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Abstract

In this paper we propose a bottom-up approach to trace the channels through which infrastructure investments promote economy-wide productivity improvements using industry level data. A distinctive feature of our empirical strategy is that it allows an examination of the role played by infrastructure provision in stimulating aggregate productivity through both a better allocation of resources in the economy and as a proper productivity driver. To achieve this objective, we propose a simple approach that relies on estimating standard production frontier models. Our empirical illustration shows that the inter-industry effects of some key infrastructures are non-trivial (at least in some countries) and have partially offset the improvements in intra-industry productivity.

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

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1. Introduction

Understanding the drivers of economy-wide productivity growth has long been of interest to academics and policy makers given that differences in aggregate productivity are a key source of large cross-country income differentials. Two main sources of productivity growth exist at aggregate level: the shift in the relative size of production units (plants, firms, industries, etc.) and the change in the individual productivities. De Avillez (2012) called the first source the *reallocation effect*, and the second source the *within effect*. In an application using sectoral data, such as the one proposed in this paper, the reallocation and within effects can be relabelled respectively as *inter* and *intra-industry* productivity change. Despite the great attention received by intra-industry productivity analyses in the literature, resource misallocation has proved one of the underlying factors for the low levels of aggregate productivity in many (poor) countries (Bartelsman et al., 2013). Thus, an understanding of the reasons for both misallocation and genuine productivity growth is essential.

Public investment in infrastructure has long been considered as one of the public policy decisions exerting the greatest impact on both economic development and aggregate productivity. The latter's relevance is reflected by 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). Chandra and Thompson (2000) also find that public investment in transportation networks has different impacts across those industries through which new roads run. Public and private investments in telecommunication infrastructure including broadband access and cellular phones are increasingly recognized as fundamental for economic and social development (see Qiang and Rossotto, 2009). Similar comments can be made about some private investments such as the investment in electricity distribution (see, e.g. Yang, 2000). Given the unequal effect that these sorts of investments might have on the structure of an economy, it is of great interest for both academics and policy makers to examine whether these infrastructure investments have promoted gains in economy-wide productivity through a better allocation of resources across an economy´s industries.

The present paper proposes a model that somewhat extends and combines several strands of the literature as summarized in Section 2. The present paper firstly extends the literature on aggregate productivity in the sense that it examines whether specific variables (e.g. infrastructure) have significant impacts on both reallocation and within productivity effects. Our model also supplements the separately evolved literatures regarding productivity growth decomposition and structural transformation. Indeed, at the very most, the latter work only examines the role of some key variables on either productivity change or resource misallocation. As mentioned above, this study is also related to the literature measuring the effect of infrastructure provision on private production. A common feature of this literature is that it tends to ignore any allocation effect of public infrastructure on aggregate productivity.[1] To the best of our knowledge, this is the first study that empirically examines the role that the infrastructure provision has played in stimulating both structural transformations and aggregate

[1] A remarkable exception is Asturias et al. (2014) that investigate the role of transportation infrastructure in explaining resource misallocation in India. This paper however uses a rich micro-level dataset of manufacturing firms to calibrate a general equilibrium model that is later on used to simulate an improvement in road quality. Thus, both the data and the approach is different to those used in the present study.

productivity through a better resource allocation in the economy. Unlike the main stream literature on resource misallocation that relies on rich micro-level datasets of firms operating in particular industries (e.g. manufacturing), we use data at the sectoral level. Thus, using the terminology coined by Restuccia and Rogerson (2013), our paper uses an indirect approach to measure the net effect of a set of aggregate measures of private and public investment, encompassing an array of different infrastructures.

With respect to the structural transformation of the economy, the papers pertaining to this literature do not connect their results with changes in intra-industry productivity and do not include any variable measuring changes over time in infrastructure provision. Moreover, as McMillan et al. (2014) pointed out, most of the empirical models used in this literature are *ad-hoc* as they have not been obtained using an *explicit* theoretical framework. This precludes inferring robust conclusions about the channels through which infrastructure provision tends to distort the structure of the economy. Furthermore, in Section 3 we show that the structural distortions attributable to infrastructure provision using these *ad-hoc* models are not theoretically consistent with the computed inter-industry productivity effects. In this sense, we propose a theoretical framework that yields *mutually* consistent decompositions of both intra and inter-industry effects.

Finally, while resource misallocation could be explained before by calibrating one of the recent multi-sector multi-region general equilibrium models proposed in the literature (see, e.g. Caliendo et al., 2017),[2] we instead propose a simpler approach that relies on estimating standard production functions where the dependent variable is the industry output or an industry-specific productivity measure. In order to distinguish between frontier and non-frontier effects, we propose estimating a stochastic production frontier model for each industry. This allows differentiating the production effect of infrastructure as an input (private) as well as a determinant of firms' total productivity.

The next section provides a brief summary of the related literature. Section 3 develops a theoretical model that yields mutually consistent decompositions of both intra and inter-industry effects. The empirical illustration is shown in Section 4. In this section we discuss the data used in the empirical analysis and its sources, and present both the parameter estimates and computed intra and inter-industry effects. Finally, Section 5 presents the conclusions.

2. Related literature

Our paper is related to several strands of literature. First, it contributes to the literature on aggregate productivity. A survey of this literature can be found in Balk (2016a,b). This literature examines the relation between productivity (growth) measures for low-level production units (industries or firms) and some aggregate productivity measure of such units. There are basically two approaches to link low and high-level productivity: the *bottom-up*

[2] These authors developed a bottom-up productivity model for the U.S. economy to study how a productivity change located within a particular sector and region spreads to all sectors and regions in the economy. They calibrate the model and explore the regional, sectoral, and aggregate effects of disaggregated productivity changes using pair-wise trade flows across US states by industry, as well as other regional and industry data. They find that eliminating U.S. regional trading costs associated with distance would result in significant aggregate total factor productivity gains.

approach that uses a weighted 'mean' of the individual productivities in order to get an aggregate productivity measure (see e.g. Baily, Hulten and Campbell, 1992, and Foster, Haltiwanger and Krizan, 2001), and the *top-down approach* that first aggregates all individual outputs and inputs and then computes the productivity of the aggregate (see e.g. Diewert, 2015). In both approaches, the production units are somehow combined and, in the ensemble, the production units are not granted equal importance as some weights reflecting their relative importance are explicitly or implicitly used.[3] Microdata studies are usually not interested in aggregate productivity and concentrate on the distributional characteristics of a large set of individual productivities. In contrast, when the production units are industries, the authors are more interested in sector-specific productivity change and its components. If these sectoral analyses show the productivity change of the aggregate (e.g.,the economy), they do not explicitly connect the sectoral and overall results. Despite the different fundamental frames of reference used in the bottom-up and top-down approaches, the decomposition provided by both approaches is somewhat similar. In both frameworks, the reallocation and within productivity effects are considered as the main productivity components. However, while the top-down decompositions are conceptually more appealing than the bottom-up decompositions (see, e.g. the criticism made by Petrin and Levinsohn, 2012), the top-down approach provides less manageable decompositions from a practical point of view (see, e.g. Diewert, 2015).[4] For this reason, we follow a bottom-up approach in this paper and leave for future research the development of a mutually consistent decomposition of both inter- and intra-industry productivity effects.

Understanding the drivers of productivity growth has for a long time entertained the curiosity of academics. The reason for decomposing productivity change into components is to use its inherent information for policy guidance. In this context, it is important that the components are economically meaningful and that they can be estimated accurately. Both parametric and non-parametric frontier techniques have been used to decompose primal or dual measures of productivity into economically meaningful terms. For a summary see Färe et al (2008), Fried et al. (2008), and Orea and Zofío (2017). Much of the literature on decomposing productivity growth focuses on two main sources of productivity growth or productivity differentials. One possibility is that some production units are relatively slow to adopt more productive technologies (i.e. they exhibit low degrees of innovation). The other is that these units do not operate technologies efficiently due to diffusion and learning limitations. In the literature using frontier techniques, these two productivity growth drivers are labeled as technical change (shifts in the technology frontier) and catching-up (efficiency change). Using a parametric approach, the first decomposition that separately identifies the efficiency change and technical change components of productivity change is due to Nishimizu and Page (1982). Later on Färe, Grosskopf, Lindgren, and Roos (1994) proposed a non-parametric frontier technique (Data Envelopment approach, DEA) to achieve a similar decomposition. These publications started a small industry of alternative productivity decompositions using both frontier techniques. For instance, there is an extensive econometric literature that links productivity and dual representations of technology in the frontier framework (see, for an early

[3] As the aggregate productivity (change) is not necessarily equal to the productivity (change) of the aggregate, Balk (2016b) investigates the connection between the *bottom-up approach* and the top-down approach.
[4] The top-down approach introduced by Diewert (2015) is also more challenging from an economic viewpoint since it includes an output price effect and its decomposition into fundamental sources requires making (maybe strong) assumptions about how output prices are set in the marketplace and how market power varies over time.

example using a cost function, Bauer, 1990). On the other hand, Orea (2002) and Färe, Grosskopf, Norris, and Zhang (1994) included a scale efficiency component into the decomposition using econometric and non-parametric frontier techniques respectively. Diewert and Fox (2016) include other explanatory factors such as changes in output prices, changes in primary inputs and changes in input prices when value-added based productivity measures are considered and a top-down approach is used.

Another relevant source of productivity (economic) growth is the public investment in infrastructure, specifically in transport infrastructures. In this sense, our paper is also related to the literature analyzing the effects of public investment in infrastructure on private production or economic growth in developed and developing countries. A summary of the main results and methodologies used in this literature can be found in Pereira and Andraz (2013). According to Romp and De Haan (2007), this research can be split into three groups from a methodological point of view.[5] The most popular group relies on estimating production functions where public infrastructure is treated as an input supported by governmental backing. This is the approach employed in this paper. The second group estimates dual cost (profit) functions in order to overcome some of the econometric problems of the production function approach, but in doing so relies heavily on having sound input prices. The third approach incorporates the production function into an endogenous growth model and is more focused on long-run effects. The resulting empirical model not only involves a different set of production drivers, but is also estimated using a rate-of-growth specification. Generally speaking, and despite the considerable efforts of public administration to promote economic growth in recent years by increasing transport infrastructure investment, specifically in roads and highways, the economic results are often of a smaller than expected magnitude.[6]

Our paper also contributes to the recent literature emphasizing misallocation of resources as a key source of productivity (income) differences across countries. Restuccia and Rogerson (2013) provide a nice review of this literature that mostly includes microdata applications where the production units are plants or firms. For instance, Baily et al. (1992) and Foster et al. (2001), and Foster et al. (2008) showed that 50% of productivity growth in US manufacturing is explained by reallocation across plants. Restuccia and Rogerson (2008) were two of the first authors to demonstrate that policies distorting the allocation of resources across heterogeneous firms can in fact generate higher productivity and income losses. In their review, Restuccia and Rogerson (2013) state that the literature has followed two main approaches to explore the extent to which specific policies, institutional factors and market imperfections can generate effects on aggregate productivity via misallocation: the *direct approach* and the *indirect approach*. The essence of the direct approach is to pick one (or more) factors, try to obtain direct measures of these factors, and then use a model of heterogeneous production units to quantitatively assess the extent to which these factors generate misallocation and impact aggregate productivity. While many studies indicate that large productivity losses can arise from individual factors, the effects from any one particular factor are very small relative to the

[5] Romp and De Haan (2007) mention a fourth approach that includes a set of data-oriented models which do not rely heavily on economic theory (e.g. the vector autoregressive models). In addition, Pereira and Andraz (2013) categorize each approach into three different subgroups depending on the aggregation level of the data: national and cross-country; regional; and industry studies.
[6] Using data from the European regions, Rodriguez-Pose and Fratesi, (2004), and Crescenzi and Rodriguez-Pose (2012) find that its return is even less than those obtained from investment in human capital and innovation in European regions.

scale of differences found across rich and poor economies. The indirect approach tries to focus on the whole set of underlying factors and examine their net effect on misallocation. This approach interprets misallocation as a wedge in the first order conditions for establishing optimization problems. That is, it focuses on the wedges rather than on the underlying source of the wedges. An important limitation of the indirect approach is the requirement for detailed and comparable microdata on establishments which often suffers severely from restricted access. As Restuccia and Rogerson (2013) point out, this approach often uses data on specific manufacturing sectors and the estimates can be a lower bound of the total amount of misallocation.

