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The structural and productivity effects of infrastructure provision in developed and developing countries

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Abstract

In this paper, we provide an empirical assessment of the effects of infrastructure provision on structural change and aggregate productivity using industry-level data for a set of developed and developing countries over 1995-2010. A distinctive feature of our empirical strategy is that it allows the measurement of the resource reallocation directly attributable to infrastructure provision. To achieve this, we propose a two-level top-down decomposition of aggregate productivity that combines and extends several strands of the literature. In our empirical application, we find significant production losses attributable to misallocation of inputs across firms, especially among African countries. Our empirical application also shows that infrastructure provision has stimulated aggregate TFP growth through both within and between-industry productivity gains.

Keywords: productivity growth, resource allocation, stochastic frontier analysis, structural change.

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1. Introduction

Differences in aggregate productivity account for the bulk of cross-country per-capita income differentials. Thus, understanding the drivers of productivity growth has long been of high interest to academics and policy makers. Much of the literature on productivity growth decomposition (see Färe et al., 2008) focuses on two key ingredients: the introduction of more productive technologies (i.e., technical change), and the barriers to diffusion and learning that prevent firms from adopting those technologies (i.e., the catching-up effect or efficiency change). Another strand of the literature (see Balk, 2016a,b) stresses that aggregate productivity growth depends not only on industry-level productivity change (within effect), but also on the shift in industry relative size (reallocation effect). Recent papers suggest that countries can increase output and aggregate total factor productivity (TFP) substantially by reallocating resources more efficiently across firms and industries (e.g., Hsieh and Klenow 2009). Moreover, in their summary of the literature, Restuccia and Rogerson (2008, 2013) conclude that weak public institutions may distort the allocation of resources and thus become a source of productivity and income losses. Basu et al. (2021) have recently pointed out that an increase in aggregate TFP due to reallocation or better use of scale economies is as much of a welfare gain for the representative consumer as a change in technology of the same magnitude and persistence. Therefore, TFP losses due to allocative inefficiency are of direct interest if we aim to connect TFP measures with welfare.[1]Public investment in infrastructure has long been considered as one of the key policy levers to affect both economic development and aggregate productivity. Its relevance is reflected in the large number of studies quantifying its effects on private production (Pereira and Andraz, 2013). In particular, one of the components that has generated the greatest interest has been the investment in highways, due to its uncertain effects on regional economic growth and territorial disparities (see, e.g. Crescenzi and Rodríguez-Pose 2012). Public and private investments in telecommunication infrastructure and electricity distribution are increasingly recognized as fundamental for economic and social development (see, e.g. Qiang and Rossotto, 2009; Yang, 2000). Given the uneven effect that these sorts of investments might have across the economy, it is of great interest for both academics and policy makers to examine whether such infrastructure investments have also promoted gains in aggregate productivity through a better allocation of resources across firms and industries.

In this paper, we provide evidence on the effects of infrastructure provision on aggregate productivity using industry-level data for a set of developed and developing countries. To achieve this, we propose a two-level decomposition of aggregate productivity that combines and extends several strands of the literature. The first level, which does not require estimating any model, is a simplified version of the top-down TFP decomposition introduced by Diewert (2015).[2] The second level of our productivity decomposition allows measuring aggregate TFP improvements directly attributable to infrastructure provision, and to other productivity drivers. A distinctive feature of this theoretical decomposition is that it traces two different channels through which infrastructure provision might promote aggregate productivity gains: i) by raising the productivity level of each industry (the within effect); and ii) by stimulating the

[1] Basu et al. (2021) show that one can measure welfare using data on aggregate TFP and the capital stock per capita, provided that TFP is calculated using domestic absorption rather than GDP as the output concept. They, however, do not decompose their aggregate TFP measure into its sectoral components.

[2] This top-down decomposition relies on a productivity measure that first aggregates all individual outputs and inputs and then computes the productivity of the aggregate. Petrin and Levinsohn (2012) pointed out that the top-down productivity decompositions are conceptually more appealing than the bottom-up decompositions that uses a weighted 'mean' of the individual productivities in order to get an aggregate productivity measure (see e.g., Baily et al. 1992, and Foster et al., 2001). Indeed, Petrin and Levisohn (2012) showed that in the latter case the computed aggregate productivity can be negatively correlated with the degree of efficiency in the allocation of resources in the economy.

structural transformation of the economy (the reallocation effect). Thus, our theoretical model allows measuring inter-industry reallocation effects directly attributable to the infrastructure provision, which are often ignored in the literature measuring the effect of infrastructure provision on private production.[3]

Decomposition of the within term into its fundamental explanatory factors requires estimating several production models. We also use the estimated production models to decompose the reallocation term capturing the output side of the adjustments taking place in the economy as it can be written as a function of several sectoral production models. These models are estimated using stochastic frontier (SF) techniques for two reasons. First, as advocated by Straub (2011), this empirical strategy allows infrastructure provision to have a *direct* effect on sectoral production as a standard input, and an *indirect* effect as a productivity externality. Second, although we use sector-level data, the technical inefficiency term of our production frontier model allows us to capture the production losses caused by a suboptimal allocation of resources across firms operating in the same industry. A proper inter-firm allocative inefficiency term requires knowledge of the marginal products at both the observed inputs and at the optimally allocated inputs for each firm. However, as the final effect of inter-firm allocative inefficiency is a reduction in aggregate industry output (Ten Raa, 2005), it is captured by the sector-specific technical inefficiency term that appears in our SF models. Thus, while the theoretical model allows measuring inter-industry reallocation effects, our SF specification permits measuring inter-firm reallocation effects directly attributable to infrastructure provision.[4]

The decomposition of the reallocation term capturing the input side of the adjustments taking place in the economy is much more challenging because employment is an intrinsically complex phenomenon influenced by many factors (see Vivarelli, 2012). A proper decomposition requires "endogenizing" industry-specific input levels using a suitable theoretical framework. The choice of theoretical framework is far from obvious, however, and instead we opt for estimating a set of auxiliary regressions to examine the effect of infrastructure provision on both industry labor and capital volumes and shares.

We illustrate our decompositions using industry-level data for a set of developed and developing countries over the 1995-2010 period. The first-level decomposition shows that in many developing countries the simple aggregation of industry TFP growth rates does not properly describe aggregate TFP growth because the productivity gains attributable to reallocation of inputs across industries far exceed the poor TFP growth rates found in many industries. We also find significant production losses attributable to misallocation of inputs across firms in many industries, especially in Africa. Our empirical application finally shows that infrastructure provision has stimulated aggregate TFP growth through both within and between-industry productivity gains.

The next section outlines the top-down approach used by Diewert (2015) to decompose aggregate productivity growth using a continuous-time setting. In Section 3 we develop a theoretical model that yields mutually consistent decompositions of both within and reallocation effects, once a set of production functions and auxiliary regressions are estimated.

[3] Remarkable exceptions are Asturias et al. (2019) and Perez-Sebastian and Steinbuks (2017), who calibrate a general equilibrium model to investigate respectively the role of transportation infrastructure in explaining inter-firm resource misallocation in India (using a rich micro-level dataset), and the structural transformation of the economy attributed to public infrastructure in Brazil (using industry-level data).

[4] Our interpretation of the inefficiency term as a proxy for inter-firm misallocation of resources relies on the theoretical model developed by Asturias et al. (2019) who defined a "first best level" of productivity in the economy than can only achieved when there is no misallocation. Although they do not use any "frontier" terminology, their model seems to justify the use of SF techniques.

In Section 4 we discuss the data used in the empirical analysis and its sources. Section 5 presents both the parameter estimates and the computed productivity effects. This section also includes a discussion on the implications of the analysis for the design of strategies aimed at raising aggregate TFP, especially in developing countries. Finally, Section 6 presents the conclusions.

2. Diewert's (2015) TFP decomposition

This section outlines, using a continuous-time setting, the top-down approach proposed by Diewert (2015) to decompose an aggregate TFP productivity measure (M) that can be defined as aggregate real output (Y) divided by aggregate real input (X):[5]

$$M = \frac{\sum_{n=1}^{N} P_n Y_n / P}{\sum_{n=1}^{N} W_n X_n / W} = \frac{Y}{X} \tag{1}$$

where the subscript n stands for industry or sector, Y_n is industry n real output (value-added), P_n is the corresponding industry value added output price, and P the aggregate output price index. On the other hand, X_n is industry n aggregate input, W_n is industry n aggregate input price, and W the aggregate input price index. While X_n can be viewed as a weighted average of industry labor and capital volumes, X is a weighted average of industry-specific inputs.

Diewert (2015, eq. 28) shows that it is possible to relate aggregate TFP level (M) to the industry TFP levels ($M_n = Y_n/X_n$) as follows:

$$M = \sum_{n=1}^{N} \left(\frac{p_n}{w_n}\right) s_{Xn} M_n \tag{2}$$

where $p_n = P_n/P$ is the industry n real output price, $w_n = W_n/W$ is the industry n real input price, and

$$s_{Xn} = \frac{W_n X_n}{\sum_{s=1}^{N} W_s X_s} = \frac{W_n X_n}{WX} \tag{3}$$

is the *nominal* input share of industry n in aggregate cost.[6] Thus, aggregate TFP is a weighted sum of industry-specific TFP productivities where the weight for each industry is its real output-input price ratio (p_n/w_n) times its input cost share (s_{Xn}). Next, Diewert (2015) develops an expression for the rate of growth of aggregate TFP. Using definition (1) and equation (2), aggregate TFP growth is equal to:

$$\dot{M} = \sum_{n=1}^{N} s_{Yn} \dot{M}_n + \sum_{n=1}^{N} s_{Yn} \dot{p}_n - \sum_{n=1}^{N} s_{Yn} \dot{w}_n + \sum_{n=1}^{N} s_{Yn} \dot{s}_{Xn} \tag{4}$$

where a dot over a variable indicates a rate of growth, and s_{Yn} is the *nominal* value added or output share of industry n in total value added:

$$s_{Yn} = \frac{P_n Y_n}{\sum_{s=1}^{N} P_s Y_s} = \frac{P_n Y_n}{PY} \tag{5}$$

The first term in (4) can be interpreted as the aggregate TFP growth that would obtain if all real output and input prices and industry relative sizes were to remain constant over time. Notice that this term is just the straightforward aggregation of industry specific TFP growth rates, and thus it can be labelled as multifactor within effect (WE). The second and third terms in (4) indicate that aggregate TFP growth can also change due to changes in industry real output and input prices, respectively. We shall label these two terms respectively as OPE and IPE. The last term indicates that aggregate TFP growth can also change due to changes in industry input cost shares. As this term has to do with transformation of the economy, measured by relative industry input usage, it represents an *input reallocation effect*, and thus it is labelled hereafter as IRE. Accordingly, if all real output and input prices remain constant, individual

[5] Diewert (2015) also proposed a decomposition of an aggregate measure of labor productivity.

[6] Hereafter we use lowercase "s" to denote *nominal* shares, and uppercase "S" to denote *real* shares.

industries can contribute positively to aggregate productivity change in two ways: if their own TFP level increases, or if those industries with above-(below-) average input cost share increase (decrease) in relative size.

