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Benefits and Spillover Effects of Infrastructure: A Spatial Econometric Approach*

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This paper estimates the effects of transport (road and rail) & energy and ICT infrastructure (telephone, mobile, and broadband) on GDP growths in neighboring countries as well as own countries. We confirm positive direct contributions of infrastructure, access to Internet, and human capital on economic growth. The spatial panel regression models indicate that there exist positive externalities of the broadband infrastructure and human capital, and these results are robust regardless of the choice of spatial weight matrices. Our findings on spillover effects of infrastructure suggest the key role of neighboring countries' infrastructure on own country's economic growth.

Keywords: Infrastructure, Spillover Effects, Economic Growth, Production Function, Spatial Econometrics

JEL Classification: C21, D24, D62

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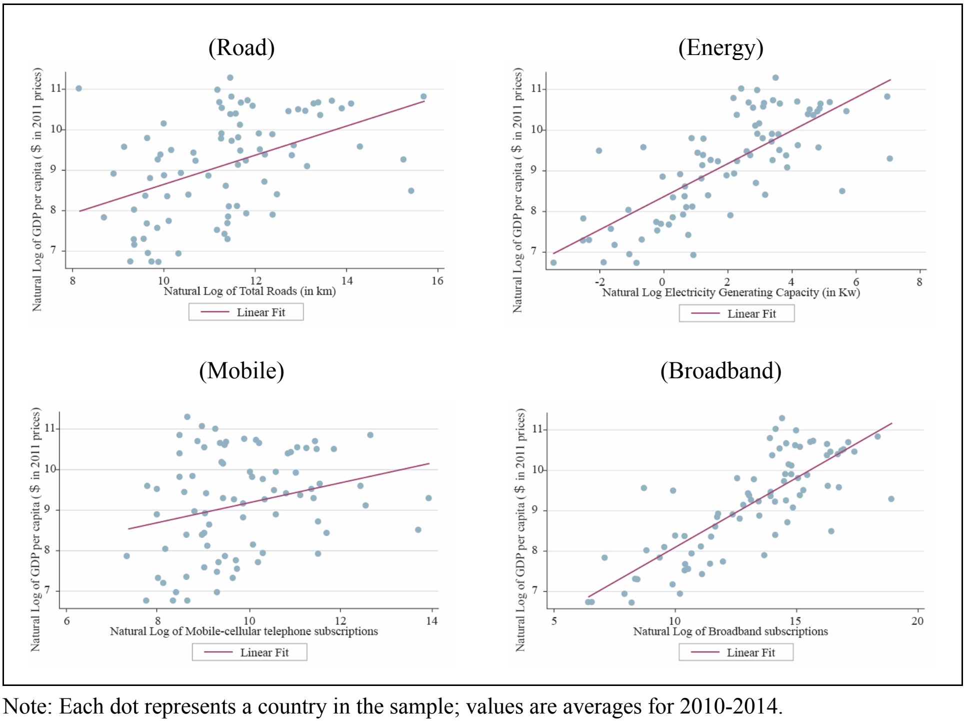
I. Introduction

The positive contribution of infrastructure on economic growth has long been found in a large body of the literature, although the magnitude of the impact is the subject of considerable uncertainty. As one of the major production factors, higher infrastructure capital is strongly associated with higher income. Figure 1 indicates strong positive correlation between per capita income and selective proxies for infrastructure capital stock including road, energy, mobile, and broadband. When combined with financially interconnected markets, infrastructure allows people and capital to move more freely not just within own countries but to other countries in the neighborhood that can be defined in terms of geographical or economic proximity, creating spillover effects across borders.

Figure 1. National Income vs Infrastructure by Type (2010-2014 average)



Note: Each dot represents a country in the sample; values are averages for 2010-2014.

Sources: Penn World Table 9.0 (Feenstra et al., 2015); International Road Federation (IRF); U.S. Energy Information Administration (EIA) and International Telecommunication Union (ITU)

For instance, these intra- and inter-country externalities, in the case of building and enhancing a transport network, are made possible through redistribution of production resources and productivity gains due to agglomeration (Tong et al., 2013). And the transport network enables the impact of the global value chains, a formal source of spillover effects, to more easily extend across multiple economies. At the same time the use of ICT increases productivity internally by raising the quality and productivity of other inputs, and externally by facilitating dissemination of knowledge from one firm, industry, or country to another (Moshiri, 2016). Rising interconnectedness through infrastructure and its externalities suggests that investigating economic benefits of infrastructure should take into account not only direct impacts within a country, but also indirect impacts that propagate over its neighboring countries.

This paper estimates the economic benefits of infrastructure on output. Two broad categories of infrastructure are examined: (1) transport (roads and rails) and energy, and (2) the ICT infrastructure that covers telephone, mobile, and fixed broadband subscriptions. We employ spatial econometric analysis to estimate separately the direct as well as indirect or cross-border benefits of infrastructure.