Our own methodology is capable of explaining changes in the relative importance of each industry, and as such the present paper contributes towards the scant literature on structural transformation. Said literature aims to identify the drivers of structural transformation, especially those associated with different reform programs designed to restructure the economies of several developing countries. The sectoral-level empirical literature on structure transformation provides useful insights as to the allocation (or inter-industry) productivity effects and their determinants. Dabla-Norris et al. (2013) document stylized facts on the process of structural transformation around the world and empirically analyse its determinants using data on real value added by sector of economic activity. Their analyses using simple linear and quantile regression methods suggest that a large proportion of the cross-country variation in sector shares can be accounted for by country-specific characteristics, such as demographic structure, population size, human and physical capital, and policy and institutional variables. Later on, using a standard shift-share decomposition of labor productivity, McMillan et al. (2014) show that structural change since 1990 has been growth reducing in both Africa and Latin America. These authors also regress the allocation or structural change component with respect to a set of determinants. Mensah et al. (2016) examine the determinants of structural transformation in the sub-Saharan African region. They set up an empirical model within the framework of the neoclassical growth model where the output of each sector is expressed as a function of inputs and a set of policy reform variables.

3. Mutually consistent decomposition of intra and inter-industry productivity effects

3.1. Baseline model

Following Balk (2016a, p. 33), the aggregate productivity level of a particular country (P) can be defined as a weighted geometric average of the industry-specific productivity levels. In logs, this is equivalent to $lnP = \sum_{j=1}^{J} S_j lnP_j$, where P_j is a measure of firms' productivity at industry level, subscript j stands for industry or sector, the weight of each industry S_j is the relative size of sector j in the whole economy. We hereafter consider simple labor productivity, that is, value added per unit of labor; i.e. $P_j = Y_j/L_j$.[7] The relative size of a particular industry

[7] Diewert (2015) finds substantial reallocation effects in his empirical application to Australian market sector data if labor productivity is used. However, the reallocation effects are close to zero when a multifactor productivity growth is used to take into account the growth of all inputs. Thus, on average, what counts in this setting are the intra-industry productivity gains. This result has encouraged us to develop our productivity decompositions using labor productivity instead of a total factor productivity index. It is worth mentioning that the lack of significant inter-industry productivity effects likely has to do with the constant returns to scale used to compute the total

can be given by either its value-added share ($S_j = y_j/\sum_{h=1}^{H} y_h$) or its labor share ($S_j = L_j/\sum_{h=1}^{H} L_h$).[8] Thus, the aggregate (or mean) rate of productivity growth can be decomposed as follows:

$$dlnP = \sum_{j=1}^{J} S_j dlnP_j + \sum_{j=1}^{J} lnP_j dS_j = d\overline{lnP} + d\bar{S} \tag{1}$$

While the first term in (1) is a weighted average of intra-industry rates of productivity growth, the second term relates to industry relative size changes and is weighted by normalized industry-specific productivity levels. Accordingly, the industries can contribute positively to aggregate productivity change in two ways: if their own productivity level increases (*intra-industry* effect), or if the industries with above (below) average productivity levels increase (decrease) in relative size (*inter-industry* effect).

Using a Bennet-type symmetric method, the discrete-time counterpart of our continuous-time decomposition in equation (1) can be written as:

$$lnP_t - lnP_{t-1} = \sum_{j=1}^{J} \frac{S_{jt-1}+S_{jt}}{2}(lnP_{jt} - lnP_{jt-1}) + \sum_{j=1}^{J} \frac{lnP_{jt}+lnP_{jt-1}}{2}(S_{jt} - S_{jt-1}) \tag{2}$$

Notice that this geometric productivity decomposition looks like a Törnqvist productivity index and it basically corresponds to the arithmetic one used in Griliches and Regev (1995), and Diewert and Fox (2010). It is worth mentioning that we do not need to introduce the conventional covariance-type term that appears, for instance, in Baily et al. (1992) and Foster et al. (2001, method 1) in the above decomposition. This term appears in a discrete-time setting if the weights of a particular period (e.g. Laspeyres-type or Paasche-type measures) are used to compute both intra and inter productivity changes. However, Balk (2016a) points out that we can avoid the Laspeyres-Paasche dichotomy by using a symmetric Bennet-type method that relies on the arithmetic average of the Laspeyres-type and Paasche-type measures. In this case, the covariance-type term disappears from the productivity decomposition, as in our equation (1). Moreover, Foster et al. (2001) argue that these Bennet-type decompositions, (there called method 2), are presumably less sensitive to random measurement errors than the asymmetric methods.

Regarding the *intra-industry* productivity effect, it can in turn be decomposed into a component attributable to changes in the provision of H different infrastructures labeled hereafter as $z = (z_1, \dots, z_H)$ such as transport, electricity, telecommunication, etc.; and a component associated to the traditional factors of production, capital (K) and labor (L), that is:

$$dlnP_j = \sum_{h=1}^{H} \frac{\partial lnP_j}{\partial z_h} dz_h + \frac{\partial lnP_j}{\partial lnK} dlnK + \frac{\partial lnP_j}{\partial lnL_j} dlnL_j \tag{3}$$

Notice that, while the labor variable is an industry-specific variable, the capital variable does not have an industry subscript as it is not possible to get industry-specific values of this variable without reducing substantially the sample mean.[9] Also worth noting is that, on purpose, we have not included a traditional technical change effect in (3) because some of our infrastructure variables (e.g. the percentage of population with internet connection, or the percentage of cellular subscriptions) has to do with improvements in technology. Finally, it

factor productivity measure (i.e. Diewert has assumed that for all industries the return of the whole set of inputs is unity). We leave this interesting finding for future research.

[8] Interestingly enough, in the top-down decomposition of labor productivity introduced by Diewert (2015, see eq. 14), the intra-industry productivity component is an output-based average of individual productivities, while the inter-industry component is computed using changes in labor-based industry shares.

[9] This subtle difference yields that the derivatives of each industry share with respect to capital and labor will not formally coincide. This difference should thus be taken into account when measuring the reallocation effects of both inputs.

should be mentioned that our z variables also include a variable measuring human capital which can be viewed as a proxy of the returns of public and private investments in education.

Infrastructure provision might also cause changes in the structure of the economy. The change in the relative size of existing industries can be decomposed into a component attributable to changes in infrastructure provision, and a component associated with other determinants. If we generally label the latter determinants as $q = (q_1, \dots, q_M)$,[10] the change in the relative size of industry *j* can be decomposed as:

$$dS_j = \sum_{h=1}^{H} \frac{\partial S_j}{\partial Z_h} dz_h + \sum_{m=1}^{M} \frac{\partial S_j}{\partial q_m} dq_m \tag{4}$$

Thus, if we define the average rate of growth in labor as $dlnL = \sum_{j=1}^{J} S_j dlnL_j$, the aggregate rate of productivity growth can be decomposed as:

$$dlnP = \sum_{h=1}^{H} \left\{ \frac{\partial \overline{lnP}}{\partial Z_h} + \frac{\partial \bar{S}}{\partial Z_h} \right\} dz_h + \frac{\partial \overline{lnP}}{\partial lnK} dlnK + \frac{\partial \overline{lnP}}{\partial lnL} dlnL + \sum_{m=1}^{M} \frac{\partial \bar{S}}{\partial q_m} dq_m \tag{5}$$

where the partial derivatives in (5) can be interpreted as (intra and inter-industry) marginal effects of individual (production or structural) drivers on aggregate productivity:

$$\frac{\partial \overline{lnP}}{\partial Z_h} = \sum_{j=1}^{J} S_j \frac{\partial lnP_j}{\partial Z_h} \tag{6}$$

$$\frac{\partial \overline{lnP}}{\partial lnK} = \sum_{j=1}^{J} S_j \frac{\partial lnP_j}{\partial lnK} \tag{7}$$

$$\frac{\partial \overline{lnP}}{\partial lnL} = \sum_{j=1}^{J} S_j \frac{\partial lnP_j}{\partial lnL_j} \frac{dlnL_j}{dlnL} \tag{8}$$

$$\frac{\partial \bar{S}}{\partial Z_h} = \sum_{j=1}^{J} lnP_j \frac{\partial S_j}{\partial z_h} \tag{9}$$

$$\frac{\partial \bar{S}}{\partial q_m} = \sum_{j=1}^{J} lnP_j \frac{\partial S_j}{\partial q_m} \tag{10}$$

While the first term on the right in (5) measures the average intra and inter-industry productivity change attributable to changes in infrastructures provision (our target variables), the second and third terms measure respectively the average intra-industry productivity effect attributable to capital and labor. Notice that (7) and (8) differ slightly due to the fact that capital does not vary across sectors, while labor does. The last term in (5) captures several shift-share or inter-industry reallocation effects attributable to changes in q_m that cause changes in the relative size of existing industries.

The rest of this section is devoted to computing equation (5) using the parametric estimates of a standard production model.

3.2. Decomposing intra-industry productivity changes

The intra-industry productivity change and its decomposition can be computed applying a traditional production model where the dependent variable is the industry's output estimated using industry level data. In order to distinguish between frontier and non-frontier effects, we propose estimating a stochastic production frontier model for each industry, which may be written as follows:

[10] We do not explicitly label them here as they will appear instinctively later on. Solely mention here that some production drivers might also appear in the "q" vector.

$$lny_{jt} = \beta_{0j} + \beta_{Kj} lnK_t + \beta_{Lj} lnL_{jt} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} + v_{jt} - u_{jt}(z_t) \tag{11}$$

where y_{jct} represents the value-added for every industry $(j = 1, \dots, J)$, t identifies the time period $(t = 1, \dots, T)$; K_t denotes the capital stock of the whole country, L_{jt} stands for the labor force used in each industry; z_{ht} is the provision of infrastructure h in period t; and $z_t = (z_{1t}, \dots, z_{Ht})$ is the vector of infrastructure variables. For notational ease we have dropped a country-specific subscript from all the variables *and* from the intercept as a fixed-effect type estimator is used later on to control for unobserved heterogeneity. Equation (11) also includes two error terms, v_{it} and u_{it}. While the former term is a symmetric error term measuring pure random shocks, the latter term is a non-negative error term measuring country-sector inefficiency.

Please note that the provision of infrastructures first enters the production function as a standard factor of production. The infrastructure variables contribute to production via the production of specific services (or intermediate inputs) such as transport, energy and communication services. As the production of these intermediate inputs is unobserved, our specification can be viewed as a reduced-form of that advocated by Straub (2011). This author states that the inclusion of the infrastructure variables as simple inputs is questionable because, despite the increasing market mediation of infrastructure, this type of capital is not completely remunerated according to its marginal productivity in the real world. This has prompted several authors to instead consider infrastructure as part of a total factor productivity term, i.e. as an efficiency-enhancing externality specifically linked to the accumulation of infrastructure capital. However, a non-frontier Cobb-Douglas specification of the production function à la Barro (1991), does not allow researchers to distinguish the direct effect of infrastructure (i.e. through the production of specific services) from the indirect effect (i.e. the efficiency-enhancing infrastructure externalities). This problem can be addressed if we use a frontier specification of the production model and additionally treat the set of infrastructure variables as efficiency determinants, as can be observed in (11).