Up to this point, our analysis follows that of Diewert (2015), but now we extend his decomposition further. He links the OPE term to changes in the price weights of the industry output growth rates in (1), which in turn affects aggregate TFP growth. We show in Appendix A that Diewert's output price effect is (the negative) of an *output reallocation effect* that measures changes in the structure of the economy using industry real output shares, instead of using relative industry input usages as IRE. We also show in Appendix A that, although the output changes in the structure of the economy might be remarkable, the OPE term tends to be negligible in practice as it mainly depends on the difference between real and nominal output shares. This term vanishes if both output shares coincide. Notice that this happens if all industry output prices P_n are equal to the aggregate output price P. As both prices are likely similar in applications using industry-level data, we should not expect large OPE values in practice.[7]

A similar conclusion can be obtained for the IPE and IRE terms. We demonstrate in Appendix B that the sum of these two input-based terms capture input reallocation effects, and that their combined effect (labelled hereafter as *Input Price Reallocation Effect*, $IPRE$) depends on how the structure of the economy in terms of output and inputs differs. As the relative size of a particular industry in output and input terms might differ notably in practice, we thus expect larger values for $IPRE$ than for OPE.

In summary, aggregate TFP growth can alternatively be decomposed as follows:

$$\dot{M} = WE + OPE + IPRE \tag{6}$$

where

$$WE = \sum_{n=1}^{N} s_{Yn}\dot{M}_n$$
$$OPE = -\sum_{n=1}^{N} s_{Yn}\dot{S}_{Yn} = \sum_{n=1}^{N}(S_{Yn} - s_{Yn})\dot{Y}_n$$
$$IPRE = \sum_{n=1}^{N} s_{Yn}\dot{S}_{Xn} = \sum_{n=1}^{N}(s_{Yn} - S_{Xn})\dot{X}_n$$

Several comments are in order regarding the above decomposition. First, it is a simplified version of the top-down TFP decomposition introduced by Diewert (2015) as it only includes three productivity sources. Equation (6) yields a decomposition with no price effects that instead incorporates the traditional within effect and two reallocation terms that capture both the input and output sides of the adjustments taking place in the economy. In this sense, equation (6) treats symmetrically the two variables used to compute aggregate TFP productivity, total input and total output. Second, as written above, the OPE and $IPRE$ terms and their components can be readily evaluated with the help of the sectoral production and input models that will be used in the next section to proceed with the second level of our decomposition. Third, as the output shares of the highest (lowest) productivity industries tend to be larger (smaller) than their input shares, the IPRE term simply suggests that to raise aggregate TFP the input share of high-productivity sectors should increase and the input share of low-productivity sectors should decrease. In this sense, the IPRE term has an economic interpretation similar to that of the traditional shift-share term that often appears in a bottom-up decomposition of aggregate productivity growth.

[7] Note that, by construction, all industry and aggregate output prices are equal to unity in the base year because they are indices. If the period examined includes (or is close to) the base year, all output prices do not likely differ too much in practice. This likely explains why the overall productivity contribution term due to changes in industry real output prices found in Diewert (2015) is practically zero.

3. Decomposing the within and reallocation effects

We next try to decompose the above-mentioned three general productivity effects into their basic drivers using the parametric estimates of a set of production functions and auxiliary regressions.

3.1. Decomposing the within effect

As is customary in regional economics, we hereafter assume that the output of industry n depends on its own use of private capital and labor, and on a set of country-level variables measuring the provision of different infrastructures such as transport, electricity, information, communication, etc. Moreover, in order to distinguish between an industry's pure (i.e., technological) productivity improvements and those caused by a more efficient allocation of resources among its constituent firms, we propose estimating a stochastic production frontier model for each industry, which may be written as follows:

$$lnY_n = \beta_{0n} + \beta_{Kn}lnK_n + \beta_{Ln}lnL_n + \delta_n t + \gamma_n lnZ + v_n - u_n(lnZ) \tag{7}$$

where for notational ease we have dropped the standard subscript t indicating time, and we include a country-specific fixed-effect (with the country subscript omitted) to control for unobserved cross-country heterogeneity in the estimation. K_n denotes the capital stock of industry n, and lnZ is an indicator measuring infrastructure provision (including transport, electricity distribution, telecommunication networks, etc.). It is also worth noting that we have included a conventional time trend in (7) in order to capture global technological shocks over time (i.e., technical change).[8] Lastly, equation (7) also includes two error terms, v_n and u_n. While the former term is a symmetric error term measuring pure random shocks, the latter term is a non-negative error term measuring industry inefficiency, which we link to misallocation of resources across firms. As Asturias et al. (2019) and Perez-Sebastian and Steinbuks (2017) found evidence that inter-firm resource misallocation in India and Brazil depends on (transportation) infrastructure, we allow our industry inefficiency term to depend on our indicator measuring infrastructure provision.[9]

Using the production model in (7), the changes in industry production can be decomposed as:

$$\dot{Y}_n = \beta_{Kn}\dot{K}_n + \beta_{Ln}\dot{L}_n + \theta_n\dot{Z} + \delta_n \tag{8}$$

where

$$\theta_n = \frac{\partial lnY_n}{\partial lnZ} = \gamma_n - \frac{\partial u_n}{\partial lnZ} \tag{9}$$

Equation (9) just indicates that the effect of infrastructure provision on industry output is a combination of a *direct* effect through the frontier, and an *indirect* effect through the allocative efficiency term. Alternatively, we can rewrite the changes in industry production in (8) as:

$$\dot{Y}_n = \beta_n\dot{X}_n + \theta_n\dot{Z} + \delta_n \tag{10}$$

where $\beta_n = \beta_{Kn} + \beta_{Ln}$, and

$$\dot{X}_n = \left[\frac{\beta_{Ln}}{\beta_n}\dot{L}_n + \frac{\beta_{Kn}}{\beta_n}\dot{K}_n\right] \tag{11}$$

[8] In our empirical application, the time trend is replaced by a set of time dummies that in reality capture any common factor (e.g. the global cycle) or measurement error that affects all countries equally.

[9] In our application we follow Battese and Coelli (1992) and include a time trend as an additional covariate of u_n in order to capture the effect of other factors on the efficiency of the allocation of resources across firms operating in the same industry.

The above equations suggest that the estimated coefficients in (7) can be used to both compute (the change of) an aggregate input measure at industry level, and decompose changes in industry production. They can also be used to decompose (the change of) an industry TFP measure if we simply subtract from both sides of equation (10) the aggregate input measure:

$$\dot{\mathrm{M}}_n = \dot{\mathrm{Y}}_n - \dot{X}_n = (\beta_n - 1)\dot{X}_n + \delta_n + \theta_n \dot{Z} \tag{12}$$

where $(\beta_n - 1)$ is a measure of the returns to scale at industry level. Equation (12) decomposes industry TFP changes into a size effect associated to an increase in the usage of inputs, technical change, and the overall effect of the Z variables. Using (12) we can now decompose the within effect that appears in (6) as follows:

$$WE = \sum_{n=1}^{N} (\beta_n - 1) s_{Yn} \dot{X}_n + \sum_{n=1}^{N} s_{Yn} \delta_n + \sum_{n=1}^{N} s_{Yn} \theta_n \dot{Z} \tag{13}$$

3.2. Decomposing the output price effect

Next we discuss how to decompose the OPE term. We show in Appendix A that Diewert's output price effect can be interpreted as an output reallocation effect that measures changes in the structure of the economy using industry real output shares. Unlike the $IPRE$ term, we do not need a new theoretical framework to decompose OPE because the production model used in Subsection 3.1 to decompose WE also provides information on the industry output shares.

$$\frac{\partial lnS_{Yn}}{\partial lnZ} = \theta_n - \sum_{s=1}^{N} S_{Ys} \theta_s = \theta_n - \theta \tag{14}$$

This equation indicates that the effect of infrastructure provision on the relative size of industry *n* depends on how different the within productivity effect is with respect to the average. Recall that we have found that OPE can be defined as $-\sum_{n=1}^{N} s_{Yn} \dot{S}_{Yn}$. Therefore, the productivity effect of infrastructure provision through structural changes in the economy disappears if θ_n is the same for all industries.

The output share of each industry also depends on capital and labor, and the time trend. Therefore, these ingredients also generate inter-industry reallocation effects. Taking next into account that OPE can alternatively be defined as $\sum_{n=1}^{N} (S_{Yn} - s_{Yn}) \dot{Y}_n$, the output price effect can be decomposed as follows:

$$OPE = \sum_{n=1}^{N} (S_{Yn} - s_{Yn}) \left[\beta_{Kn} \dot{K}_n + \beta_{Ln} \dot{L}_n + \theta_n \dot{Z} + \delta_n\right] \tag{15}$$

It should be emphasized that all decompositions in this subsection rely on the same parameters that have been used (and estimated) to decompose the within effect in the previous subsection. In this sense, our decomposition of OPE is theoretically consistent with the decomposition of WE. In other words, both WE and OPE decompositions are mutually consistent.

3.3. *Decomposing the input price reallocation effect*

Lastly, we discuss how to evaluate the components of the $IPRE$ term that appears in our TFP decomposition (6). Recall that $IPRE$ is equivalent to $\sum_{n=1}^{N} (s_{Yn} - S_{Xn}) \dot{X}_n$, Therefore, its decomposition requires explaining changes in the aggregate input, X_n. Using a Divisia index and our parameter estimates, the effect of infrastructure provision on X_n can be computed as follows:

$$\frac{\partial lnX_n}{\partial lnZ} = \frac{\beta_{Ln}}{\beta_n} \frac{\partial lnL_n}{\partial lnZ} + \frac{\beta_{Kn}}{\beta_n} \frac{\partial lnK_n}{\partial lnZ} \tag{16}$$

where $\frac{\partial lnL_n}{\partial lnZ}$ and $\frac{\partial lnK_n}{\partial lnZ}$ respectively measure the effect of infrastructure provision on labor and capital demand by industry *n*. Decomposing these input demands is more challenging than decomposing the industry output shares. Indeed, the decomposition of $IPRE$ requires "endogenizing" the industry-specific input levels using a theoretical framework. As we do not know a priori which framework is more appropriate (e.g. cost vs. profit-based), we adopt a holistic approach and propose estimating for each industry the following auxiliary regressions:

$$lnL_n = \sum_{c=1}^{C} b_{0nc}D_c + b_{1n}t + b_{2n}t^2 + b_{zn}lnZ + \varepsilon_{Ln} \tag{17}$$

$$lnK_n = \sum_{c=1}^{C} a_{0nc}D_c + a_{1n}t + a_{2n}t^2 + a_{zn}lnZ + \varepsilon_{Kn} \tag{18}$$

where (a_{0nc}, a_{1n}, a_{2n}, a_{zn}) and (b_{0nc}, b_{1n}, b_{2n}, b_{zn}) are new parameters to be estimated. We use industry and country-specific intercepts and a time polynomial with industry parameters to control for the net effect of an unknown set of demand drivers that vary over time and across industries and countries.[10] Using the above equations, we get:

$$\frac{\partial lnX_n}{\partial lnZ} = \frac{\beta_{Ln}}{\beta_n} b_{zn} + \frac{\beta_{Kn}}{\beta_n} a_{zn} \tag{19}$$

Finally, the portion of $IPRE$ that can be attributed to infrastructure provision can be computed as $\sum_{n=1}^{N}(s_{Yn} - S_{Xn})\frac{\partial lnX_n}{\partial lnZ}$.

4. Sample and data

To illustrate the proposed decompositions, we use a balanced data panel for 39 countries and 5 industries over the period 1995-2009. Most countries exhibited in this period remarkable increases in mature and/or technological infrastructure. The industries examined in this paper are fairly aggregated: Agriculture, Energy, Manufacturing, Construction and Services. To simplify the empirical exercise, we have aggregated mining together with electricity, gas and water supply into one sector. In addition, the Services sector includes a large range of services such as wholesale and retail trade, hotels, transport, storage, and communications, finance and insurance. The dataset includes annual observations on sectoral value-added and prices, physical capital and labor, and a set of mature and technological infrastructure asset stocks, namely transportation, electricity distribution, and information and telecommunication. Except for industry value-added, output prices and labor, the remaining variables are measured at the country level.