In our preferred spatial panels models, significant and positive cross-border spillover effects of the broadband infrastructure and human capital are found under the assumption that economic connectivity is represented by physical proximity. These results are robust to the choice of a spatial weight matrix. Our results also indicate that rail infrastructure show positive and significant output impacts on neighboring countries as well as on own countries.

While most studies have employed this method in the analysis of subnational economy spillovers, this paper is one of the few studies that explicitly applies the spatial econometric approach to cross-county infrastructure panel data. The results highlight the need to distinguish the non-infrastructure variable from the total capital stock variable that are commonly used in the empirical models together with infrastructure stock variables that are already included in the estimates of total capital. Our paper also attempts to shed light on the literature on regional public goods (RPGs). RPGs are defined as public goods whose non-excludable and non-rivalry benefits extend beyond a single nation's territory to some well-defined region (Sandler, 2006). A transportation network is a good example of an RPG. Most literature in this area is theoretical or qualitative, while attempts to measure RPGs are usually limited to the input side or investments in RPGs. Thus, another value-added of this paper is the attempt to measure the output side of RPGs by estimating the direct benefits and spillover effects of infrastructure as an RPG.[1]

The paper is organized as follows. Section II outlines a brief survey of the literature discussing the benefits and spillover effects of infrastructure, followed by the motivations for the use of the spatial econometric models in achieving this paper's objectives. Section III explains the structure of the non-spatial and spatial panel models to be estimated. Section IV discusses the data, and Section V presents the results of non-spatial and spatial models. Section VI concludes.

II. Literature Review

1. Benefits and Spillover Effects of Infrastructure

The key role of physical infrastructure is often highlighted in terms of facilitating trade and reducing trade costs in the empirical studies where variants of the gravity models are commonly used. The majority of the infrastructure variables in those studies are perception-based indicators collected from surveys, which makes it difficult to interpret the degrees of their changes by nature.

Several studies confirm the existence of spillover effects of transport and ICT infrastructure on output. These are mostly based on sub-national studies such as in the People's Republic of China (PRC), and in a few developed countries. For recent examples, exploring cities in Hunan province, PRC, Hu and Luo (2017) find that road infrastructure has a significant positive direct as well as indirect effect on economic growth, with the indirect effect greater than the direct effect. Yu et al. (2013) find the existence of both positive and negative spatial spillovers of infrastructure in the PRC regions. For the US states, Tong et al. (2013) find that road disbursement has a

[1] It might be more reasonable to limit our focus to cross-border infrastructure given its intended influence on multiple countries targeted. However, cross-country data on cross-border infrastructure are rarely available. Instead, this study uses national level infrastructure data which conceptually covers the infrastructure that connects to other countries. Our approach can be viewed from the perspective that being connected locally is a necessary condition for being connected across borders, thus local infrastructure in place ultimately contributes to higher cross-border connectivity. For the percentage of cross-border (or regional) infrastructure of total infrastructure projects, an indicative measure for Asia points to approximately 4%, which is comparable to Europe (Bhattacharyay, 2010).

significant positive direct effect on a state's agricultural output, while also beneficial to agricultural development in other states.

For ICT infrastructure, Moshiri (2016) shows that ICT can have a positive impact on labor productivity, but with differences across regions, industries, and time (Moshiri, 2016).[2] The results show that the impact of ICT investment in the US on Canada, a major trading partner, has spilled over to some Canadian provinces and industries while the overall ICT effects are concentrated in those ICT-intensive provinces and industries. ICT capital is also found to be an important source of total factor productivity growth (van Leeuwen and van der Wiel, 2003). More recently, Lin et al. (2017) find the evidence of the spillover effect of the Internet, highlighting its effects on growth as a conduit through which new technology flows to neighboring regions to generate new knowledge and to facilitate the exchange of knowledge.

Spillover effects of infrastructure can also be negative, as found in the literature. An increase in infrastructure in neighboring countries may negatively affect the own region's economy. While intra-regional effects of infrastructure are generally positive, the negative inter-regional spillover effects can be explained by a competing economic relationship between the own and neighboring regions in acquiring resources for production (while a positive inter-regional spillover means a complementary relationship) or the regions may be competing for markets for the products that they produce. The studies at the subnational level find that infrastructure investment in one region may draw mobile production factors away from other regions (for examples on the US, see Boarnet, 1998; Cohen and Manaco, 2007 and Sloboda and Yao, 2008). Regional competition takes various forms depending on horizontal/vertical competitive relations and the type of competition and competitors (Batey and Friedrich, 2000). In the case of cross-country spillover effects, one can expect smaller degrees of negative (or positive) externalities, if any, given the higher restrictions imposed on factor movements across countries.