On the other hand, notice that the above production equation can be rewritten as follows if we consider simple labor productivity:

$$lnP_{jt} = \beta_{0j} + \beta_{Kj} lnK_t + (\beta_{Lj} - 1) lnL_{jt} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} + v_{jt} - u_{jt}(z_t) \tag{12}$$

If we compare (11) and (12) we immediately conclude that all production drivers in (11) are simultaneously drivers of labor productivity. Thus, this equation suggests that the estimated coefficients in (11) can be easily used to decompose labor productivity changes.[11]

It is also worth mentioning that the effect of infrastructure provision on industry labor productivity in (12) is a combination of a *direct* effect through the frontier, and an *indirect* effect through the inefficiency term:

$$\frac{\partial lnP_{jt}}{\partial z_h} = \theta_{jht} = \gamma_{jh} - \frac{\partial u_{jt}}{\partial z_h} \tag{13}$$

Although a Cobb-Douglas production model is estimated, this effect varies across countries and industries over time because generally $\partial u_{jt}/\partial z_h$ is a (complex) function of country-specific and time-varying variables. Taking into account (13), the intra-industry

[11] The same conclusion can be inferred for total factor productivity (TFP) if we alternatively rearrange equation (11) as follows:

$$lnTFP_{jt} = lny_{jt} - lnX_{jt} = \beta_{0j} + \tau_j \cdot lnX_{jt} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} + v_{jt} - u_{jt}(z_t)$$

where $\tau_j = (\beta_{kj} + \beta_{Lj} - 1)$ is a measure of the returns to scale at industry level and lnX_{jt} is an aggregate input index defined as $lnX_{jt} = \{\beta_{kj}/(\beta_{kj} + \beta_{Lj}) lnK_t + \beta_{Lj}/(\beta_{kj} + \beta_{Lj}) lnL_{jt}\}$.

marginal effect of infrastructure *h* on overall productivity in (6) can be computed using a Bennet-type symmetric specification as:

$$\frac{\partial \overline{lnP_t}}{\partial Z_h} = \sum_{j=1}^{J} \frac{S_{jt-1}+S_{jt}}{2} \cdot \left(\gamma_{jh} - \frac{\frac{\partial u_{jt-1}}{\partial z_h}+\frac{\partial u_{jt}}{\partial z_h}}{2} \right) \quad (14)$$

Equation (14) shows the intra-industry marginal effect as a weighted average of industry-specific productivity effects, γ_{jh}^{u}. As the distribution of sectoral production across countries is far from uniform, this effect is country specific even when the industry productivity effects are the same.

Finally, it should be noticed that similar equations can be obtained for the intra-industry marginal effects of capital and labor in (7) and (8), but without an *indirect* effect through the inefficiency term.

3.3. Decomposing inter-industry productivity changes

Equation (9) measures how infrastructure provision distorts the relative importance of high- and low-level productive sectors. In practice, one empirical strategy that can be used to compute this component is to regress the overall structural-change term $d\bar{S} = \sum_{j=1}^{J} lnP_j dS_j$ on a number of plausible independent variables á la McMillan et al (2014). In this case, the structural distorts attributable to infrastructure provision are represented simply by the parameter estimated for this variable in the auxiliary regression, and hence the effect of infrastructure provision on overall structural changes is common to all countries.[12] As McMillan et al. (2014) correctly pointed out, we should view these auxiliary regressions as a first pass through the data, rather than a complete causal analysis based on an explicit theoretical model. Given the somewhat *ad-hoc* nature of such auxiliary regressions, the computations of the structural distorts attributed to infrastructure provision will not be theoretically consistent with the previously computed intra-industry productivity effect.

Given the above limitations, we next develop a decomposition of the inter-industry productivity effects attributable to infrastructure provision when the relative size of a particular industry is measured in terms of output. The corresponding expressions for other determinants of the relative industry sizes are also provided. The salient feature of this model is that the proposed decomposition is consistent with the intra-industry decomposition developed in Subsection 3.2.

3.3.1. Output-based decomposition of inter-industry effects

First, assume that the relative size of industry *j* at period *t* is given by its value-added share; i.e. $S_{jt} = y_{jt}/\sum_{s=1}^{J} y_{st}$. Given the production model in (11), this output-based share can be rewritten as:

$$S_{jt} = S_{jt}(z_t, K_t, L_t) = \frac{\mathrm{A}_{jct} {K_t}^{\beta_{kj}} {L_{jt}}^{\beta_{Lj}}}{\sum_{s=1}^{J} \mathrm{A}_{st} {K_t}^{\beta_{ks}} {L_{st}}^{\beta_{Ls}}} \quad (15)$$

[12] Alternatively, more accurate results can be obtained if a set of auxiliary equations for each industry are estimated. In this case, the structural distortions caused by changes in infrastructure provision, is a weighted average of industry-specific productivity effects. As the economic activity is not distributed uniformly across countries, the overall effect is country specific even when the industry productivity effects are the same.

where $L_t = (L_{1t}, \dots, L_{Jt})$ is the vector of industry-specific labor variables, $z_t = (z_{1t}, \dots, z_{Ht})$ is the vector of infrastructure variables common to all industries, and

$$ln\mathrm{A}_{jt} = \beta_{0j} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} + v_{jt} - u_{jt}(z_t) \quad (16)$$

can be interpreted as the logarithm of a total factor productivity index, which is a function of infrastructure provision (z_t). The effect of a particular infrastructure on industry output is given by:

$$\frac{\partial y_{jt}}{\partial z_h} = \frac{\partial lnA_{jt}}{\partial z_h} \mathrm{y}_{jt} = \theta_{jht}\mathrm{y}_{jt} = \left(\gamma_{jh} - \frac{\partial u_{jt}}{\partial z_h}\right)\mathrm{y}_{jt} \quad (17)$$

Given (17), the effect of infrastructure provision on the industry *j* output share is: [13]

$$\frac{\partial S_{jt}(z_t, K_t, L_t)}{z_h} = S_{jt}\left[\theta_{jht} - \sum_{s=1}^{J} \theta_{sht} S_{st}\right] = S_{jt}\left[\theta_{jht} - \bar{\theta}_{ht}\right] \quad (18)$$

where $\bar{\theta}_{ht} = \sum_{s=1}^{J} S_{st}\theta_{sht}$. This equation indicates that the effect of infrastructure provision on the relative size of industry *j* depends on the relative size of industry *j* (S_{jt}) and on how different the intra-industry productivity effect is with respect to the average. If the productivity effect of infrastructure provision is the same for all industries (i.e. $\theta_{jht} = \bar{\theta}_{ht}$ $\forall$j=1,…,J), the productivity effect of infrastructure provision thought structural changes in the economy disappears. If not, the overall inter-industry marginal effect of infrastructure provision in (9) can be measured in practice as:

$$\frac{\partial \bar{S}_t}{\partial z_h} = \sum_{j=1}^{J} \frac{lnP_{jt-1} + lnP_{jt}}{2} \left\{\frac{S_{jt-1} + S_{jt}}{2}\left[\theta_{jht} - \bar{\theta}_{ht}\right]\right\} \quad (19)$$

It is worth mentioning that the output-based share of each industry also depends on capital and labor. i.e. lnK_t and lnL_{jt} are “q” variables. Therefore, they also generate reallocation or inter-industry effects. The inter-industry marginal effect of capital can be computed using a similar expression to (19) because this variable is also common to all industries in our application, but without an *indirect* effect through the inefficiency term. That is:

$$\frac{\partial \bar{S}_t}{\partial lnK_t} = \sum_{j=1}^{J} \frac{lnP_{jt-1} + lnP_{jt}}{2} \left\{\frac{S_{jt-1} + S_{jt}}{2}\left[\beta_{kj} - \bar{\beta}_{K}\right]\right\} \quad (20)$$

where $\bar{\beta}_K = \sum_{s=1}^{J} S_{st}\beta_{ks}$. The inter-industry marginal effect of labor should be computed using a slightly different expression because this variable is specific for each industry. The effect of L_j on the output-based share of industry *j* and industry *s≠j* is given by:

$$\frac{\partial S_{jt}}{\partial lnL_j} = \beta_{Lj} S_{jt}(1 - S_{jt}) \quad (21a)$$

$$\frac{\partial S_{st}}{\partial lnL_j} = -\beta_{Lj} S_{jt} S_{st} \quad (21b)$$

Thus, the overall inter-industry marginal effect of a particular industry labor variable can be measured in practice as:

$$\frac{\partial \bar{S}_t}{\partial lnL_j} = \beta_{Lj} \frac{S_{jt-1} + S_{jt}}{2}\left[\frac{lnP_{jt-1} + lnP_{jt}}{2} - \sum_{s=1}^{J} \frac{lnP_{st-1} + lnP_{st}}{2}\frac{S_{st-1} + S_{st}}{2}\right] \quad (22)$$

3.3.2. A discussion on input-based decompositions of inter-industry effects

[13] Notice that this derivative is conditional on labor and capital variables. Thus, it might be ignoring or underestimating the structural and economic transformations associated to the well-known rural-to-urban migrations which have occurred in many countries.

The question regarding which weights (output- or input-based?) are appropriate to ensemble the industries, has received some attention in the literature because of the potentially significantly different results (see, e.g. Karagiannis, 2013). Using a theoretical approach instead, Balk (2016a, section 9) examined whether several aggregate productivity measures based on different weighting strategies are equal to the productivity of the aggregate. This author showed that a labor-share weighted mean of labor productivities understates aggregate labor productivity, whereas a value-added-share weighted mean overstates aggregate labor productivity. The latter result has to do with the decomposition of economy-wide labor productivity proposed by Diewert (2015) using a top-down perspective. He shows that while the intra-industry (within) effects are computed using output-based shares, the inter-industry (reallocation) effects should be computed using labor shares. Thus, both types of shares should be used in a top-down decomposition of labor productivity.

It should be highlighted here that, regardless of whether we use a top-down approach to decompose an economy-wide labor productivity measure or alternatively follow a bottom-up approach to aggregate the productivity measure of each industry using labor shares, the inter-industry (reallocation) term is computed using rates of growth of industry labor shares. The decomposition of this term is, however, much more challenging than the decomposition in Subsection 3.3.1. for several reasons. First, measuring the effect of a particular variable on labor is a difficult task as employment is an intrinsically complex phenomenon. As Vivarelli (2012) points out in his literature review on employment and innovation, employment is influenced by many factors: namely, macroeconomic and cyclical conditions, labor market dynamics, demographic structure, policy and institutional mechanisms, trends in working time and so on. Second, it requires "endogenizing" the industry-specific input levels using a theoretical framework that more than likely ignores many relevant features of the labor market. Third, the development of such a theoretical model requires making behavioral assumptions about firms' objectives. Not only the selection of a proper framework is uncertain but also the computed inter-industry effects might change a lot depending on whether e.g. firms maximize profits or minimize cost. Indeed, we show in Appendix B that the cost-based effect of infrastructure provision on the industry j labor share is negative in those industries where the output effect (θ_{jht}) is larger than the average effect ($\bar{\theta}_{ht}$),[14] whereas it is positive if we compute a profit-based effect. Moreover, both effects are likely to over or under-estimate the true effects because output and input prices are taken as given. If we allowed a fully adjustment of the economy, we should expect changes in both prices.

Given the above limitations and the need to estimate a production model in order to obtain the intra-industry effects of infrastructure provision, we will use the analytical expressions developed in Subsection 3.3.1. to compute the inter-industry productivity effects of our empirical application. We leave for future research the use, and selection, of a dual approach to decompose the inter-industry effects in both bottom-up and top-down frameworks.

