs, respectively. $\alpha^X_{isct}$ is the share of expenditure on input $X$ in firm revenue. In column 4, total cost is calculated as the sum of material, labor, electricity and 0.1*replacement value of capital.

Table 2: Summary statistics of openness measures and dispersion in markups and TFPR

| | Var($\mu^l_{va}$) | Var($\mu^l_{gross}$) | Var($\mu^m_{gross}$) | Var(TFPR VA) | Var(TFPR Gross) | Log Openness | |
|---|---|---|---|---|---|---|---|
| | | | | | | Import | Export |
| p1 | 0.14 | 0.13 | 0.12 | 0.07 | 0.00 | 0.45 | -0.25 |
| p10 | 0.37 | 0.46 | 0.27 | 0.25 | 0.10 | 1.99 | 1.71 |
| p25 | 0.57 | 0.62 | 0.47 | 0.43 | 0.20 | 2.64 | 2.50 |
| p50 | 0.81 | 0.88 | 0.75 | 0.64 | 0.33 | 3.55 | 3.20 |
| Mean | 0.88 | 0.94 | 0.84 | 0.76 | 0.43 | 3.50 | 3.15 |
| p75 | 1.10 | 1.15 | 1.08 | 0.92 | 0.54 | 4.37 | 3.85 |
| p90 | 1.40 | 1.50 | 1.49 | 1.40 | 0.94 | 4.90 | 4.46 |
| p99 | 2.51 | 2.87 | 2.39 | 2.66 | 1.58 | 7.69 | 6.25 |

Notes: TFPR and markups are in log values. P1, P10, P25, P50, P75, P90, and P99 represent the 1, 10, 25, 50, 75, 90, and 99 percentile values of the statistics. Import and Export openness are measured as $\frac{\text{industry import}}{\text{industry output}} \times 100$ and $\frac{\text{industry export}}{\text{industry output}} \times 100$, respectively.

Table 3: Monotonicity of markups with physical productivity: firm-level regressions

| | Value-added PF | Gross PF | | Revenue-cost approach |
|---|---|---|---|---|
| | $\log(\frac{\theta^l_{isct}}{\alpha^l_{isct}})$ | $\log(\frac{\theta^l_{isct}}{\alpha^l_{isct}})$ | $\log(\frac{\theta^m_{isct}}{\alpha^m_{isct}})$ | $\log(\frac{\text{Revenue}}{\text{Total costs}})$ |
| | Panel A: Independent variable is TFPQ VA | | | |
| TFPQ VA | 0.979*** | 0.980*** | 0.487*** | 0.602*** |
| | (0.021) | (0.024) | (0.031) | (0.020) |
| $N$ | 31589 | 31803 | 31589 | 29646 |
| $R^2$ | 0.640 | 0.781 | 0.292 | 0.604 |
| | Panel B: Independent variable is TFPQ Gross | | | |
| TFPQ Gross | 1.108*** | 1.127*** | 1.063*** | 0.856*** |
| | (0.033) | (0.036) | (0.029) | (0.029) |
| $N$ | 31942 | 31942 | 31942 | 29965 |
| $R^2$ | 0.510 | 0.700 | 0.493 | 0.627 |

Notes: All regressions include country, industry and year fixed effects. Bootstrap standard errors clustered at country level in parenthesis. All regressions also include three firm size dummies: small (< 20 employees), medium (20-99 employees) and large (100 and more employees). All the dependent variables are in log units so that the point estimates can be interpreted as elasticity of markups with respect to TFPQ. $\theta^X$ is revenue elasticity with respect to variable input $X$. In the column 1 $\theta^X$ is estimated from a value-added production function. In columns 2 and 3, it is estimated from Gross production function as output elasticity with respect to labor and material inputs, respectively. $\alpha^X_{isct}$ is the share of expenditure on input $X$ in firm revenue. In column 4, total cost is calculated as the sum of material, labor, electricity and 0.1*replacement value of capital. There is slight difference in the number of observations across columns due to missing values of some of the variables needed to compute the dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Proportionality of markups with revenue productivity: firm-level regressions

| | Panel A: Dependent variable is Log TFPR VA | | | |
|---|---|---|---|---|
| LogMarkup VA: $\log(\frac{\theta^l_{isct}}{\alpha^l_{isct}})$ | 0.696*** | | | |
| | (0.026) | | | |
| LogMarkup gross labor: $\log(\frac{\theta^l_{isct}}{\alpha^l_{isct}})$ | | 0.695*** | | |
| | | (0.027) | | |
| LogMarkup gross material: $\log(\frac{\theta^m_{isct}}{\alpha^m_{isct}})$ | | | 0.396*** | |
| | | | (0.025) | |
| LogMarkup R/C: $\log(\frac{\text{Revenue}}{\text{Total costs}})$ | | | | 1.068*** |
| | | | | (0.046) |
| $N$ | 31589 | 31803 | 31589 | 29646 |
| $R^2$ | 0.891 | 0.891 | 0.797 | 0.885 |
| | Panel B: Dependent variable is Log TFPR Gross | | | |
| LogMarkup VA: $\log(\frac{\theta^l_{isct}}{\alpha^l_{isct}})$ | 0.431*** | | | |
| | (0.031) | | | |
| LogMarkup gross labor: $\log(\frac{\theta^l_{isct}}{\alpha^l_{isct}})$ | | 0.427*** | | |
| | | (0.031) | | |
| LogMarkup gross material: $\log(\frac{\theta^m_{isct}}{\alpha^m_{isct}})$ | | | 0.468*** | |
| | | | (0.025) | |
| LogMarkup R/C: $\log(\frac{\text{Revenue}}{\text{Total costs}})$ | | | | 0.799*** |
| | | | | (0.030) |
| $N$ | 31942 | 31942 | 31942 | 29965 |
| $R^2$ | 0.876 | 0.877 | 0.879 | 0.911 |