We were forced to drop many countries from the sample given that many years suffered from missing values. Despite these data issues, we were able to work with a broad sample of countries from different world regions (see Appendix C). As these regions exhibit different time patterns in their productivity indicators, the relative importance of the intra and inter-industry effects for the observed productivity growth rates should be expected to vary substantially across regions.

The *Groningen Growth and Development Centre (GGDC) 10-Sector Database* provides annual data for a large set of countries on real gross value added (Y_n) and nominal gross value added (P_nY_n) and employment (L_n) for each industry. Aggregate real value added ($Y = \sum_{n=1}^{N} Y_n$) and aggregate nominal gross value added ($\sum_{n=1}^{N} P_nY_n$) are also available in this database, as is total employment ($L = \sum_{n=1}^{N} L_n$). Sectoral and aggregate deflators are simply obtained by dividing each nominal value added by its corresponding real value. While nominal (real) output is measured at current (constant 2005) national prices in millions, the labor input is measured in thousands of jobs..

[10] Similar results are obtained if we use a time polynomial á la Cornwell et al. (1990) with both country-specific and industry-specific parameters, which suggests that we are controlling quite well for other factors determining industry labor/capital demand (such as input prices).

The aggregate private capital stock (K) was obtained from the International Monetary Fund, and it is originally measured in billions of national currencies. Notice that we do not have information on industry-specific capital input (K_n), just the aggregate stock. To address this issue, we propose modeling the gap between K_n and K econometrically. The industry-specific but unobserved capital stock can be written as $K_n = S_{Kn}K$, where S_{Kn} is the share of capital used by industry n. This variable is however not observed. As S_{Kn} is likely correlated with S_{Ln}, we will assume in our empirical application that $lnS_{Kn} = d_n S_{Ln}$, where d_n is a new parameter that captures such a correlation.[11] Once this parameter is estimated with our production functions, all capital shares are adjusted proportionately in order to impose $\sum_{n=1}^{N} K_n = K$.

We collected four indicators on aggregate infrastructure provision. From the World Bank, we use three indicators on transportation (the length of the total road network in millions of kilometers), information network (the number of internet users), and telecommunication network (the number of fixed telephone and mobile cellular subscriptions). The last infrastructure variable used in our empirical application is electric generation capacity (measured in thousands of KW), provided by the US Energy Information Administration.

Attempting to capture the multidimensionality of infrastructure by introducing a variety of infrastructure indicators as inputs in our production functions could lead to imprecise and unreliable estimates of the contribution of the individual infrastructure indicators. For this reason, we follow Calderón et al (2015) and use a principal component analysis (PCA) to build a synthetic index (Z) summarizing the above-mentioned dimensions of infrastructure: telephone lines and mobile phones, internet, road transport and power.[12]

We also compute a PCA composite (Q) of four indicators of institutional quality provided by the World Bank, namely corruption, government effectiveness, quality of regulation and rule of law. This synthetic index is interacted with Z in order to allow the production effect of public investment in infrastructure to depend on the quality of institutions (see, e.g. Crescenzi et al, 2016; and Esfahani and Ramírez, 2003).

Computing aggregate TFP (M) requires computing the aggregate real input, X, which in turn requires computing first industry-specific real input, X_n. Diewert (2015, p. 372) states that the exact functional form for X_n does not matter for his analysis. He only assumes that $W_n X_n$ equals industry n's input cost. In his application to Australian sector data, he computes X_n using the Fisher index number formula, which is a superlative index (Diewert, 1976). We in turn propose using a Törnqvist index, the discrete counterpart of a Divisia index. As both indices are superlative indices, their results using annual data tend to converge. Using the Divisia index, the rate of growth of our aggregate input variable can be written as a weighted average of $\dot{L}_n$ and $\dot{K}_n$. In his Australian application, Diewert computed each input weight using the *observed* industry shares for both labor and capital. This is not possible in our multi-country application because we do not have such information at the industry level. To address this issue, we propose using the estimated elasticities of our industry production functions (see next section) to compute the above weights. That is, we replace *observed* weights with *estimated* weights.[13] Once we have computed $X_n = L_n^{\beta_{Ln}/\beta_n} \cdot K_n^{\beta_{Kn}/\beta_n}$ for each industry using estimated

[11] The sign of d_n is not known a priori. If large (small) industries use not only more (less) labor but also more (less) capital, we expect a positive value for d_n. But if labor is used to replace capital, we should expect a negative value for d_n.

[12] We used a within-transformation of the (logged) individual infrastructure indicators before implementing the principal component analysis because the production models will be estimated using a FE-type estimator that only uses the temporal variation of the data.

[13] Equating elasticities and shares not only requires assuming constant returns to scale technologies, but also the existence of perfect competitive input markets and long-run equilibria.

weights, labor volumes, and real capital stocks, they should be aggregated in order to compute the aggregate real input, X. We compute X simply by aggregating the industry-level real inputs (i.e. $X = \sum_{n=1}^{N} X_n$).

The corresponding input price variables are computed using the same assumption as in Diewert (2015, p. 374), i.e., that value added equals input cost for each industry,[14] so that with our industry nominal value-added volumes ($P_n Y_n$) and our estimates of aggregate input quantities by industry (X_n) we can obtain estimates of $W_n = P_n Y_n / X_n$ by industry. These implicit price indexes for each industry input were normalized to equal 1 in 2005. Finally, we compute W as a weighted average of the individual industry input price indexes, where the weights are the real input cost shares of each industry in total input, that is: $W = \sum_{n=1}^{N} W_n X_n / X$.

We also compute industry output and input shares using the above output and input volumes. While the *nominal* input share s_{Xn} of industry *n* is computed using equation (3), the *real* input share S_{Xn} is computed as X_n / X. The *nominal* and *real* output shares of industry *n* are computed equally. That is, while the *nominal* output share s_{Yn} is computed using equation (5), the *real* output share S_{Yn} is computed as Y_n / Y. The variation over time of these four industry shares provides useful information about the output and input-oriented structural changes taking place in ea.

Figure 1 depicts the average temporal evolution of these industry output and input shares for the whole set of countries of our empirical application. Two comments are in order regarding this figure. First, it shows that, on average, the structure of the sample economies has changed markedly over the 1995-2009 period. For instance, both output and input shares in agriculture and manufacturing have declined over time. The production factors (in particular, labor) released by the agricultural sector as part of the well-known rural-to-urban migrations occurred in many countries have been absorbed mostly by services and the construction sector. Second, Figure 1 also shows that, while *nominal* and *real* industry shares are similar, the *output* and *input* industry shares differ notably in many cases. Therefore, we expect larger values for $IPRE$ (which heavily depends on differences between the relative size of the industries in output and input terms) than for OPE (which mainly depends on the difference between nominal and real output shares).

[Insert Figure 1 here]

Table 1 summarizes the descriptive statistics of the variables used in the empirical application. It also includes the annual rates of growth (or annual changes) of the key variables used to compute our TFP measures. Notice that, by construction, the rate of growth of the aggregate real input (3.19%) is a weighted average of the rate of growth of labor (1.85%) and the rate of growth of total capital (6.10%). As the increase in aggregate real output (3.78%) exceeded the increase in aggregate input (3.19%), aggregate TFP rose (0.58%) over the sample period. The growth in aggregate labor productivity was much larger (1.93%) due to the moderate expansion of the labor input, and the large accumulation of capital occurred in this period.[15] It is finally worth mentioning that our infrastructure synthetic index also exhibits a non-negligible increase during the sample period. Therefore, it might have contributed substantially to the above increase in both aggregate TFP and labor productivity. This is one of the issues we examine in the next section. We also try to examine whether infrastructure

[14] Notice that this implies constant returns to scale for each industry under perfect competition.

[15] The largest (smallest) increase in labor productivity growth (not shown in Table 1) is found in the agriculture (construction) sector. This result is mostly caused by labor mobility, from the agriculture sector to the construction sector. The services sector also saw an increase in employment, but its productivity performance outpaced that of the construction sector due to its faster output growth. Aggregating all industry outputs and labor quantities, we obtain an aggregate labor productivity growth rate of about 2 percent.

provision has had an uneven effect across industries, and whether infrastructure development has enhanced (or weakened) aggregate productivity through a more (less) efficient allocation of resources across industries and firms.

[Insert Table 1 here]

5. Results

5.1. Parameter estimates

The proposed productivity decompositions rely on the estimation of a heteroscedastic stochastic frontier (SF) production model for five industries: Agriculture, Energy & Mining, Manufacturing, Construction and Services. We have assumed that the inefficiency term u_{nt} in equation (7) is distributed as a heteroscedastic half-normal random variable, i.e. as $N^{+}(0, \sigma_u^2)$ where $ln\sigma_u$ is a linear function of a set of covariates that might affect the allocation of resources within the industry. On the other hand, the noise term v_{nt} is assumed to be distributed as a homoscedastic normal random variable, i.e. as $N^{+}(0, \sigma_v^2)$.

The five SF production models extend the specification provided by equation (7). First, all the models are estimated using a set of country-specific dummy variables to control for unobserved country heterogeneity. In this sense, our model can be viewed as a heteroscedastic version of the True Fixed Effect (TFE) stochastic frontier model introduced by Greene (2005). Second, for the estimation the simple time trend in (7) is replaced by a set of time dummies in order to capture better common technological shocks that reflect shifts of the global technological frontier over time. Third, in keeping with the majority of earlier literature, constant returns to scale have been imposed. That is, we impose the restriction $\beta_{Kn} + \beta_{Ln} = 1$ when we estimate our models by maximum likelihood.

Fourth, in the empirical implementation equation (7) is augmented adding the synthetic index of infrastructure provision (lnZ) times the institutional quality index (Q), to allow the production effect of public infrastructure to depend on the quality of institutions. Moreover, as equation (9) indicates, infrastructure provision not only has a *direct* or frontier effect on industry output, but also an *indirect* effect through the efficiency term. For this reason, σ_u depends on Z.

Fifth, as mentioned above, lnK_n in equation (7) is replaced with $d_n S_{Ln} + lnK$ because we do not have industry data on capital (lnK_n). This implies that our SF production models are estimated using aggregate private capital (lnK) plus the industry share of labor (S_{Ln}). Moreover, lacking estimates of capital utilization by industry, we opt for using the labor-to-capital ratio of neighboring countries as a proxy of capacity utilization.[16] As labor is a variable input while capital is a quasi-fixed input, the ratio varies with the cycle of the economy. The implicit assumption here is that the cycles of neighboring economies are correlated.

Finally, endogeneity problems can arise in our SF models if economic affects both private capital and labor inputs (Kumbhakar et al., 2013). Some authors (e.g., Feng and Wu, 2018) similarly argue that public capital is likely to be an endogenous variable due to the likely reverse causality between output and infrastructure. We deal with this issue using the two-step procedure proposed by Amsler et al. (2016). They suggest estimating first a set of reduced form equations for the endogenous variables (using exogenous frontier variables and a set of external instruments), [17] and then using the reduced form residuals in the estimation of a standard SF model by maximum likelihood.

[16] Other countries in our sample that belong to the same region (Asia, Africa, Europe & US, or Latin America) are considered here as neighboring countries.

[17] We have used spatial lags of the endogenous variables (and their squared values) as external instruments.