4. Empirical illustration

4.1. Data and sample

[14] This somewhat counterintuitive result is caused by the fact the computed effect is conditional on industry output levels. Thus, the estimated adjustments in labor do not take into account the output side of the adjustments that are arising in the economy. This limitation then calls for a model that also endogenizes the output of each industry.

To illustrate the proposed decompositions of both the inter and intra-industry productivity effects of several types of infrastructures we use a balanced data panel for 39 countries and 5 industries over the period 1995-2010. 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, physical capital and labor, the quality of labor, and the telecommunication, transport and electricity networks in each country. In order to implement the proposed decomposition, we were forced to drop many countries from the sample given that many years suffered from missing values in value-added or labor at sectoral level or/and in the provision of infrastructures at country level. Moreover, we found that the (lack of) information in infrastructures and in economic variables did not coincide in most cases. In order to work with a reasonable number of observations, we were forced to use the amount of physical capital for the whole country in all the sectoral regressions.[15] Otherwise, the sample size would have been reduced to only 11 countries. Despite these data issues, we were able to work with a sample of countries that belong to different regions in the World (see Appendix A). As these regions exhibit different temporal patterns in their productivity indicators, the relative importance of the intra and inter-industry effects on the observed productivity growth rates will probably vary substantially across regions.

Unlike most of the economic growth literature that adopts a country-wide perspective, we required data collection at sectoral level in order to examine the intra and inter-industry productivity effects of infrastructure provision. In this regard, the *Groningen Growth and Development Centre (GGDC) 10-Sector Database* provides a long-run global set of variables for gross value added (Y) and labor (L) for each industry. While the output variable Y is measured at constant local currency, the input L is measured in thousands of jobs. Equally, the latter source provides capital stock (K) at constant local currency as well as the human capital index (Human capital), based on years of schooling. Unfortunately, this variable does not vary across industries as it is only available for the whole economy. The data on *technological indicators* that have to do with the expansion of telecommunication networks are taken from the World Development Indicators (*World Bank*). In particular, we use two technological indicators. The first one is the percentage of cellular subscriptions (Cellular Phones), which is defined as the weight of mobile cellular subscriptions over total fixed line and mobile cellular subscriptions. The second technological indicator is the percentage of internet users over total population (Internet). The latter variable aims to proxy digital literacy and IT assets provision.

We have also collected from the World Bank a couple of indicators that have to do with more mature infrastructures, namely transportation and electricity. The first variable (Roads) is fairly standard and measures the length of the total road network in millions of kilometers. The second variable (Electricity Access) is the percentage of population that has access to electricity, which can be viewed as a proxy of the available electricity distribution network in the country.

Finally, it should be noted that we have not expressed our monetary variables in a unique currency for two reasons. First, because many exchange rates with respect to the US

[15] Thus the estimated parameter of this variable is not only capturing the true elasticity of output with respect to capital in each industry, but also the bias caused by replacing an industry-specific variable with its value for the whole economy.

dollar are quite volatile in the sample period (see, e.g. the Argentinian peso). The second reason has to do with the estimators used in our empirical application. We use fixed-effect type estimators that ignore the cross-sectional information contained in the data to estimate the parameters of the model. As only the temporal variation of the data is employed, it is not necessary to express our monetary variables in a unique currency.

Table 1 summarizes the descriptive statistics of the variables used in the empirical application.

[Insert Table 1 here]

The temporal evolution of the infrastructures variables is of special interest given the objective of the current paper. We depict in Figure 1 the regional temporal patterns of the standard and technological infrastructure variables in order to identify which type of investment (e.g. telecommunications, transportation, electrification or education) has been more intense. As expected, while the infrastructure network in roads and electricity has only changed slightly over time, the infrastructure in internet and mobile phone networks has risen notably over the last decades. This increase is especially large in Africa. This figure also shows that the variable human capital, which can be interpreted as a proxy of investment in education, has also increased over time, although the initial levels are quite different between regions. The distinct patterns found in the four regions, the notable labor productivity differences across industries and the potentially diverse effect of infrastructure variables on each sector's production, together lead us to expect some noteworthy inter-industry or reallocation productivity effects attributable to these variables on a regional basis..

[Insert Figure 1 here]

4.2. Parameter estimates

The proposed productivity decompositions rely on the estimation of a heteroscedastic production frontier model for five industries: Agriculture, Energy, Manufacturing, Construction and Services. We have followed Reifschneider and Stevenson (1991), Caudill and Ford (1993) and Caudill et al. (1995) and assumed that the inefficiency term, u_{it}, is distributed as an heteroscedastic half-normal distributed random variable, i.e. as $N^+(0, \sigma_{it}^2)$ where $\sigma_{it}\,(z_{it}, \theta)$ depends on a set of covariates and some parameters θ. As pointed out by Álvarez et al. (2006), the so-called RSCFG model has the scaling property because it is equivalent to saying that the distribution of u_{it} can be multiplicatively decomposed as the product of a scaling function that depends on z_{it} and a basic inefficiency term that does not depend on z_{it}. Moreover, as mentioned above, all the models have been estimated using a set of country-specific dummy variables in order to control for country unobserved heterogeneity. In this sense, our model can be viewed as a heteroscedastic version of the so-called True Fixed Effect (TFE) stochastic frontier model introduced by Greene (2005).[16]

The industry-specific parameter estimates are shown in Table 2. Our estimates are consistent with the literature, since both capital stock and labor exhibit positive elasticities in all industries. The simple arithmetic means of the elasticities of private capital and labor are 0.45 and 0.50 respectively. Therefore, the effect of both private inputs follows conventional growth accounting, where labor elasticity is higher (around two thirds) than the capital elasticity (around one third). We also find significant coefficients for many of the infrastructure variables. Moreover, quite often the estimated coefficients differ substantially across

[16] As all slope parameters are still common to all countries, regardless they are developed or developing countries, we will examine in the near future whether a random coefficient stochastic frontier model (e.g. using a latent class structure) is more appropriate.

industries. As shown in Section 3.2. the inter-industry effects rely greatly on an uneven distribution of the estimated coefficients associated to the infrastructure variables. This result, together with the large rates of growth found in some of the infrastructure variables (in particular, in internet and cellular phones penetration) appears to anticipate the existence of non-negligible inter-industry or reallocation productivity effects attributable to these variables, at least in some regions.

Electricity access has a positive and significant effect in all sectors, except in the construction sector. By far the largest direct effect of access to electricity is in Agriculture, a reasonable result due to the fact that the production of this industry often takes place in rural areas located far away from the main electricity networks. As expected, the infrastructure in roads is a production input with a significant positive effect in all industries. The largest effects are found in Manufacturing and Services. It is well known in the literature that the production activity in the manufacturing sector relies particularly on transportation. The effect on Services is twice that of the manufacturing sector, a result that can be explained because it includes transportation services. Regarding the technological indicators that have to do with telecommunication infrastructure, they mostly have a direct positive effect on production. However, we find that a larger penetration of cellular phones in a country tends to penalize production in the Energy and Manufacturing sectors. Regarding the use of internet, the effect is positive in Agriculture, Manufacturing and, in particular, in the Services sector. In general we do not find a positive effect for human capital as standard input. Moreover, its effect is remarkably negative in the construction sector. However, it should be taken into account that this variable might have a positive indirect effect on sector production if it tends to reduce sectors' inefficiency. The same applies to other infrastructure variables.

In this context, Table 2 shows that many of the inefficiency drivers have a negative sign. For instance, the penetration of cellular phones in the population tends to reduce inefficiency in all sectors, except in Construction. We also found that internet not only plays a significant role as a standard input, but also it tends to reduce the other sectors' inefficiency. A notable exception is the Service sector. This might indicate that internet boosts growth, but it also increases the differences between those firms providing services. In addition to shifting the production frontier, the investment in road network infrastructures has had a catching up effect. This result clearly supports the hypothesis defended by Straub (2011) and other authors that consider public infrastructures as an efficiency-enhancing externality. Finally, although we did not find a significant (positive) effect for human capital as a standard input, a more educated population tends to improve the Agriculture and Services sectors’ production through an increase in efficiency. In contrast, human capital has a negative indirect effect on production in the Energy, Manufacturing and Construction sectors.

In Table 3 we show the overall effect of the efficiency determinants taking into account that these variables also have a direct or frontier effect on an industry’s output. The indirect effect might reinforce, attenuate or even reverse the frontier effect of these variables. For instance, the catching-up effect that the investment in roads networks has in most sectors serves to reinforce the direct effect that this infrastructure has on the sectors’ output. Thus, this infrastructure promotes economy-wide economic growth through two channels: as an input and as a total factor productivity driver. In contrast, the negative frontier effect found in the Manufacturing (Energy) sector is offset completely (partially) by its indirect effect as inefficiency tends to decrease with the penetration of cellular phones in the population of these sectors. As a result, the total marginal effect of cellular phones is positive or much less negative. A similar story is found regarding the other technological indicator, the percentage of internet users. The positive effect of this variable on the Energy and Construction sectors’ efficiency is so large that it is able to offset completely the large negative frontier effects present in these two sectors. Regarding the last efficiency determinant, the negligible direct effect of human capital on a sector's output tends to be negative in the Energy, Manufacturing and Construction sectors because a more educated population tends to exacerbate the differences between efficient and inefficient production units in these sectors.

[Insert Table 3 here]

4.3. Decomposing aggregate productivity into intra and inter-industry effects

In this subsection we first compute the rates of growth of labor productivity for each industry. We next aggregate all sector productivities and decompose the economy-wide productivity growth rates into intra (within) and inter-industry (reallocation) effects. Table 4 summarizes the descriptive statistics of the computed rates of growth of labor productivity. The largest (smallest) increase in labor productivity growth 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 has also employed more labor, but its productivity performance was better than in the construction sector due to a better performance of its production. On the other hand, the moderate performance of labor productivity in the Energy and Manufacturing sectors are mainly caused by the rise in the production figures, given the moderate increase in labor occurring in both sectors.

[Insert Table 4 here]

Aggregating all sectors, we obtain an average labor productivity rate of growth of about 1.5 percent. Using equation (2), we have decomposed the economy-wide increase in labor productivity into intra and inter-industry effects. As expected, aggregate productivity growth is mainly explained by improvements in industry-specific productivities. This better performance would yield an increase in labor productivity of 1.6 percent. The productivity growth attributable to changes in an economy's structure is much smaller on average (moreover, it is slightly negative) because when some industries increase their relative size, other industries reduce it. Two comments are in order regarding this result. First, it should be recalled that an apparently small rate of growth might have a noteworthy accumulated effect if the period examined is sufficiently large. Second, notice that these numbers are mean values of annual rates of growth, and this statistic tends to hide relatively large rates of growth that some countries have experienced in specific years. In this sense, it should be empathized that the minimum and maximum inter-industry productivity effects in Table 4 are larger than those computed for intra-industry productivity. Therefore, it seems that there is room in our empirical application for non-negligible inter-industry productivity effects attributable to infrastructure provision.

Table 4 shows that the intra and inter-industry effects also vary across regions. The Asian countries show the better performance with an overall increase of 2.7%, and a positive and relatively large (0.3%) inter-industry effect. The set of European countries included in our sample and USA exhibit a more moderate performance (1.3%). Interestingly enough, this result may be attributable to a large negative inter-industry effect (-0.5%) that has partially offset the positive intra-industry productivity growth (1.8%). In the next subsection we will examine whether the negative reallocation effects found in this region are to any extent caused by investments in infrastructure. The productivity growth associated with transformations in the economy is slightly negative in African and South American countries. The poor performance of these countries is also explained by a modest increase in sector productivities.

4.4. Intra and inter productivity effects of infrastructure

In this subsection we use the parameter estimates of the variables approximating different types of infrastructure provision to examine the role that the telecommunication, transportation and electricity networks have played in both intra and inter-industry productivity growth. To achieve this objective, we use equations (14) and (19). This information is presented by regions using accumulated productivity indices.