Notes: All regressions include country, industry and year fixed effects. Bootstrap standard errors clustered at country level in parenthesis. All regressions also include three firm size dummies: small (< 20 employees), medium (20-99 employees) and large (100 and more employees). All the dependent variables are in log units so that the point estimates can be interpreted as elasticity of markups with respect to TFPR. $\theta^X$ is revenue elasticity with respect to variable input $X$. In the column 1 $\theta^X$ is estimated from a value-added production function. In columns 2 and 3, it is estimated from Gross production function as output elasticity with respect to labor and material inputs, respectively. $\alpha^X_{isct}$ is the share of expenditure on input $X$ in firm revenue. In column 4, total cost is calculated as the sum of material, labor, electricity and 0.1*replacement value of capital. There is slight difference in the number of observations across columns due to missing values of some of the variables needed to compute the dependent variable. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Openness and average markup level: The dependent variable is log average markup within country-industry-year cells

| | (1) | (2) | (3) |
|---|---|---|---|
| Log Import openness | -0.052** | | -0.054** |
| | (0.023) | | (0.023) |
| Log Export openness | | -0.027 | -0.031 |
| | | (0.025) | (0.026) |
| Log GDP-per capita | 0.283 | 0.252 | 0.295 |
| | (0.452) | (0.465) | (0.443) |
| $N$ | 373 | 373 | 373 |
| $R^2$ | 0.735 | 0.730 | 0.737 |

Notes: All regressions include country, industry and year fixed effects. Bootstrap standard errors clustered at country level in parenthesis. Openness measures are calculated at ISIC-2digit level. Import openness is calculated as industry import divided by industry output. Export openness is industry export divided by industry output. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Openness and dispersion in Markup within country-industry-year cells: The dependent variable is variance of log markup in panel A and log (P90markup/P10 markup) in the Panel B.

| | | | |
|---|---|---|---|
| | Panel A: Dependent variable is Var(logMarkup) | | |
| Log Import openness | -0.061*** | | -0.061*** |
| | (0.019) | | (0.019) |
| Log Export openness | | 0.002 | -0.003 |
| | | (0.022) | (0.022) |
| Log GDP-per capita | -0.125 | -0.174 | -0.124 |
| | (0.498) | (0.513) | (0.497) |
| $N$ | 373 | 373 | 373 |
| $R^2$ | 0.695 | 0.683 | 0.695 |
| | Panel B: Dependent variable is Log (P90/P10) | | |
| Log Import openness | -0.063** | | -0.063** |
| | (0.025) | | (0.025) |
| Log Export openness | | 0.017 | 0.011 |
| | | (0.028) | (0.028) |
| Log GDP-per capita | 0.137 | 0.082 | 0.133 |
| | (0.467) | (0.489) | (0.466) |
| $N$ | 373 | 373 | 373 |
| $R^2$ | 0.660 | 0.648 | 0.660 |

Notes: All regressions include country, industry and year fixed effects. Bootstrap standard errors clustered at country level in parenthesis. Openness measures are calculated at ISIC-2digit level. Import openness is calculated as industry import divided by industry output. Export openness is industry export divided by industry output. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Openness and dispersion in TFPR within country-industry-year cells: The dependent variable is variance of logTFPR.

| | Panel A: Dependent variable is Var(logTFPR) (Value-added production function) | | |
|---|---|---|---|
| Log Import openness | -0.054** | | -0.054** |
| | (0.024) | | (0.025) |
| Log Export openness | | -0.003 | -0.007 |
| | | (0.028) | (0.029) |
| Log GDP-per capita | -0.516 | -0.533 | -0.510 |
| | (0.614) | (0.629) | (0.610) |
| $N$ | 365 | 365 | 365 |
| $R^2$ | 0.636 | 0.630 | 0.636 |
| | Panel B: Dependent variable is Var(logTFPR) (Gross production function) | | |
| Log Import openness | -0.029** | | -0.029** |
| | (0.015) | | (0.015) |
| Log Export openness | | -0.003 | -0.005 |
| | | (0.020) | (0.020) |
| Log GDP-per capita | -0.392 | -0.400 | -0.387 |
| | (0.393) | (0.401) | (0.391) |
| $N$ | 365 | 365 | 365 |
| $R^2$ | 0.646 | 0.642 | 0.646 |

Notes: All regressions include country, industry and year fixed effects. Bootstrap standard errors clustered at country level in parenthesis. Openness measures are calculated at ISIC-2digit level. Panel A is based on TFPR estimated from value-added production function. Panel B is based on TFPR estimated from gross production function. Import openness is calculated as industry import divided by industry output. Export openness is industry export divided by industry output. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

# Appendices

## A Quantifying the aggregate productivity effect of misallocation (dispersion in markups)

Table A.1: Index Method: Openness and dispersion in TFPR within country-industry-year cells: Panel A: Dependent variable is Var(logTFPR): Value-added production function

| | | | |
|---|---|---|---|
| Log Import openness | -0.056* | | -0.059* |
| | (0.033) | | (0.035) |
| Log Export openness | | -0.042 | -0.046 |
| | | (0.037) | (0.037) |
| Log GDP-percapita | -0.255 | -0.240 | -0.215 |
| | (0.884) | (0.902) | (0.877) |
| $N$ | 365 | 365 | 365 |
| $R^2$ | 0.638 | 0.636 | 0.640 |

Notes: All regressions include country, industry and year fixed effects. Bootstrap standard errors clustered at country level in parenthesis. Openness measures are calculated at ISIC-2digit level. Import openness is calculated as industry import divided by industry output. Export openness is industry export divided by industry output. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

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