The industry-specific parameter estimates are shown in Table 2. The means across industries of the industry-specific elasticities of capital and labor are 0.36 and 0.64 respectively. They are close to the elasticities typically used in growth accounting – a labor elasticity around two-thirds, and a capital elasticity around one-third.[18] Notice also that the labor share coefficient is negative and highly significant for Energy & Mining and Construction. This suggests that labor replaces capital in these two industries.

[Insert Table 2 here]

We also find positive and significant coefficients for the infrastructure index, especially when it is interacted with the index measuring the quality of institutions. Like Crescenzi et al. (2016), the implication is that the effects of infrastructure depend on government quality. Moreover, in many cases the estimated coefficients differ substantially across industries, suggesting the existence of non-negligible structural effects attributable to infrastructure provision. In addition to shifting the production frontier, the expansion of mature and technological infrastructures , infrastructure tends to reduce industry inefficiency in most industries. This particularly occurs at the beginning of our sample period in Agriculture and Construction, or at the end of the period in Manufacturing and Services. The result is consistent with the view advanced by Straub (2011) of public infrastructure as an efficiency-enhancing externality. It is also consistent with the hypothesis defended by Asturias et al. (2019) that transportation infrastructure increases competition between firms, and thus helps reduce resource misallocation through a less dispersed distribution of markups in the industry.

Notice, however, that we find large (and significant) coefficients on the time trend in the inefficiency term. While the coefficient is positive in Agriculture, Energy & Mining and Construction, it is negative in Manufacturing and Services. This implies that other (unknown) factors have significantly worsened the allocation of resources between firms operating in the former three industries, whereas they have improved the allocation of resources across manufacturing and services firms. These time patterns are totally or partially offset by the estimated time effects (not shown in Table 2). Indeed, we find that the global technological shocks penalized production in Energy & Mining, Manufacturing, Services, and Construction (but turned positive since 2003). However, we also find that the agriculture sector experienced exogenous productivity improvements.

While our productivity decompositions provide information on changes over time in industry productivity, the estimated fixed effects provide information on country-specific differences in productivity.[19] The average industry-specific fixed effects estimates are shown in Figure 2 by regions. All of them measure productivity performance relative to the U.S.. Three comments are in order. First, the productivity gaps between Europe and the U.S. are not large, except in Energy & Mining and Construction, where we find higher productivity levels for Europe. Second, productivity performance in the energy and mining industry in developing countries outstrips those of Europe and the U.S., particularly in the cases of Africa and Latin America. This result can likely be explained by the abundance of natural resources in these countries. Finally, developing countries exhibit lower productivity levels in other industries when compared with Europe and the U.S., especially in Agriculture. As pointed out by Calderón et al. (2022), this result likely reflects a host of adverse factors, including technological gaps, geographic disadvantages, poor infrastructure, financial market imperfections, etc. that hamper

[18] Notice that these proportions are roughly satisfied in all industries, except Agriculture. This means that the aggregate input X_n is computed using very similar weights in all sectors except Agriculture.

[19] As we are assuming constant returns to scale technologies, the fixed effects explain most of the (persistent) technological differences in TFP across countries. The other main (frontier) cross-sectional productivity driver is infrastructure provision.

their productivity levels. Our results also corroborate some of the stylized facts found in the literature (see e.g. Adamopoulos and Restuccia 2014) in the sense that the productivity gap between poor and rich countries tends to be bigger in agriculture than in non-agricultural activities.

[Insert Figure 2 here]

There is ample empirical evidence that firm-level misallocation of resources is an important factor behind differences in measured TFP across rich and poor countries (e.g. Restuccia and Rogerson 2008, Hsieh and Klenow 2009, Calderón et al., 2022). Recall that we use the SF approach to measure the degree of misallocation across firms within the same industry because distortions in the optimal allocation of labor and capital across firms will lead to (conditional) industry production losses, and, in turn, larger industry technical inefficiency. The average production losses attributable to firm-level misallocation of resources are shown in Figure 3 by industries and regions. Production losses due to misallocation are especially significant in Construction (12.3%), followed by Manufacturing (7.5%). However, it is worth highlighting that the agriculture and services sectors across African countries tend to exhibit a great degree of misallocation. Production losses are larger in Africa, especially in the agriculture sector (9.6%, compared with less than 4% in other regions). Similar results have been found in the literature. For instance, in their survey of the literature, Calderón et al. (2022) find evidence of severe misallocation in agriculture and manufacturing across sub-Saharan African countries. Like in our study, they also conclude that the dispersion of revenue productivity in these countries is larger than that of other developing countries (China and India) as well as the efficiency benchmark (United States).

[Insert Figure 3 here]

The decomposition of the productivity term capturing reallocation of resources across industries (i.e., what we have labeled the $IPRE$ term) relies on the estimation for each industry of auxiliary regressions for both labor and capital. In Table 3 we show the estimated coefficients of the auxiliary regressions defined in equations (17) and (18). Notice that the fixed effects plus the two synthetic indexes of infrastructure and quality of institutions and the time polynomial allow us to achieve an almost perfect fit. Infrastructure provision tends to increase both capital and labor usage, but the effect is slightly larger for capital than for labor. The effect of the quality of institutions on input usage is biased towards capital: while we find a positive effect on capital demand in most industries, we find a negative effect on labor demand.

[Insert Table 3 here]

5.2. *First-level decomposition*

In this subsection, we decompose the aggregate TFP rates of growth using equation (6), i.e. our simplified version of the top-down TFP decomposition introduced by Diewert (2015). Recall that equation (6) provides a decomposition with no price effects that instead incorporates the traditional within effect and two reallocation terms capturing transformations in the structure of the economy. Table 4 summarizes the descriptive statistics of the computed TFP rates of growth and their components. [20]

[Insert Table 4 here]

[20] In this paper, we use a Bennet-type symmetric method to obtain the discrete-time counterparts of all continuous-time decompositions. For instance, following the method introduced by Bennet (1920), the discrete-time counterpart of equation (6) can be written as:

$$\ln\left(\frac{M_t}{M_{t-1}}\right) = \sum_{n=1}^{N} \frac{s_{Ynt-1}+s_{Ynt}}{2} ln\left(\frac{M_{nt}}{M_{nt-1}}\right) + \sum_{n=1}^{N} \frac{s_{Ynt-1}+s_{Ynt}}{2} ln\left(\frac{s_{Ynt}}{s_{Ynt-1}}\right) + \sum_{n=1}^{N} \frac{s_{Ynt-1}+s_{Ynt}}{2} ln\left(\frac{s_{Xnt}}{s_{Xnt-1}}\right)$$

Several comments are worth making. First, the aggregation of within-industry TFP growth rates (i.e. the WE term) is positive on average in Europe and the U.S. (0.78%), but negative in other regions, especially in Latin America (-0.42%). We also find that the output price effect is, on average, much smaller. As in Diewert (2015), the aggregate TFP productivity contribution of changes in real output prices is practically zero (the world average is just-0.01%). As discussed before, this is an expected result because the nominal and real output shares are similar in our application (their coefficient of correlation ranges between 90 and 99%).

Notice as well that while the small OPE term indicates that changes in industry output shares are of little help to explain changes in TFP, as expected, the large IPRE terms in some regions indicate that changes in labor and capital input shares do account for a remarkable proportion of aggregate TFP growth. Moreover, we find that the IPRE term is the most important TFP driver for the set of countries examined in this paper. Indeed, the improved allocation of inputs across industries explains, on average, almost 100% of the TFP gains occurred in the world.

Table 4 decomposes a TFP growth measure that takes into account the growth of all inputs. If the input mix does not vary over time, both TFP and labor productivity growth should coincide. Labor productivity growth exceeds TFP growth if capital per worker increases over time.[21] While TFP grows by 0.58% annually in our empirical application, labor productivity grows by 1.93% annually. Therefore, the accumulation of capital accounts for most of the observed labor productivity growth, but the contribution of TFP growth is remarkable as well. Similar figures are found in Calderón et al. (2022), who conclude that the share due to TFP that explains labor productivity disparities is about 30 percent. They also find that the contribution of TFP growth has increased significantly over the past two decades. The larger TFP contribution could be attributed to an improving allocation of resources, in line with Hsieh and Klenow (2009).

5.3. Second-level decomposition

Next we turn to the second level of our decomposition, where we try to measure the aggregate TFP changes that can be directly attributable to infrastructure provision and other productivity drivers. The average effects for each region, and for the whole set of countries, are shown in Table 5.

[Insert Table 5 here]

5.3.1. Decomposing the within effect

We first decompose the within effect (WE) using equation (13). As we have assumed constant returns to scale technologies, the size effect associated with an increase in the usage of inputs vanishes. The other productivity drivers are: global technological shocks, changes in infrastructure provision, changes in the quality of institutions, and a residual comprising other effects not included above.

The contribution of each of these productivity drivers is shown in the first decomposition of the WE in Table 5. In all regions, the main factor raising within-industry TFP growth is infrastructure provision. Within-industry TFP rises on average 1.11% annually due

[21] Using equation (12), the changes in industry labor productivities can be decomposed as $\dot{\mathrm{X}}_n = \dot{\mathrm{M}}_n + (1 - \beta_{Ln})(\dot{K}_n - \dot{L}_n)$. The second term measures the productivity effects of changes in the input mix. It vanishes if $\dot{K}_n = \dot{L}_n$.

to the expansion of both mature and technological infrastructure. Interestingly, the contribution is much larger in Africa as infrastructure provision raises TFP 1.47% per annum. These positive effects are partially offset by a deterioration in the quality of institutions. An appropriate infrastructure network that complements private capital and labor represents a source of TFP growth (Kim and Loayza, 2019). However, as Calderón and Servén (2010, 2014) argue, it also requires an institutional framework that regulates efficiently the provision of infrastructure. In turn, as the large (negative) estimated contribution of the time effects in Table 5 exceeds the (positive) contribution of infrastructure, within-industry productivity changes are positive only in Europe and the U.S., and negative in the other regions, especially in Latin America.

It is worth mentioning that a portion of the measured within-industry productivity gains is due to reallocation of resources across firms, and therefore it does not reflect pure technological advancement. In this regard, the frontier WE can be computed and decomposed as in (12), but using frontier elasticities instead of total elasticities (e.g. using γ_n instead of θ_n). This amounts to measuring gains in industry productivity when there is no inter-firm misallocation (i.e. when $u_n = 0$) as in Asturias et al. (2019). The total WE not explained by the frontier WE is the non-frontier WE, which captures productivity gains attributable to the changing allocation of resources between firms within the industry.

Hence, the second decomposition of the WE term that appears in Table 5 decomposes the WE into frontier (pure) and non-frontier (misallocation) effects. Generally speaking, this second decomposition shows that the productivity growth attributable to reallocation effects within the industry is of similar magnitude to that of the productivity growth due to pure (frontier) technological improvements in the industry. However, one tends to counterbalance the other. Indeed, as we find negative technological shocks in most sectors, frontier TFP growth is negative in all regions.[22] This negative performance is partially or totally offset by improved within-industry allocation of resources. Recall that the infrastructure expansion has had a catching-up effect in most industries. Thus, infrastructure provision has helped achieve allocation of resources between firms in the same fashion as in Asturias et al. (2019).

5.3.2. Decomposing the output price effect

We next decompose the output price effect (OPE) using equation (15). Table 5 breaks down the OPE term into changes in infrastructure, global technological shocks, and changes in other factors. This allows us to study to what extent each of these forces has contributed to improve (worsen) the output allocation across the different sectors of the economy.