We start with Asia, the region with the largest increase in labor productivity. Figure 2 depicts the productivity indices attributable to the education system (human capital) and to our variables measuring the provision of network infrastructures (internet, cellular phones, road and electricity) in the Asian countries. We find that the infrastructure that has promoted aggregate productivity the most in this region is the investment in <u>roads</u>. This is mainly caused by an annual rate of growth of 3.4% in road networks in these countries. It should be noted that the inter-industry effect of this infrastructure is extraordinary, at least during a decade (i.e. from 1995 to 2005). The investment in <u>electricity</u> networks, which allows larger percentages of population to have access to electricity, has had a more moderate effect on Asian productivity. Its negligible inter-industry effect indicates that this infrastructure has generated similar productivity increases in all sectors. The technological indicator measuring the investment in <u>internet</u> networks is also a relevant productivity driver in Asia. However, unlike the road infrastructure, it does not have significant inter-industry effects. Thus, the investment in both electricity and internet networks has promoted similar (at least positive) productivity gains in most sectors. Regarding the use of <u>cellular phones</u>, it is worth highlighting that both intra and inter-industry effects are quite large but with opposite signs. The more extended use of mobile phones has increased labor productivity on average, but this improvement has not been evenly spread across sectors (recall that we found negative marginal effects for this variable in Energy and Construction). Finally, the moderate increase in <u>human capital</u> did not reveal any relevant intra or inter-industry productivity effect. This is caused by the slow increase in the years of schooling and its non-significant effect on most sectors' production.

[Insert Figure 2 here]

In summary, the inter-industry productivity effects found for the Asian countries are relatively important for the investment in road and cellular networks. Therefore, they should not be ignored in a study measuring the productivity effects of these two network infrastructure investments. In other words, the traditional intra-industry measures tend to over or under-estimate the overall productivity effects of road and cellular networks.

Figure 3 depicts the cumulative productivity indices associated with infrastructure provision in a set of European countries and the USA. As these countries developed almost completely their transportation and electricity networks a long time ago, they did not experience productivity effects on their economies during the sample period. Only the investment in new roads had a small intra-industry effect on aggregate productivity. The investments in information and telecommunication (IT) networks have promoted noteworthy aggregated productivity in these countries. We find a cumulative effect of the investment in internet and cellular phones networks of 13% and 2%, respectively. The generalization of internet in society is the greatest productivity driver in Europe and the USA. Unlike the Asian countries, the investment in internet networks has had negative reallocation effects on aggregate productivity. The negative inter-industry effects have partially offset the positive intra-industry effects associated with this technological indicator. In summary, the traditional intra-industry measures tend to overestimate the overall productivity effects of IT investment. Again, the productivity effect of human capital is negligible due to years of schooling rarely changing over time and it has a quite modest effect, if any, on sector production.

[Insert Figure 3 here]

Figure 4 depicts the cumulative productivity indices associated with infrastructure provision in a set of Latin or South American countries. The productivity effect of the investment in new roads is pretty small and a bit erratic. This casts doubts about the quality of this variable in Latin America, and thus we do not discuss more results based on the road numbers. The access to electricity in the Latin American countries has increased over time. This explains the slightly positive effect that this variable has had on aggregate productivity, through both inter and intra-industry channels. Again the investment in IT networks has caused increases in aggregate productivity, but with a much more modest effect than in Europe and the USA. Similar to the latter countries, the intra-industry productivity effects associated with these two technological indicators are higher than the overall effects because we found negative reallocation effects associated with this region's IT networks. Again, like the other regions, human capital has barely changed aggregate productivity during the sample period.

[Insert Figure 4 here]

Figure 5 shows the cumulative productivity indices associated with infrastructure provision in our sample of African countries. In line with the other regions, road network investments have been very modest in the African countries included in our sample. However, the improvements in access to electricity in this region are slightly higher than in other regions. This explains why access to electricity is the main productivity driver with a cumulative effect of 11% in fifteen years. It should also be noted that the investment in electricity networks has not only improved individual productivities in all sectors, but has also promoted a better allocation of resources due to most of the productive sectors increasing their relative size. Unlike the previous regions, the use of internet in Africa has hardly changed over time during the sample period. This explains the small effect of this technological indicator on aggregate productivity. Its cumulative effect is 2.5% which is far behind the level of 13% in Europe and USA and 8% in Asia. Although the internet network has not been properly developed in the African countries, the use of cellular phones displayed an improvement in our sample, with an annual increase of 6 percentage units. Thus the investment in cellular phones networks in Africa has caused larger increases in aggregate productivity than in other World regions. However, similar to other countries, we found negative reallocation effects associated with communication networks in this region, indicating that not all sectors in the African countries have benefited equally from this technological investment. Finally, and unlike other regions, human capital has had a larger but negative effect on aggregate productivity during the sample period.

[Insert Figure 5 here]

5. Conclusions

In this paper we have tried to examine the role that infrastructure provision has played in stimulating aggregate productivity through both a better allocation of resources in the economy and as a proper productivity driver. To achieve this objective, we propose a simple approach that relies on estimating standard production frontier models. To illustrate the proposed decompositions, we have used the sector-level data of 39 countries over the 1995-2010 period.

Our industry-specific parameter estimates are consistent with the literature, since both capital stock and labor exhibit positive elasticities. Our results also support the hypothesis defended by previous researchers that consider public infrastructures as both a standard input and an efficiency-enhancing externality. The estimated coefficients vary considerably across industries, a necessary result for non-negligible inter-industry or reallocation productivity effects attributable to infrastructures.

The average rate of growth of labor productivity in our sample is about 1.5 percent. As expected, aggregate productivity growth is mainly explained by improvements in industry-specific productivities. The productivity growth attributable to changes in the structure of the economy is small on average, but displaying large rates of growth in some countries. We found that the intra and inter-industry effects also vary across regions. The Asian countries show the better performance, followed by the set of European countries and the USA. The inter-industry effects are non-trivial in some countries and have partially offset the improvements in intra-industry productivity.

Finally we used our theoretical framework and parameter estimates to examine the role that the telecommunication, transportation and electricity networks have played in both intra and inter-industry productivity growth. The results vary across regions. The infrastructure that stimulated aggregate productivity in Asia the most during the sample period is the investment in new roads, followed by the investment in internet and cellular phones networks. It should be noted that the inter-industry effects of some of these infrastructures are notable, and should not be ignored in a study examining the productivity impacts of infrastructure provision. In other words, the traditional intra-industry measures tend to over or under-estimate the overall productivity effects of these infrastructure variables.

The generalization of internet in society is the greatest productivity driver in Europe and the USA. Unlike the Asian countries, the investment in internet networks has had negative reallocation effects on aggregate productivity. Thus, traditional intra-industry measures tend to overestimate the overall productivity effects of IT investment in most developed countries. Again, the investment in internet and cellular phones networks has caused increases in Latin America aggregate productivity, but with a much more modest effect than in Europe and the USA. The improvements in the access to electricity are the main productivity drivers in the African countries. It should also be noted that the investment in electricity networks has not only improved individual productivities in all sectors, but has also promoted a better allocation of resources due to the most productive sectors increasing their relative size. However, in line with other countries, we found negative reallocation effects associated with communication networks in this region, indicating that not all sectors in the African countries have benefited equally from this technological investment.

In this paper we propose a bottom-up approach to trace the channels through which infrastructure investments stimulate economy-wide productivity improvements. As aforementioned, the top-down decompositions are conceptually more appealing than the bottom-up decompositions. Thus, a natural extension of this study is the use of a top-down approach to obtain a mutually consistent decomposition of both inter- and intra-industry productivity effects. This approach is more challenging that our bottom-up approach as it requires modelling how market power varies over time as a result of the provision of new infrastructures.

So far we have used value-added-shares to compute aggregate labor productivity. Thus, a second extension of this paper is to decompose the inter-industry (reallocation) effects using labor-shares. The decomposition of this term is, however, much more challenging than the decomposition developed here for two reasons. First, because employment is influenced by many factors that are difficult to fully control in practice; and second because different theoretical frameworks (e.g. cost vs. profit-based) yield very different results (see Appendix

B) and we do not know a priori which framework is more appropriate. Finally, we have decomposed an aggregated measure of labor productivity. This is a partial productivity measure and does not take into account the effect of other inputs. Thus, an interesting research topic is the development of a similar productivity decomposition using an aggregate measure of total factor productivity, assuming or not constant returns to scale.

References

- Alvarez, A., Amsler, C., Orea, L. and Schmidt, P. (2006). Interpreting and testing the scaling property in models where inefficiency depends on firm characteristics. *Journal of Productivity Analysis*, 25(3), 201-212.
- Asturias, J., García-Santana, M. and Ramos, R. (2014). *Misallocation, Internal Trade, and the Role of Transportation Infrastructureú*. PEDL Research.
- Baily, M. N., Hulten, C. and Campbell, D. (1992). Productivity Dynamics in Manufacturing Plants. *Brookings Papers on Economic Activity: Microeconomics*, 2, 187-249.
- Balk, B. M. (2016a). The Dynamics of Productivity Change: A Review of the Bottom-up Approach, in *Productivity and Efficiency Analysis*, edited by Greene, W.H., Khalaf, L., Sickles, R.C., Veall, M. and Voia, M.-C. Proceedings in Business and Economics (Springer International Publishing, Switzerland).
- Balk, B. M. (2016b). *Aggregate Productivity and Productivity of the Aggregate: Connecting the Bottom-Up and Top-Down Approaches*. Paper prepared for the 34th IARIW General Conference Dresden, Germany, August 21-27, 2016.
- Barro, R. J. (1991). Economic growth in a cross section of countries. *Quarterly Journal of Economics*, 106(2), 407-443.
- Bartelsman, E., Haltiwanger, J. and Scarpetta, S. (2013). Cross-Country Differences in Productivity: The Role of Allocation and Selection. *American Economic Review*, 2013, 103 (1), 305–334.
- Bauer, P. (1990). Recent developments in the econometric estimation of frontiers. *Journal of Econometrics*, 46(1-2), 39-56.
- Caliendo, L., Parro, F., Rossi-Hansberg, E. and Sarte, P. D. (2017). The impact of regional and sectoral productivity changes on the US economy. *Review of Economic Studies*,. rdx082, https://doi.org/10.1093/restud/rdx082.
- Caudill, S. B. and Ford, J. M. (1993). Biases in frontier estimation due to heteroscedasticity. *Economics Letters*, 41(1), 17-20.
- Caudill, S. B., Ford, J. M. and Gropper, D. M. (1995). Frontier estimation and firm-specific inefficiency measures in the presence of heteroscedasticity. *Journal of Business and Economic Statistics*, 13(1), 105-111.
- Chandra, A. and Thompson, E. (2000). Does public infrastructure affect economic activity?: Evidence from the rural interstate highway system. *Regional Science and Urban Economics*, 30(4), 457-490.
- Crescenzi, R. and Rodríguez-Pose, A. (2012). Infrastructure and regional growth in the European Union. *Papers in Regional Science*, 91(3), 487-513.
- Dabla-Norris, M. E., Thomas, M. A. H., Garcia-Verdu, M. R. and Chen, M. Y. (2013). *Benchmarking structural transformation across the world*. No. 13-176. International Monetary Fund.
- De Avillez, R. (2012). Sectoral contributions to labour productivity growth in Canada: does the choice of decomposition formula matter?”. *Productivity Monitor*, No. 24, Fall, pp 97–117.