Recall that Diewert's output price effect can be interpreted as an output reallocation effect that depends on two factors: i) changes in industry real output shares; and ii) differences between real and nominal output shares. Regarding the first factor, we obtained quite different coefficients across sectors for our infrastructure index when estimating the industry production functions, suggesting non-negligible structural effects attributable to infrastructure provision, at least in some regions. In practice, however, these structural changes have little effect on aggregate TFP because real and nominal output shares are very similar in our application.

Indeed, aggregate TFP only decreases a 0.01% annually on average due to the structural changes in industry production. Although the reallocation of value added across industries is not too large on average, the most relevant OPE drivers are the time effects, which we interpret as technological shocks, and infrastructure provision. The time effects generate a worsened

[22] A negative frontier effect might appear if the input elasticities are over-estimated due to our constant returns to scale assumption. We estimated our industry production models without this assumption in early versions of this paper, but we decided to impose this restriction because we got incredibly large or small returns to scale in some of the industries.

allocation of value added across industries, whose TFP contribution is slightly negative (-0.11%). In turn, the infrastructure index does not have major output reallocation effects as aggregate TFP only increases on average 0.08% annually due to the improved allocation of value added across industries attributable to infrastructure development.

5.3.3. Decomposing the input price reallocation effect

Lastly, we decompose the so-called input price reallocation effect ($IPRE$) using the parameter estimates of our auxiliary regressions. Table 5 breaks the OPE term into changes in infrastructure, changes in quality of institutions and changes in other factors. Given that we did not find significant output reallocation effects from infrastructure development, this decomposition allows us to study to what extent infrastructure provision has, in contrast, generated aggregate TFP improvements due to improved allocation of inputs between the different sectors of the economy.

We find much larger capital and labor reallocation effects than those found in terms of value added. Indeed, aggregate TFP rises 0.59% annually on average due to structural changes in industry input usage. The TFP gains associated to better allocation of inputs across industries are quite large in developing countries, especially those in Africa (1.12%) and Asia (0.78%). Our infrastructure indicator explains a remarkable portion (about one-fourth) of all the productivity growth attributable to inter-industry input reallocation, which represents a 0.13% annual increase in aggregate TFP. While this contribution is almost negligible in Latin America (-0.06%) and Europe and the U.S. (-0.08%), it is especially large in Africa (0.36%) and Asia (0.20%). The bottom line is that infrastructure provision has promoted aggregate TFP growth by both within- and between-industry productivity gains in these two regions. These findings highlight the importance of boosting infrastructure development in Africa and Asia. This agrees with the conclusion in Calderón et al. (2022) that adequate infrastructure can help overcome geographical disadvantages in those regions.

It should be finally mentioned that, due to lack of data, we have not been able to identify other relevant drivers that explain the remainder 0.46% annual increase in aggregate TFP associated to inter-industry input reallocation effects. This is again an expected result given that employment and capital use are intrinsically complex phenomena that depend on many other factors, which in our auxiliary regressions are summarized by a simple time polynomial.

5.3.4. Discussion

This subsection draws implications of the analysis for the design of strategies aimed at promoting aggregate TFP improvements, especially in developing countries.

Figure 4 summarizes the productivity growth decomposition of each country. It shows the relative importance of the two main productivity growth drivers, namely the within-industry effect (WE) and the input-oriented inter-industry reallocation effect (IPRE). The vertical and horizontal lines on the graphs show the average values for the respective regions, and thus allow us to organize the countries in each region into four quadrants. The countries located in the upper right quadrant have WE and IPRE terms above the region's averages, and hence they tend to exhibit the best TFP performance in their regions. This is the case of China, India and Hong Kong in Asia, the United Kingdom in Europe, along with the United States, Peru in Latin America, and Tanzania in Africa.[23]

[23] It should be pointed out, however, that being in the north-east quadrant does not guarantee top TFP performance because what matters is the sum of the two components, not that both be 'high'. While China is the Asian's TFP leader with a TFP growth rate of 3.52% and belongs to the upper right quadrant, the other regional leaders belong

[Insert Figure 4 here]

At the other end, countries located in the bottom left quadrant tend to be among the worst TFP performers in their respective region, with below-average WE and IPRE values. Moreover, some of these countries have simultaneously negative WE and IPRE terms, implying that their aggregate TFP fell over the sample period due to poor performance along both the WE and IPRE dimensions. Countries in the bottom left quadrant can improving their aggregate productivity by raising the TFP of some of their industries or by stimulating structural change in their economies favoring their high TFP industries..

The remaining countries, located in the bottom right and upper left quadrants, have exhibited performance above the regional average in only one of the two main productivity growth drivers. These countries therefore might improve their relative position by focusing their policy measures on the productivity driver with the poorest performance. That is, the countries located in the bottom right quadrant could try to enhance the WE productivity component by improving the TFP of some of their industries, while those located in the upper left quadrant should try instead to adopt measures that result in inter-industry reallocation of capital and labor toward high TFP industries, thereby raising their aggregate TFP. Notice in this sense that most African, Latin American, and Asian countries located in these two quadrants exhibit large WE components but small IPRE components, indicating that there may be room for substantial TFP improvement, relative to the regional average, from implementing reforms that facilitate the transformation of their economies.

The next two figures help identify more specific strategies for promoting aggregate productivity growth associated to the within-industry productivity effect (WE) and the inter-industry reallocation effect (IPRE). Figure 5 depicts the estimated sectoral fixed effects of our production models (equation (7)) that explain most of the (persistent) differences in TFP across countries, along with the estimated degree of inter-firm misallocation of resources for each industry in terms of production losses. The estimated fixed effects capture differences not only in sectoral production conditions that are mostly out of the control of the country's economic authorities -- such as the abundance of natural resources, climatic and geographic conditions -- but also differences in other factors more amenable to policy action such as sectoral technology and the quality of the country's infrastructure and institutions. Figure 5 thus allows us to identify two potential channels of productivity gains associated with the WE term: i) improvements in actionable sectoral production conditions; ii) improvements in the allocation of labor and capital among the firms operating in the same industry. The policy actions that the two channels would require are likely different. For instance, while improving sectoral technology might involve incentives to innovation activities or technology imports, enhancing the allocation of labor and capital likely demands enhancing the flexibility of labor and financial markets.

[Insert Figure 5 here]

Each country might try to improve the TFP of their industries using either or both of the above-mentioned strategies. The choice should be dictated by the economic situation and the feasibility of the desired policy measures. Figure 5 splits the sample countries into four groups, defined again using by the average value for their respective regions. As the initial economic situation of each group of countries is likely different, this figure thus shows areas in which there may be a chance for non-negligible sectoral productivity improvements. Countries located in the upper left quadrant exhibit above-average efficiency in the allocation of their sectoral inputs, and their sectoral production conditions (technologies) are also relatively favorable,

to other quadrants. This is the case of Sweden in Europe with a 3.59% increase in TFP, Chile in Latin America with a poorer TFP growth rate of 0.85%, and Malawi in Africa with a remarkable increase in TFP of 2.63%.

suggesting no obvious choice of strategy to improve their TFP performance. In contrast, countries located in the bottom right quadrant exhibit relatively large production losses associated to suboptimal input across firms within the industry, and relatively poor production conditions, suggesting that either policy strategy could be helpful. Finally, countries located in the bottom right and upper left quadrants might want to give priority to the policy strategy targeting the dimension along which they underperform the regional average.

In summary, Figure 5 shows that the country taxonomy is quite diverse, and hence the appropriate strategy to boost sectoral TFP should be tailored to each country's circumstances. For instance, in Figure 4 we saw that Singapore and Indonesia exhibit negative within-industry TFP growth during the sample period. Figure 5 now suggests that Indonesia might try to remedy this situation by implementing reforms aiming to improve, say, its relatively poor production conditions in the services sector, while Singapore might try to enhance the allocation of capital and labor across firms in the Agriculture and Construction sectors. Another interesting comparison is that between Botswana and Nigeria. Both countries exhibit a poor within-industry TFP contribution. Figure 5 shows that Botswana has relatively large fixed effects (i.e. good production conditions) in most industries, and hence it might focus on policy measures aiming to reduce the relatively large degree of inter-firm misallocation of resources found in Agriculture, Energy and Mining, and Construction, which translates into above-average production losses in these industries. However, Nigeria's production conditions are much poorer in Manufacturing, Services and Construction. In this case, the priority might be to implement policy measures aiming to improve production conditions in these three industries.

Another strategy to boost aggregate TFP is to through structural change that improves the allocation of inputs across industries. Recall that the IPRE term in equation (6) shows that aggregate TFP rises when the input share of high-productivity sectors increases and the input share of low-productivity sectors declines. Taking advantage of this mechanism requires implementing economy-wide reforms that facilitate the shift of resources from low-productivity (usually traditional) sectors to high-productivity (usually modern) sectors. The output shares of the highest (lowest) productivity industries tend to be larger (smaller) than their input shares, and thus Figure 6 depicts the differences between industry output and input shares for each country and industry in order to identify the high-productivity industries that should capture production resources from low-productivity industries. The figure also shows the input share of each industry. If high-productivity sectors use a relatively small proportion of the aggregate input, policy should aim to increase their weight in the economy.

As in previous figures, we divide the figure into four quadrants using the average values for the regions under consideration. Notice that in many of the industries (and regions) the two variables shown are negatively correlated. For example, this is the case of the traditional agricultural and construction sectors in developing countries. We observe that several developing countries employ a relatively large proportion of their inputs in these two sectors, even though their productivity is lower than in other countries.[24] One way to raise aggregate TFP then is to reduce the weight of these industries in the economy. Hence, policy makers in these countries should focus not only on raising the productivity of these sectors, but also on facilitating the transfer of labor and capital to higher productivity sectors of their economies, thus speeding up the process of structural transformation. Finally, it is worth noting that the two variables depicted in Figure 6 are positively correlated in other industries (see e.g. Energy and

[24] Developing countries, especially in Africa, exhibit very large shares of employment in agriculture, in contrast with the small agricultural employment share typically found in advanced economies; see e.g., Calderón et al. (2022).

Mining) and regions (see e.g. Europe and USA). In these cases, the policy objective should be to increase the weight of these industries in the economy.

[Insert Figure 6 here]

Previous figures suggest strategies for promoting aggregate productivity growth that may require implementing policy measures of different nature. However, this is not always the case. For instance, in our sample we have found that infrastructure provision stimulated aggregate TFP growth through both within- and between-industry productivity gains. That is, the expansion of mature and/or technological infrastructure helped raise aggregate TFP not only through improvements in sectoral technology (one of the strategies reviewed above), but also through an improved allocation of resources across both firms and industries (the other strategy reviewed above). Moreover, the TFP gains due to improved allocation of inputs were quite large in Africa and Asia, and the development of infrastructures contributed significantly to such gains.[25]

6. Conclusions

We provide novel insights about the relevance of infrastructure development as one of the policy tools exerting the greatest impact on both economic development and aggregate productivity. A distinctive feature of our empirical strategy is that it allows measurement of the resource reallocation across both firms and industries directly attributable to infrastructure provision, an effect often ignored in the literature measuring the effect of infrastructure provision on private production.

In order to achieve this objective, we propose a two-level decomposition of aggregate total factor productivity that combines and extends several strands of the literature. The first level is a simplified version of the top-down TFP decomposition introduced by Diewert (2015) and evaluates the aggregate TFP attributable to both the aggregation of industry TFP growth rates and the reallocation of inputs from low-productivity sectors to high-productivity sectors. The second level of our decomposition analyses the impact of infrastructure on aggregate productivity by improving the sectoral production technologies, allowing better within-industry allocation of capital and labor, and/or stimulating the structural transformation of the economy.

We illustrate our decompositions using industry-level data for a set of developed and developing countries over the 1995-2010 period. The first-level decomposition shows that the within-industry productivity effect was negative in most developing regions, but positive in the European Union and the U.S. The reallocation of inputs across industries improved overall productivity in all regions, and especially among African and Asian countries. Moreover, our results indicate that the simple aggregation of industry TFP growth rates does not portray accurately TFP performance in many developing countries.

A more detailed country-by-country analysis hints at the different strategies that different countries might try to implement to raise their TFP. In this regard, the contribution of

[25] This is consistent with the evidence that agricultural and manufacturing firms are often constrained by high transport cost (Diao and Yanoma, 2003), which can be attenuated by improvements in road quality. For instance, Asturias et al. (2019) and Perez-Sebastian and Steinbuks (2017) assess using rich micro-data sets the significance of transportation infrastructure in the reallocation of inputs to more productive activities in two developing countries (India and Brazil). In their models, the accumulation of infrastructure accelerates structural transformation through effects channeled by cross-sector differences in public capital intensity and entry costs. Overall, public capital formation explains about 15% of the Brazilian structural transformation process. On the other hand, Shiferaw et al. (2015) point out that improving infrastructure provision can encourage the entry and the size of manufacturing firms and the mobility of factors across sectors.

infrastructure provision to productivity in Africa and other developing countries merits special attention. We find that expansion of mature and/or technological infrastructures did enhance aggregate TFP, as in Calderón and Servén (2010). Unlike previous literature measuring the effect of infrastructure provision on private production, we find that infrastructure provision not only helped improve within-firm productivity, but also helped improve the allocation of inputs across both firms and industries. Given the multiple positive productivity effects associated to infrastructure provision, and the key role of productivity growth in raising living standards, the implication is that infrastructure expansion and upgrading should remain a top policy priority for most developing countries.

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Figure 1. Output and Input shares