- Diewert, W. E. and Fox, K. (2010). On measuring the contribution of entering and exiting firms to aggregate productivity growth. *Price and productivity measurement*, 6, 41-66.
- Diewert, W. E. (2015). Decompositions of productivity growth into sectoral effects. *Journal of Productivity Analysis*, 43(3), 367-387.
- Diewert, W. E. and Fox, K. (2016). *Decomposing Value Added Growth over Sectors into Explanatory Factors*, In Third Conference of the Society for Economic Measurement, Thessaloniki, September. 6-8.
- Färe, R., Grosskopf, S., Norris, M. and Zhang, Z. (1994). Decomposition of Productivity Growth in Industrialized Countries into Technical Change and Change in Performance. *American Economic Review*, 84(1), 66–83.
- Färe, R., Grosskopf, S., Lindgren, B. and Roos, P. (1994). Productivity developments in Swedish hospitals: a Malmquist output index approach, In *Data envelopment analysis: Theory, methodology, and applications*. Springer, Dordrecht, 253-272.
- Färe, R., Grosskopft, S. and Margaritis, D. (2008). Efficiency and Productivity: Malmquist and More, in Fried, H., Lovell, K. and Schmidt, S. (Eds.). *The measurement of productive efficiency and productivity growth*. Oxford University Press, Chapter 5.
- Foster, L., Haltiwanger, J. and Syverson, C. (2008). Reallocation, firm turnover, and efficiency: Selection on productivity or profitability?. *American Economic Review*, 98(1), 394-425.
- Foster, L., Haltiwanger, J. and Krizan, C. J. (2001). Aggregate Productivity Growth: Lessons from Microeconomic Evidence, in *New Developments in Productivity Analysis*, edited by Hulten, C. R., Dean, E. R. and Harper, M. J. Studies in Income and Wealth Volume 63 (The University of Chicago Press, Chicago and London).
- Fried, H., Lovell, K. and Schmidt, S. (2008). Efficiency and Productivity, in Fried, H., Lovell, K. and Schmidt, S. (Eds.). *The measurement of productive efficiency and productivity growth*. Oxford University Press, Chapter 1.
- Greene, W. (2005). Fixed and random effects in stochastic frontier models. *Journal of productivity analysis*, 23(1), 7-32.
- Griliches, Z. and Regev, H. (1995). Firm Productivity in Israeli Industry, 1979-1988. *Journal of Econometrics*, 65(1), 175-203.
- Karagiannis, G. (2013). *Reallocation and Productivity Dynamics: Empirical Evidence on the Role of Aggregation Weights*. Mimeo (Department of Economics, University of Macedonia, Thessaloniki).
- Kumbhakar, S. and Lovell, K. (2003). *Stochastic frontier analysis*. Cambridge university press.
- McMillan, M., Rodrik, D. and Verduzco-Gallo, Í. (2014). Globalization, structural change, and productivity growth, with an update on Africa. *World Development*, 63, 11-32.
- Mensah, J., Adu, G., Amoah, A., Abrokwa, K. K. and Adu, J. (2016). What Drives Structural Transformation in Sub-Saharan Africa?. *African Development Review*, 28(2), 157-169.
- Nishimizu, M. and Page, M. (1982). Total factor productivity growth, technological progress and technical efficiency change: dimensions of productivity change in Yugoslavia, 1965-78. *Economic Journal*, 92(368), 920-936.
- Orea, L. (2002). Parametric decomposition of a generalized Malmquist productivity index. *Journal of Productivity Analysis*, 18(1), 5-22.

- Pereira, A. M. and Andraz, J. M. (2013). On the economic effects of public infrastructure investment: A survey of the international evidence. *Journal of Economic Development*, 38(4), 1-37.
- Petrin, A. and Levinsohn, J. (2012). Measuring aggregate productivity growth using plant-level data. *RAND Journal of Economics*, 43(4), 705-725.
- Qiang, C. Z.-W. and Rossotto, C.M. (2009). *Economic Impacts of Broadband*, Information and Communications for Development 2009: Extending Reach and Increasing Impact, 35–50. Washington, DC., World Bank.
- Reifschneider, D. and Stevenson, R. (1991). Systematic Departures from the Frontier: A Framework for the Analysis of Firm Inefficiency. *International Economic Review*, 32(3), 715-723.
- Restuccia, D. and Rogerson, R. (2013). Misallocation and productivity. *Review of Economic Dynamics*, 16 (1), 1–10.
- Restuccia, D. and Rogerson, R. (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics*, 11(4), 707-720.
- Rodríguez-Pose, A. and Fratesi, U. (2004). Between development and social policies: the impact of European Structural Funds in Objective 1 regions. *Regional Studies*, 38(1), 97-113.
- Romp, W. and De Haan, J. (2007). Public capital and economic growth: A critical survey. *Perspektiven der Wirtschaftspolitik*, 8, 6-52.
- Straub, S. (2012). Infrastructure and Development: A Critical Appraisal of the Macro-Level Literature. *Journal of Development Studies*, 47(05), 683-708.
- Vivarelli, M. (2012). *Innovation, employment and skills in advanced and developing countries: A survey of the literature*. Discussion Paper series, Forschungsinstitut zur Zukunft der Arbeit, No. 6291, Institute for the Study of Labor (IZA), Bonn.
- Yang, H. (2000). A note on the causal relationship between energy and GDP in Taiwan. *Energy Economics*, 22(3), 309-317.

Table 1. Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Technological indicators, infrastructures, and human capital					
Capital stock (mil *US$*)	585	2615655	7181440	85	48200000
Human capital (years)	585	2.46	0.60	1.13	3.69
Cellular subscriptions (%)	585	0.52	0.28	0.00	0.99
Electricity access (%)	585	0.78	0.31	0.04	1.00
Internet users (%)	585	0.18	0.24	0.00	0.91
Roads	585	0.52	1.18	0.00	6.52
Gross Value Added (million US$)					
Agriculture	585	85529	440471	48	6688307
Energy	585	67245	212980	54	2632056
Manufacturing	585	162751	339038	216	2641436
Services	585	419997	1213204	749	7502153
Construction	585	64748	155187	114	1345587
Labor (thousand jobs)					
Agriculture	585	20435	65599	5	366400
Energy	585	639	2145	5	15730
Manufacturing	585	7007	19728	27	144632
Services	585	11547	20619	81	114051
Construction	585	3041	7891	21	52412

Note: the monetary variables have been expressed in US dollars for the unique purpose of issuing this table.

Table 2. Maximum likelihood estimates

	Agriculture			Energy			Manufacturing			Services			Construction		
	Coef.		s.e.	Coef.		s.e.	Coef.		s.e.	Coef.		s.e.	Coef.		s.e.
Frontier															
ln(Capital)	0.137	**	0.063	0.808	***	0.071	0.413	***	0.055	0.160	***	0.065	0.755	***	0.070
ln(Labor)	0.499	***	0.058	0.118	***	0.036	0.550	***	0.031	0.648	***	0.053	0.713	***	0.035
Human Capital	-0.066		0.104	0.101		0.105	-0.150	*	0.079	0.040		0.088	-0.532	***	0.103
Cellulars	0.077	*	0.044	-0.129	***	0.053	-0.093	***	0.044	0.020		0.046	-0.025		0.060
Electricity access	0.665	***	0.177	0.471	**	0.207	0.311	***	0.149	0.328	**	0.153	-0.329		0.231
Internet	0.181	***	0.051	-0.214	***	0.050	0.278	***	0.061	0.363	***	0.045	-0.389	***	0.052
Roads	0.061	*	0.033	0.087	***	0.032	0.127	***	0.021	0.247	***	0.027	0.093	***	0.026
Intercept	9.994	***	0.807	4.824	***	0.768	7.879	***	0.598	10.463	***	0.658	4.181	***	0.765
Inefficiency															
Human Capital	-2.816	***	0.922	3.658	***	0.729	1.387	***	0.446	-6.235	***	1.425	1.447	***	0.338
Cellulars	-5.546	***	1.564	-2.544	***	0.607	-3.847	***	0.787	-1.520	***	0.672	0.041		0.473
Electricity access	1.014		0.997	-7.112	***	1.312	-0.420		0.709	6.091	***	1.820	-1.064	**	0.525
Internet	-3.562		4.232	-13.602	***	5.543	-0.060		0.888	6.556	***	2.032	-6.904	***	1.185
Roads	0.998	***	0.277	-15.292	***	3.670	-0.319	***	0.127	-0.429		0.319	-2.529	***	0.913
Intercept	0.574		1.250	-5.375	***	1.062	-5.693	***	0.968	3.967	***	1.453	-4.910	***	0.696
Noise															
lnsv	-4.671	***	0.065	-4.581	***	0.070	-5.650	***	0.189	-5.147	***	0.100	-5.303	***	0.154
LogL	499.21			416.16			606.55			587.62			436.69		

*Notes: ** denotes statistical significance at the 1% level and * at 5% level.*

Table 3. Total marginal effects of the efficiency determinants

	Agriculture		Energy		Manufacturing		Services		Construction	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Human Capital	-0.019	0.088	-0.043	0.324	-0.210	0.034	0.210	0.180	-0.625	0.060
Cellular phones	0.170	0.174	-0.029	0.225	0.073	0.094	0.061	0.044	-0.027	0.002
Electricity access	0.648	0.032	0.751	0.630	0.329	0.010	0.162	0.176	-0.261	0.044
Internet	0.241	0.112	0.322	1.205	0.281	0.001	0.184	0.189	0.056	0.288
Roads	0.044	0.031	0.690	1.355	0.141	0.008	0.259	0.012	0.256	0.106

Table 4. Sectoral and aggregate productivity growth

	Obs	Mean	Std. Dev.	Min	Max
Sector productivity growth rates (%)					
Agriculture	546	2.7	8.5	-54.9	43.7
Energy	546	2.2	13.1	-78.4	60.1
Manufacturing	546	1.8	5.5	-20.5	24.3
Services	546	1.1	4.6	-22.1	16.5
Construction	546	0.1	8.5	-49.1	41.3
Aggregate productivity growth and intra vs. Inter-effects (%)					
ALL Regions					
Economy	546	1.5	5.5	-41.2	25.6
Intra-effect	546	1.6	3.7	-13.1	13.9
Inter-effect	546	-0.1	4.1	-51.4	20.1
ASIA					
Economy	140	2.7	4.4	-10.1	12.4
Intra-effect	140	2.4	4.0	-9.4	10.1
Inter-effect	140	0.3	1.3	-2.9	4.8
EUR and USA					
Economy	112	1.3	2.9	-9.4	14.2
Intra-effect	112	1.8	2.9	-8.6	13.9
Inter-effect	112	-0.5	1.0	-6.5	1.6
LATIN AMERICA					
Economy	126	0.5	4.5	-14.2	9.7
Intra-effect	126	0.7	4.0	-12.5	9.5
Inter-effect	126	-0.2	2.4	-11.0	9.6
AFRICA					
Economy	168	1.2	7.7	-41.2	25.6
Intra-effect	168	1.3	3.6	-13.1	11.6
Inter-effect	168	-0.1	6.8	-51.4	20.1

Figure 1. Temporal evolution of the infrastructure variables by region.

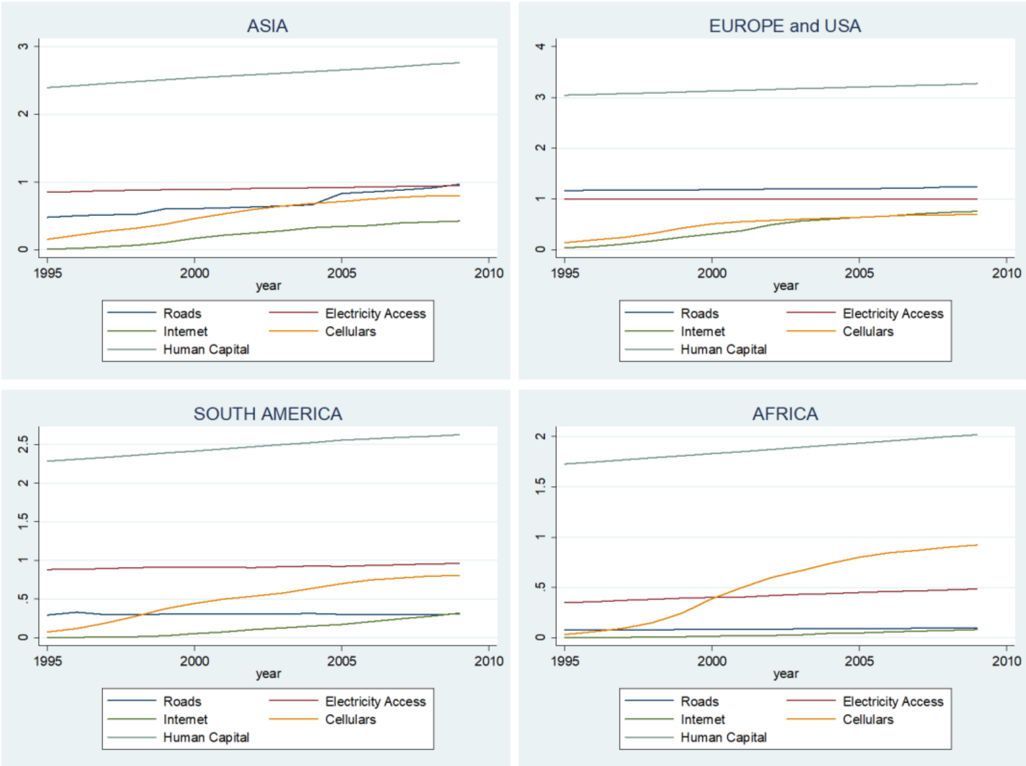


Figure 2. Intra and inter-industry effects attributed to infrastructure variables. ASIA.

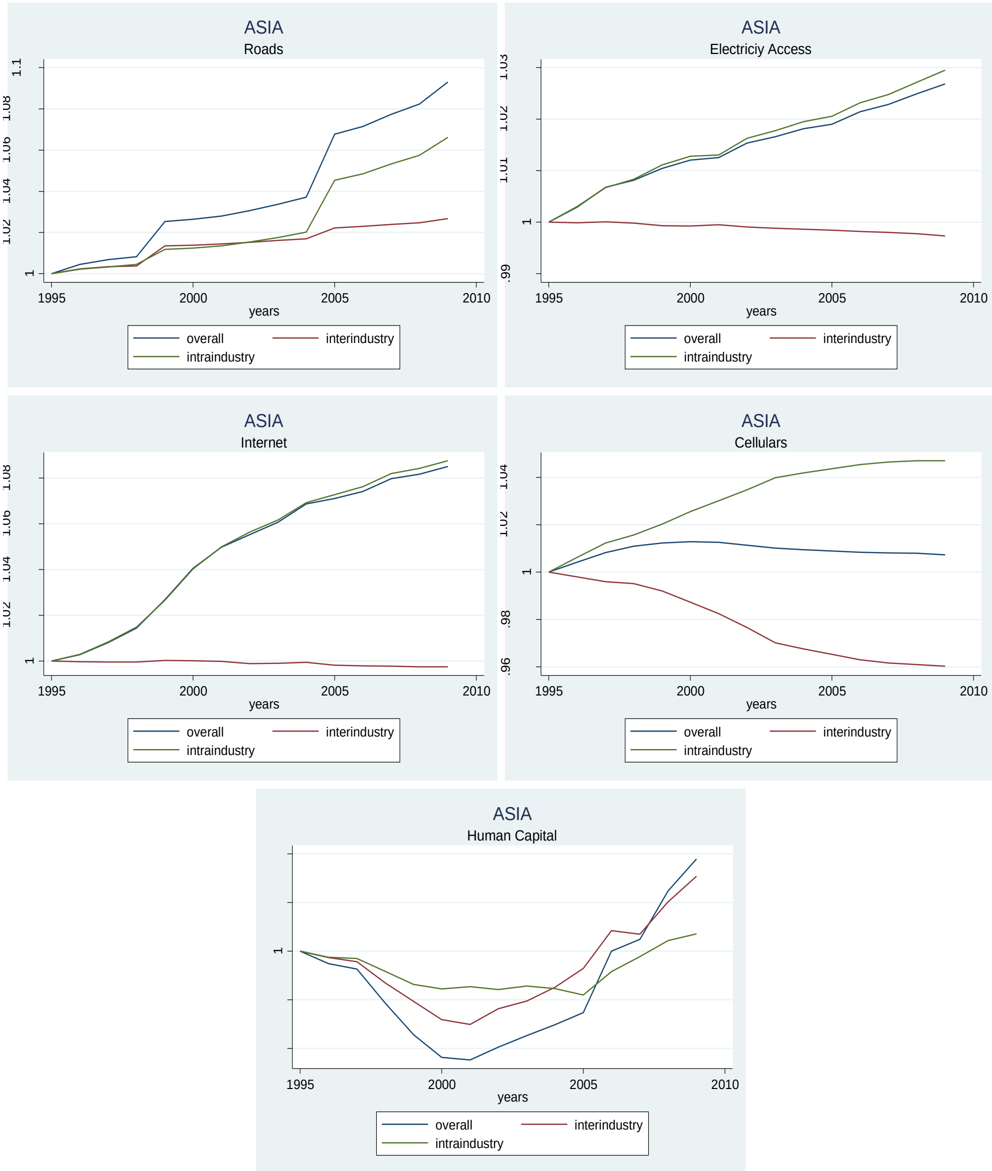


Figure 3. Intra and inter-industry effects attributed to infrastructure variables. Europe and USA.

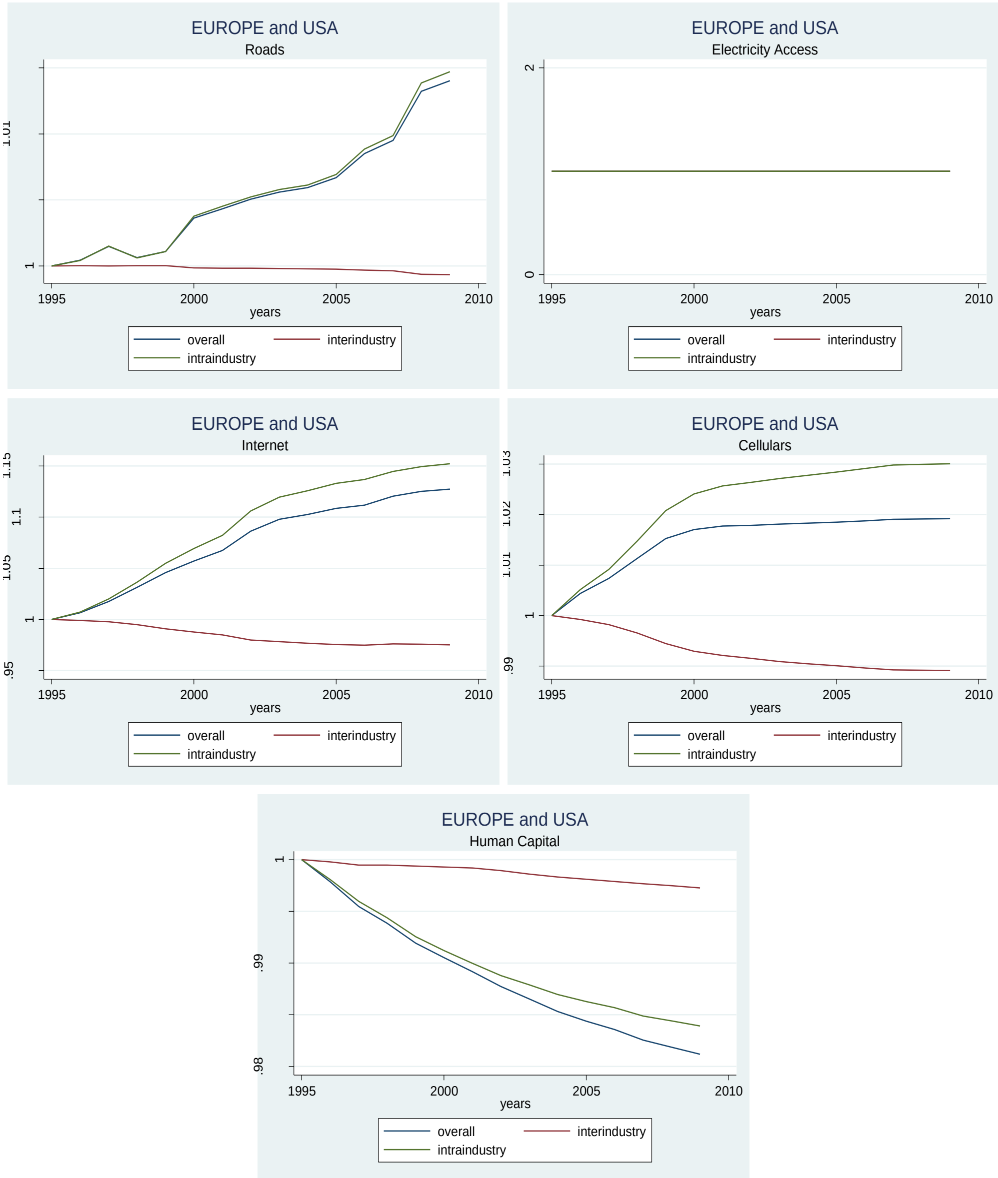


Figure 4. Intra and inter-industry effects attributed to infrastructure variables. Latin America.