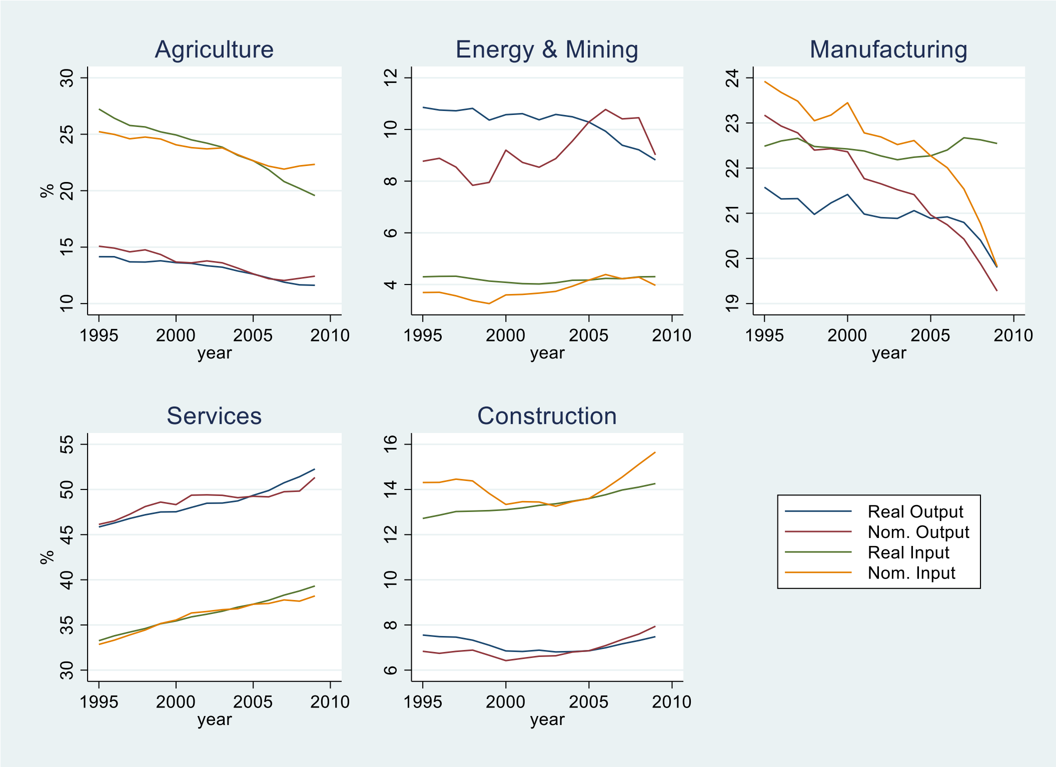

Figure 2. Estimated fixed effects

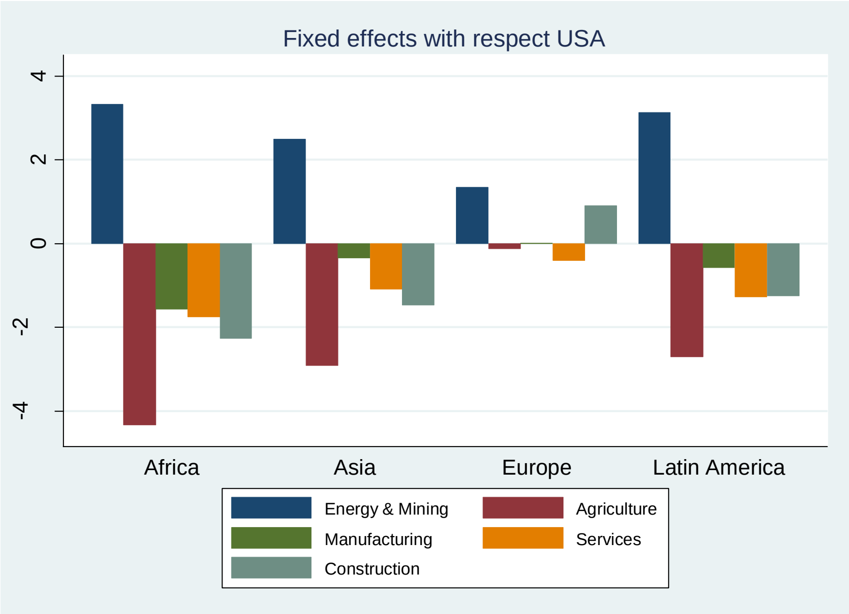

Figure 3. Degree of inter-firm misallocation of resources

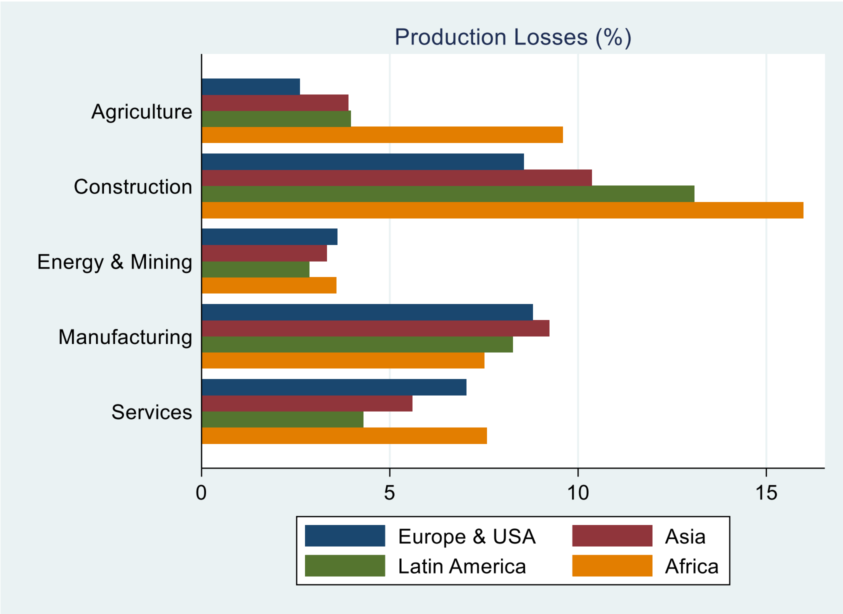

Figure 4. Computed WE and IPRE terms by country

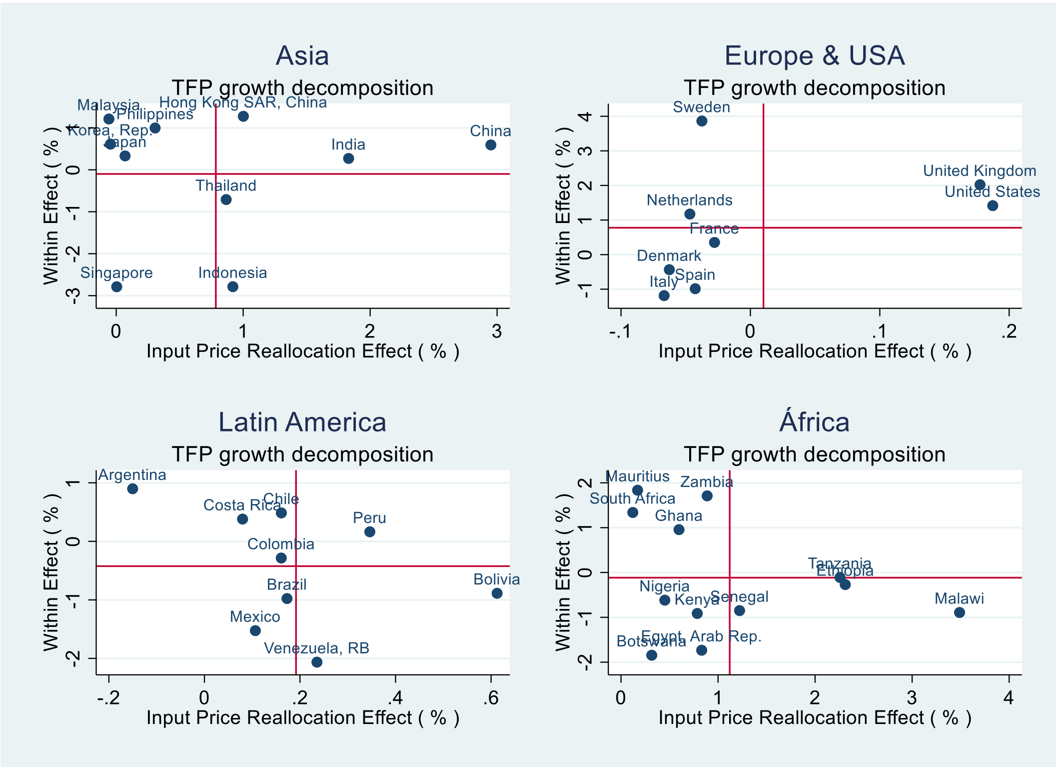

Figure 5. Estimated fixed effects and production losses by country

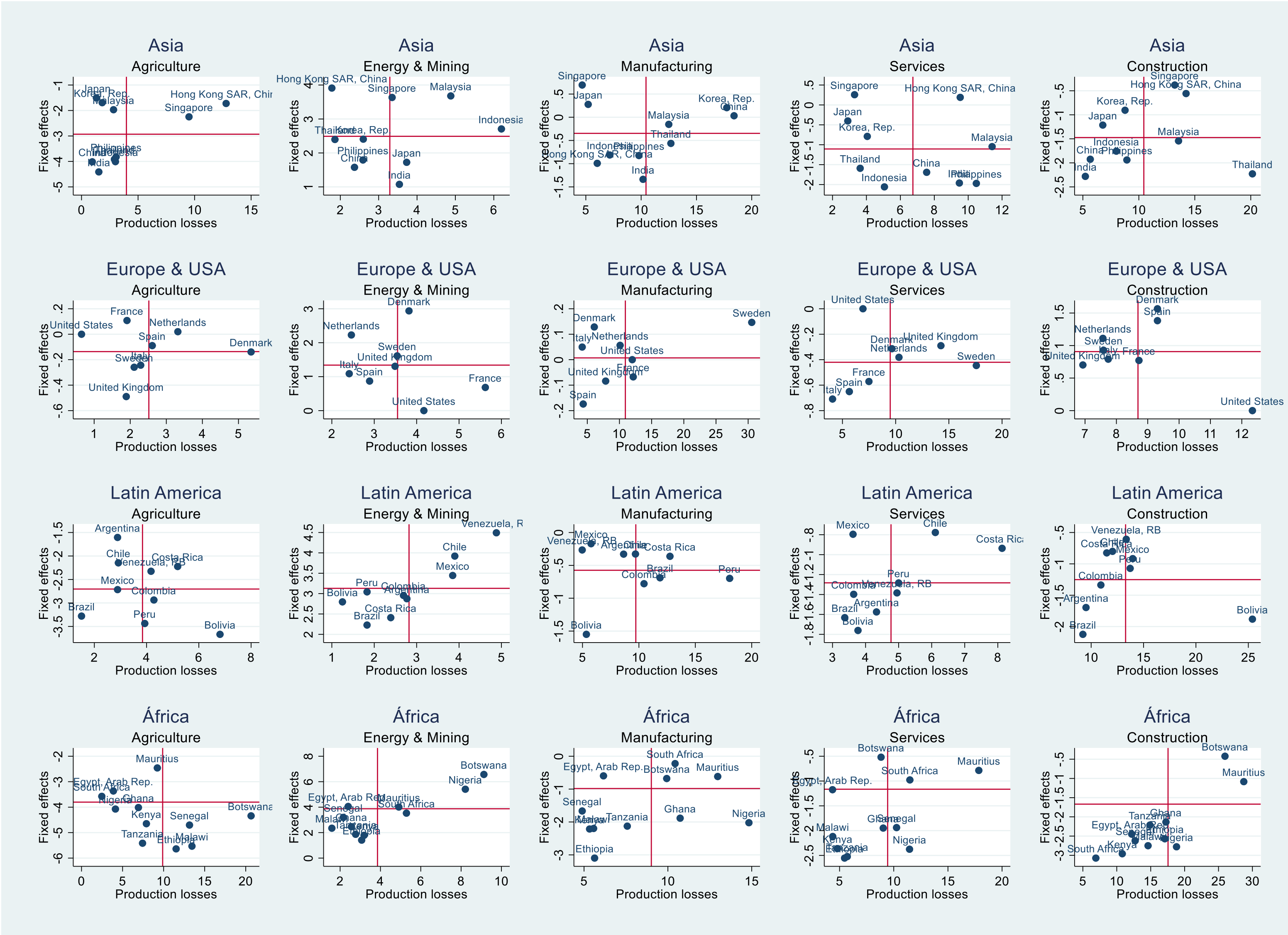

Figure 6. Share differences vs Input share by country

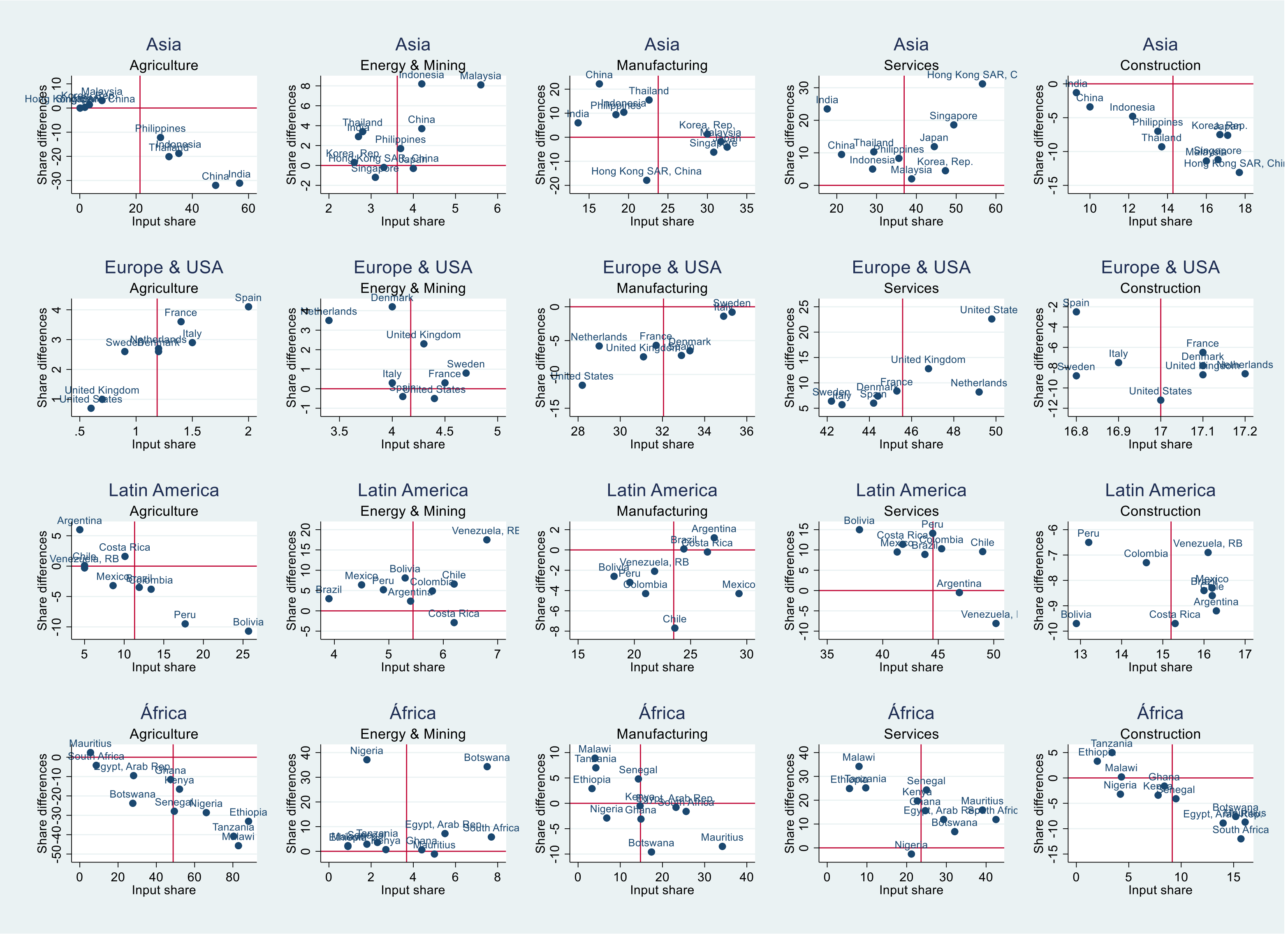

Table 1. Descriptive statistics

Industry-level variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Real Gross Value Added (thousand million US$)[a]					
Agriculture	585	56.41	195.15	0.05	1304.99
Energy	585	52.20	137.98	0.04	1464.58
Manufacturing	585	146.63	295.90	0.18	1680.13
Services	585	413.93	1169.62	0.70	8019.36
Construction	585	57.64	131.51	0.07	843.52
Real output prices (ratio)					
Agriculture	585	1.10	0.21	0.49	2.11
Energy	585	0.96	0.23	0.35	2.13
Manufacturing	585	1.03	0.11	0.73	1.84
Services	585	1.01	0.08	0.82	1.58
Construction	585	0.99	0.21	0.37	2.44
Labor (Million jobs)					
Agriculture	585	20.44	65.60	0.01	366.40
Energy	585	0.64	2.14	0.00	15.73
Manufacturing	585	7.01	19.73	0.03	144.63
Services	585	15.69	31.99	0.11	215.33
Construction	585	3.04	7.89	0.02	52.41

Country-level variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Labor and capital					
Private Capital (thousand million US$)[a]	585	1.26	3.05	0.00	20.40
Labor (Million jobs)	585	46.82	123.81	0.39	715.04
Technological indicators and infrastructures					
Fixed and mobile phones (% of population)	585	60.06	54.78	0.25	241.64
Electricity access (% of population)	585	66.35	161.12	0.13	1000.00
Internet users (% of population)	585	18.36	24.30	0.00	91.00
Roads (thousand Kms)	585	518.60	1180.58	1.72	6500.00
Annual rates of growth (%)					
Real Gross Value Added	546	3.78	4.02	-16.13	14.36
Labor	546	1.85	2.17	-10.28	9.15
Private Capital	546	6.10	8.81	-43.20	70.03
Total input [b]	546	3.19	3.10	-10.12	19.00
TFP [a]	546	0.58	4.08	-17.35	12.84
Labor Productivity	546	1.93	3.52	-16.61	13.09
Annual changes of synthetic indexes					
Infrastructure [c]	546	0.195	0.29	-0.01	3.16
Quality of Institutions [d]	546	-0.001	0.08	-0.60	0.30

Notes: (a) the monetary variables have been expressed in US dollars for the unique purpose of issuing this table. (b) This variable has been computed using the estimated elasticities for capital and labor of our industry production models. (c) This index has been computed using a PCA based on the logged total value of the above technological and infrastructure variables. (d) This index has been computed using a PCA based on four variables measuring the quality of institutions provided by the World Bank (control of corruption: government effectiveness, regulatory quality, and rule of law).

Table 2. SF production functions. Parameter estimates

	Agriculture			**Energy & Mining**			**Manufacturing**			**Services**			**Construction**		
Variables	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.	Coef.		Std. Err.
Frontier function															
Intercept	9.782	***	0.144	9.502	***	0.127	10.365	***	0.075	10.631	***	0.070	8.680	***	0.080
Capital (K)	0.111	**	0.045	0.398	***	0.064	0.453	***	0.053	0.387	***	0.032	0.439	***	0.058
Labor (L)	0.889	***	0.045	0.602	***	0.064	0.547	***	0.053	0.613	***	0.032	0.561	***	0.058
Infrastructure (Z)	0.003		0.048	0.341	***	0.061	-0.014		0.044	0.043		0.029	0.282	***	0.055
Z·Quality of Inst.	0.004		0.022	0.218	***	0.036	0.061	***	0.016	0.028	*	0.016	0.099	***	0.033
Capital function															
Labor Share (S_L)	0.558		0.490	-8.171	***	2.694	-0.551		0.675	-0.017		0.355	-5.874	***	1.680
Noise term															
Intercept	-5.199	***	0.856	-12.09	***	4.060	-0.798	***	0.131	-0.893	***	0.182	-2.771	***	0.265
Inefficiency term															
Intercept	-5.199	***	0.856	-12.09	***	4.060	-0.798	***	0.131	-0.893	***	0.182	-2.771	***	0.265
Infrastructure (Z)	-0.503	***	0.161	1.523		1.313	0.110	**	0.047	0.044		0.047	-0.416	***	0.066
Z·t	0.006		0.011	-0.110		0.089	-0.016	*	0.008	-0.024	*	0.014	0.027	***	0.006
Time trend (t)	0.242	***	0.057	0.733	***	0.274	-0.194	***	0.027	-0.244	***	0.050	0.092	***	0.022
Fixed Effects	Yes			Yes			Yes			Yes			Yes		
Time Effects	Yes			Yes			Yes			Yes			Yes		
CU proxy	Yes			Yes			Yes			Yes			Yes		
1st-Stage Residuals	Yes			Yes			Yes			Yes			Yes		
Mean log-likelihood	0.9760			0.7018			1.0128			1.1653			0.7988		
Observations	585			585			585			585			585		

Table 3. Labor and capital auxiliary regressions. Parameter estimates.

Labor

	Agriculture			Energy & Mining			Manufacturing			Services			Construction		
	Coef.		t-ratio	Coef.		t-ratio	Coef.		t-ratio	Coef.		t-ratio	Coef.		t-ratio
Infrastructure (Z)	0.101	***	13.25	0.133	***	8.93	0.207	***	17.23	0.090	***	12.69	0.197	***	12.94
Quality of Institutions (Q)	-0.126	***	-4.77	0.003		0.07	-0.129	***	-3.12	-0.038		-1.58	-0.102	*	-1.94
t	-0.049	***	-11.35	-0.081	***	-9.63	-0.067	***	-9.86	0.000		0.02	-0.046	***	-5.39
t^2	0.003	***	7.60	0.008	***	9.78	0.005	***	7.85	0.002	***	5.85	0.006	***	6.84
Fixed effects	Yes			Yes			Yes			Yes			Yes		
R-squared	0.999			0.991			0.995			0.998			0.992		

Capital

	Agriculture			Energy & Mining			Manufacturing			Services			Construction		
	Coef.		t-ratio	Coef.		t-ratio	Coef.		t-ratio	Coef.		t-ratio	Coef.		t-ratio
Infrastructure (Z)	0.169	***	8.66	0.224	***	10.60	0.230	***	11.90	0.253	***	12.87	0.225	***	10.32
Quality of Institutions (Q)	0.193	***	2.87	0.098		1.35	0.164	***	2.46	0.146	**	2.16	0.287	***	3.83
t	-0.079	***	-7.21	-0.062	***	-5.24	-0.080	***	-7.38	-0.091	***	-8.24	-0.080	***	-6.55
t^2	0.011	***	10.20	0.011	***	9.44	0.013	***	12.06	0.014	***	12.34	0.012	***	9.67
Fixed effects	Yes			Yes			Yes			Yes			Yes		
R-squared	0.987			0.993			0.994			0.994			0.990		

Table 4. Diewert's TFP growth decomposition (%)

Asia	Mean	Std Dev	Minimum	Maximum
Aggregate TFP growth (M)	0.66	4.09	-17.31	10.48
Within Effect (WE)	-0.10	4.23	-21.94	10.22
Output Price Effect (OPE)	-0.03	0.20	-0.84	0.84
Input Price Reallocation Effect (IPRE)	0.78	1.40	-3.22	6.69
Europe & USA	Mean	Std Dev	Minimum	Maximum
Aggregate TFP growth (M)	0.76	3.89	-11.32	12.84
Within Effect (WE)	0.78	3.93	-11.32	13.13
Output Price Effect (OPE)	-0.03	0.19	-0.80	0.62
Input Price Reallocation Effect (IPRE)	0.01	0.16	-0.33	0.60
Latin America	Mean	Std Dev	Minimum	Maximum
Aggregate TFP growth (M)	-0.19	3.71	-11.90	10.21
Within Effect (WE)	-0.42	3.90	-10.85	10.07
Output Price Effect (OPE)	0.04	0.36	-1.02	1.67
Input Price Reallocation Effect (IPRE)	0.19	0.74	-1.60	4.43
Africa	Mean	Std Dev	Minimum	Maximum
Aggregate TFP growth (M)	0.97	4.40	-14.76	11.60
Within Effect (WE)	-0.12	4.87	-19.27	17.28
Output Price Effect (OPE)	-0.04	0.82	-6.18	2.26
Input Price Reallocation Effect (IPRE)	1.12	2.00	-4.53	9.74
World	Mean	Std Dev	Minimum	Maximum
Aggregate TFP growth (M)	0.58	4.08	-17.31	12.84
Within Effect (WE)	0.00	4.32	-21.94	17.28
Output Price Effect (OPE)	-0.01	0.50	-6.18	2.26
Input Price Reallocation Effect (IPRE)	0.59	1.43	-4.53	9.74

Table 5. Productivity growth decompositions by region.

Decomposition level	Asia	Europe & USA	Latin America	Africa	World
First-level					
TFP growth (M)	0.66	0.76	-0.19	0.97	0.58
Within Effect (WE)	-0.10	0.78	-0.42	-0.12	0.00
Output Price Effect (OPE)	-0.03	-0.03	0.04	-0.04	-0.01
Input Price Reallocation Effect (IPRE)	0.78	0.01	0.19	1.12	0.59
Second-level					
Within Effect (WE)	-0.10	0.78	-0.42	-0.12	0.00
Infrastructure	0.85	1.17	0.88	1.47	1.11
Quality of Institutions	0.03	-0.09	-0.02	-0.10	-0.05
Global Technological Shocks	-0.50	-0.63	-1.09	-1.06	-0.84
Other Factors	-0.47	0.32	-0.20	-0.42	-0.23
Within Effect (WE)	-0.10	0.78	-0.42	-0.12	0.00
Frontier effects	-0.97	-0.89	-0.81	-0.78	-0.86
Non-frontier Effects	0.87	1.66	0.38	0.66	0.86
Output Price Effect (OPE)	-0.03	-0.03	0.04	-0.04	-0.01
Infrastructure	0.06	0.12	0.14	0.04	0.08
Quality of Institutions	0.00	0.00	0.00	0.01	0.00
Global Technological Shocks	-0.08	-0.18	-0.17	-0.05	-0.11
Other Factors	0.00	0.03	0.08	-0.03	0.01
Input Price Reallocation Effect (IPRE)	0.78	0.01	0.19	1.12	0.59
Infrastructure	0.20	-0.08	-0.06	0.36	0.13
Quality of Institutions	0.00	0.00	0.00	0.01	0.00
Other Factors	0.59	0.09	0.25	0.75	0.46

Appendix A

Diewert (2015) defines his output price effect (OPE) as a weighted average of industry real output prices:

$$OPE = \sum_{n=1}^{N} s_{Yn}\dot{p}_n \qquad (A1)$$

Notice that the industry *n* real output price p_n is the industry output price P_n divided by the aggregate output price index P, which can be defined as:

$$P = \sum_{n=1}^{N} P_n \frac{Y_n}{Y} = \sum_{n=1}^{N} P_n S_{Yn} \qquad (A2)$$

where $S_{Yn} = Y_n/Y$ is the *real* output share of industry *n* in total output. As the *nominal* output share s_{Yn} can be rewritten as $s_{Yn} = \frac{P_n}{P} S_{Yn}$, the change of aggregate output price is equal to:

$$\dot{P} = \sum_{n=1}^{N} s_{Yn}\dot{P}_n + \sum_{n=1}^{N} s_{Yn}\dot{S}_{Yn} \qquad (A3)$$

Rearranging (A3), we get:

$$OPE = -\sum_{n=1}^{N} s_{Yn}\dot{S}_{Yn} \qquad (A4)$$

Therefore, we find that Diewert's output price effect is (the negative of) an *output reallocation effect* that measures changes in the structure of the economy using industry real output shares.

Notice, however, that the change in real industry output share is $\dot{S}_{Yn} = \dot{Y}_n - \sum_{s=1}^{N} S_{Ys}\dot{Y}_s$, where the second term is common to all industries. If we replace $\dot{S}_{Yn}$ with $\dot{Y}_n - \sum_{s=1}^{N} S_{Ys}\dot{Y}_s$ in (A4), we get:

$$OPE = \sum_{n=1}^{N} (S_{Yn} - s_{Yn})\dot{Y}_n \qquad (A5)$$

Therefore, equation (A5) finally indicates that the OPE term mainly depends on the difference between nominal and real output shares.

Appendix B

Diewert (2015) defines his input price effect (IPE) as (the negative of) a weighted average of industry real input prices:

$$IPE = -\sum_{n=1}^{N} s_{Yn}\dot{w}_n \tag{B1}$$

Notice that the industry *n* real input price w_n is the industry input price W_n divided by the aggregate input price index W, which can be defined as:

$$W = \sum_{n=1}^{N} W_n \frac{X_n}{X} = \sum_{n=1}^{N} W_n S_{Xn} \tag{B2}$$

where $S_{Xn} = X_n/X$ is the *real* input cost share of industry *n* in total input. The *nominal* input price share s_{Xn} can be rewritten as $s_{Xn} = \frac{W_n}{W} S_{Xn}$. Taking into account that $\dot{W} = \sum_{n=1}^{N} s_{Xn}\dot{W}_n + \sum_{n=1}^{N} s_{Xn}\dot{S}_{Xn}$, we get:

$$IPE = \dot{W} - \sum_{n=1}^{N} s_{Yn}\dot{W}_n = \sum_{n=1}^{N}(s_{Xn} - s_{Yn})\dot{W}_n + \sum_{n=1}^{N} s_{Xn}\dot{S}_{Xn} \tag{B3}$$

The first term in (B3) indicates that Diewert's input price effect measures changes in (nominal) input prices if the structure of the economy in terms of output and inputs differ. The second term indicates that IPE also measures changes in the structure of the economy using (changes in) industry *real* input cost shares ($\dot{S}_{Xn}$), instead of industry *nominal* input cost shares ($\dot{s}_{Xn}$) as the IRE term does.

As both IPE and IRE terms are capturing input reallocation effects, it is interesting to examine their combined effects. In this sense, it is first worth highlighting that both *nominal* and *real* changes in industry input cost shares are mathematically linked, i.e. $\dot{s}_{Xn} = \dot{S}_{Xn} + \dot{W}_n - \dot{W}$. Using this equation, the IRE term is equivalent to:

$$IRE = \sum_{n=1}^{N} s_{Yn}\dot{s}_{Xn} = \sum_{n=1}^{N} s_{Yn}\dot{S}_{Xn} - IPE \tag{B4}$$

Therefore, equation (B4) indicates that the sum of IPE and IRE is equal to $\sum_{n=1}^{N} s_{Yn}\dot{S}_{Xn}$. That is, their combined effect is simply a weighted sum of changes in industry *real* input cost shares ($\dot{S}_{Xn}$) where the weight for each industry is its nominal output share (s_{Yn}). The change in real industry input cost share is $\dot{S}_{Xn} = \dot{X}_n - \sum_{s=1}^{N} S_{Xs}\dot{X}_s$. This equation indicates that the change in relative size of industry *n* depends on how different the change in $\dot{X}_n$ is with respect to the average change in the economy. As the second term is common to all industries, we get:

$$IPRE = IPE + IRE = \sum_{n=1}^{N}(s_{Yn} - S_{Xn})\dot{X}_n \tag{B5}$$

As the relative size of a particular industry in output and input terms might differ notably in practice, we expect larger values for $IPRE$ than for OPE.

Appendix C

Region	Countries
Africa	Botswana, Egypt, Ethiopia, Ghana, Kenya, Mauritius, Malawi, Nigeria, Senegal, Tanzania, South Africa, Zambia.
Asia	China, China, Indonesia, India, Japan, Republic of Korea, Malaysia, Philippines, Singapore, Thailand.
Europe and USA	Denmark, Spain, France, United Kingdom, Italy, Netherlands, Sweden, United States.
Latin America	Argentina, Bolivia, Brazil, Chile, Colombia, Costa Rica, México, Perú, Venezuela.