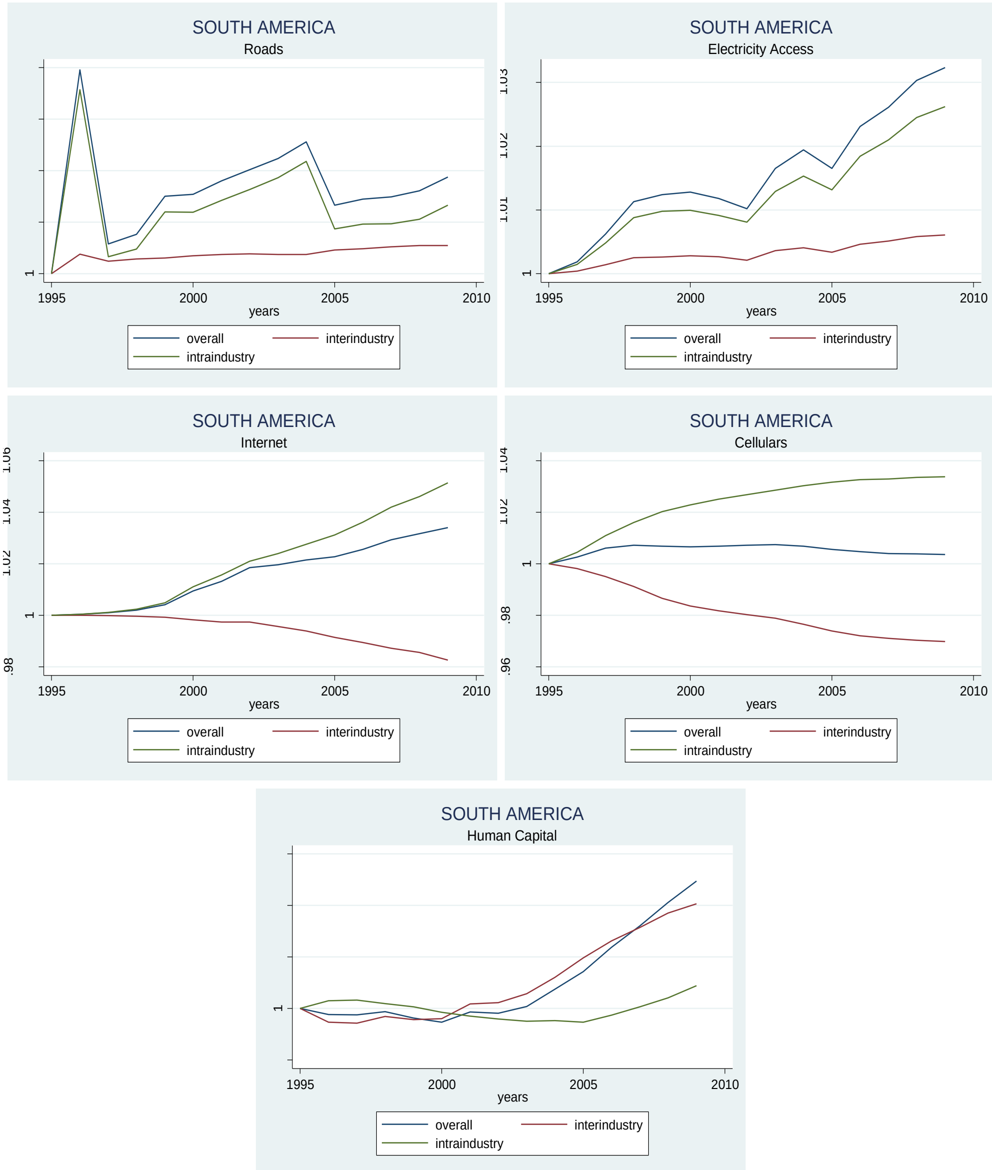
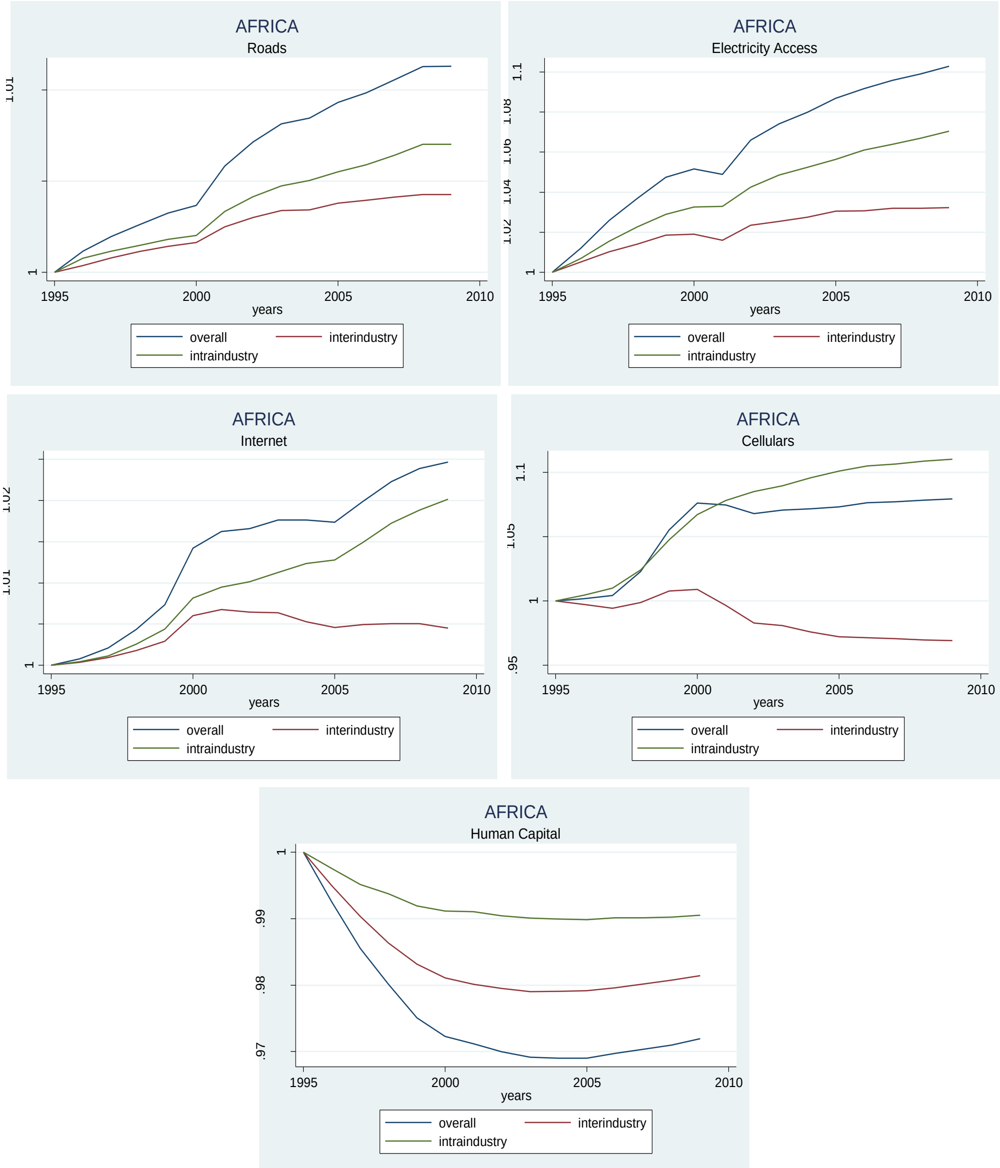


Figure 5. Intra and inter-industry effects attributed to infrastructure variables. Africa.



Appendix A. List of countries and selected regions

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.

Appendix B. Input-based decompositions of inter-industry effects

We use in this appendix a profit and cost framework to both "endogenize" the industry-specific labor levels and that appear in $S_{jt} = L_{jt}/\sum_{h=1}^{H} L_{ht}$. For simplicity we hereafter assume full allocative efficiency in both cost and profit optimization.

Cost approach

Assume that the problem of a representative firm belonging to industry j is to minimize the cost of employing K_{jt} and L_{jt}, given the capital and labor prices (r_{jt} and w_{jt}), and the technology. The solution to the optimization problem yields a cost function that is dual to the production function (11):

$$\mathrm{C}_{jt} = \Psi_{jt} {w_{jt}}^{\beta_{Lj}/\beta_j} \cdot {r_{jt}}^{\beta_{Kj}/\beta_j} \cdot {\mathrm{y}_{jt}}^{1/\beta_j} \quad \text{(B.1)}$$

where $\beta_j = \beta_{Lj} + \beta_{Kj}$ and $ln\Psi_{jt} = ln\beta_j - \frac{1}{\beta_j} ln\mathrm{A}_{jt} - \frac{1}{\beta_j}\left(\beta_{Lj} ln\beta_{Lj} + \beta_{Kj} ln\beta_{Kj}\right)$. The optimal labor demand can be obtained by means of the Shepard lemma. After taking logs, the labor demand is equivalent to:

$$lnL_{jt} = ln\left(\beta_{Lj}/\beta_j\right) + ln\alpha_j - \frac{1}{\beta_j}\left(\beta_{0j} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} - u_{jt}(z_t)\right) - \frac{1}{\beta_j}\left(\beta_{Lj} ln\beta_{Lj} + \beta_{Kj} ln\beta_{Kj}\right) + \left(\frac{\beta_{Lj}}{\beta_j} - 1\right) lnw_{jt} + \frac{\beta_{Kj}}{\beta_j} lnr_{jt} + \frac{1}{\beta_j} ln\mathrm{y}_{jt} \quad \text{(B.2)}$$

Given (B.2), the effect of infrastructure provision on the labor demand is:

$$\frac{\partial L_{jt}}{\partial z_h} = -\Theta_{jht} L_{jt} \quad \text{(B.3)}$$

where $\Theta_{jht} = \theta_{jht}/\beta_j$. The cost-based effect of infrastructure provision on the industry j labor share is:

$$\frac{\partial S_{jt}(z_t, y_t, w_t, r_t)}{z_h} = S_{jt}\left[\overline{\Theta}_{ht} - \Theta_{jht}\right] \quad \text{(B.4)}$$

where $\overline{\Theta}_{ht} = \sum_{s=1}^{J} S_{st}\Theta_{sht}$. The overall inter-industry marginal effect of infrastructure provision in (9) can then be measured in practice as:

$$\frac{\partial \bar{S}_t}{\partial z_h} = \sum_{j=1}^{J} \frac{lnP_{jt} + lnP_{jt-1}}{2}\left\{\frac{S_{jt-1} + S_{jt}}{2}\left[\overline{\Theta}_{ht} - \Theta_{jht}\right]\right\} \quad \text{(B.5)}$$

Profit approach

Kumbhakar and Lovell (2000, p. 188) show that if the production frontier takes the Cobb-Douglas form as in (11), the first-order conditions for profit maximization (ignoring v) can be written as:

$$\mathrm{ln}L_{jt} = \beta_{0j} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} + (1 + \beta_{Lj}) lnL_{jt} + \beta_{Kj} lnK_{Kt} - ln\left(\frac{w_{jt}}{\mathrm{p}_{jt}}\right) - u_{jt} \quad \text{(B.6)}$$

$$\mathrm{ln}K_{jt} = \beta_{0j} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} + \beta_{Lj} lnL_{jt} + (1 + \beta_{Kj}) lnK_{Kt} - ln\left(\frac{r_{jt}}{\mathrm{p}_{jt}}\right) - u_{jt} \quad \text{(B.7)}$$

The profit-maximizing choice of both output and input levels gives the following output supply and labor demand equations:

$$\mathrm{ln}y_{jt} = \frac{1}{1-\beta_j}\left(\beta_{0j} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} - u_{jt}\right) + \frac{1}{1-\beta_j}\beta_{Lj}\left(ln\beta_{Lj} - ln\left(\frac{w_{jt}}{\mathrm{p}_{jt}}\right)\right) + \frac{1}{1-\beta_j}\beta_{Kj}\left(ln\beta_{Kj} - ln\left(\frac{r_{jt}}{\mathrm{p}_{jt}}\right)\right) \quad \text{(B.9)}$$

$$\ln L_{jt} = \frac{1}{1-\beta_j}\left(\beta_{0j} + \sum_{h=1}^{H} \gamma_{jh} z_{ht} - u_{jt}\right) + \frac{1}{1-\beta_j}\left(\beta_{Lj} + (1-\beta_j)\right)\left(ln\beta_{Lj} - ln\left(\frac{w_{jt}}{p_{jt}}\right)\right) + \frac{1}{1-\beta_j}\beta_{Kj}\left(ln\beta_{Kj} - ln\left(\frac{r_{jt}}{p_{jt}}\right)\right) \quad \text{(B.10)}$$

The effect of infrastructure provision on labor demand is given by:

$$\frac{\partial L_{jt}}{\partial z_h} = \Omega_{jht} L_{jt} \quad \text{(B.11)}$$

where $\Omega_{jht} = \theta_{jht}/(1-\beta_j)$. The profit-based effect of infrastructure provision on the industry j labor share is:

$$\frac{\partial S_{jt}(z_t, w_t, r_t, p_t)}{z_h} = S_{jt}\left[\Omega_{jht} - \overline{\Omega}_{ht}\right] \quad \text{(B.12)}$$

where $\overline{\Omega}_{ht} = \sum_{s=1}^{J} S_{st}\Omega_{sht}$. Finally, the overall inter-industry marginal effect of infrastructure provision in (9) can then be measured in practice as:

$$\frac{\partial \bar{S}_t}{\partial z_h} = \sum_{j=1}^{J} \frac{lnP_{jt} + lnP_{jt-1}}{2}\left\{\frac{S_{jt-1} + S_{jt}}{2}\left[\Omega_{jht} - \overline{\Omega}_{ht}\right]\right\} \quad \text{(B.13)}$$