[2] Unlike transport infrastructure generally measured by the lengths of total roads and rails, the proxies for ICT infrastructure come in various forms due to its wider scope of coverage (OECD, 2002): for example, telephone and mobile/cellular phone subscriptions, access to the Internet, the number of computers, software, and communications, electrical and electronic equipment (O'Mahony and Vecchi, 2005; Skorupinska and Torrent-Sellens, 2015; Calderón et al., 2015; Shahiduzzaman et al., 2015; Wamboye et al., 2016 and Lin et al., 2017).

2. Motivation for the Use of Spatial Econometric Models

To provide a basis for the use of the spatial econometric methods in achieving the objectives of the paper, we briefly review the following: (1) an omitted variables motivation, (2) spatial heterogeneity motivation, and (3) externalities-based motivation (LeSage and Pace, 2009).

In spatial samples, an omitted variable bias easily arises when unobservable factors (e.g. locational advantages) that are likely to be spatially correlated have an influence on the dependent variable (e.g. national income). A spatial autoregressive (SAR) model can address this omitted variable bias with a spatial lag (i.e. a linear combination of neighbors' y's).

$$\text{SAR model in a matrix form: } y = \rho W y + X\beta + \varepsilon \tag{1}$$

where y is the $n \times 1$ vector of a dependent variable; W is the $n \times n$ spatial weight matrix representing the neighboring structure between n observational units; ρ is the spatial AR coefficient (a scalar); X is the $n \times p$ matrix of explanatory variables; β is the $p \times 1$ coefficient vector.

Unlike a panel regression model with the coefficients assumed to be identical for all observational units, a spatial panel model allows each spatial unit to react differently mainly because each unit has different set of neighbors and is affected by them. This can be easily shown in the reduced form of the SAR model with $\text{abs}(\rho) < 1$:

$$\text{Reduced form SAR model: } y = (I - \rho W)^{-1} X\beta + (I - \rho W)^{-1}\varepsilon \tag{2}$$

where $(I - \rho W)^{-1} = I + \rho W + \rho^2 W^2 + \rho^3 W^3 + \cdots$. The W represents immediate (first-order) neighbors, W^2 neighbors to the first-order neighbors, and so on. Note that ρ is zero in non-spatial panel models.

As the impact of a shock dissipates over time through a temporal lag in the AR model, the SAR model allows us to model a spatial dependence where a shock in the error at any location is transmitted to other regions, with its impact dissipating over physical or economic distance (Anselin, 2003). Moreover, externalities from neighbors' characteristics (WX) can be reflected together with the spatial term in the spatial Durbin Model (SDM):

$$SDM\ in\ a\ matrix\ form: y = \rho W y + X\beta + WX\gamma + \varepsilon \tag{3}$$

III. Model

1. Non-spatial Panel Regression Model

For the non-spatial panel models, the Cobb-Douglas production function is used, following Calderón et al. (2015).

$$Y_{it} = A_{it}K_{it}^{\alpha}Z_{it}^{\gamma}\left(e^{\phi H_{it}}P_{it}\right)^{1-\alpha-\gamma} \tag{4}$$

Y denotes real output, A total factor productivity, K and Z physical and infrastructure capital, respectively, H human capital, and P total population. i is the index corresponding to country $i = \{1, \ldots, n\}$, while t is the index corresponding to time $t = \{1, \ldots, T\}$. Constant returns to scale is assumed following prior studies. Dividing by the population and taking natural logarithms, we estimate the panel regression model by:

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 h_{it} + \mathbf{z}_{it}\boldsymbol{\eta} + \mu_i + \gamma_t + \varepsilon_{it} \tag{5}$$

where k_{it} is the per capita capital stock, h_{it} is human capital, $\mathbf{z}_{it}$ is a vector of infrastructure variables, μ_i is the unobserved country effect, γ_t is the time fixed effect, ε_{it} is a random fluctuation, and β_1, β_2, and $\boldsymbol{\eta}$ are elasticities. The μ_i captures any idiosyncratic effect in the i^{th} country that may affect its output. On one hand, the idiosyncratic effect could be economic in nature, which may be correlated with the capital and human capital stock. On the other hand, the idiosyncratic effect could be cultural in such a way that it is unique to the country and is independent of the economy.

2. Spatial Panel Regression Model

(1) Spatial weight matrix[3]

The economic growth of a country is affected by the characteristics of its neighbors when spatial spillover effects are present. The definition of a neighborhood depends on a symmetric weight matrix, denoted by $\mathbf{W}_{n \times n} = \{w_{ij}\}$, where $w_{ij} > w_{ik}$ implies that country i is closer to country j than with country k. The weight matrix is often measured in terms of geographic distance, e.g. $w_{ij} = 1/d_{ij}$ where d_{ij} is the geographic distance between country i and j.[4] The neighborhood can also be defined in terms of economic distance, e.g. the total trade flows between the two countries. The $\mathbf{W}_{n \times n}$ is often row-standardized to aid interpretation. Three weight matrices are used, namely (1) exponential decay $\mathbf{W}_1 = \{\exp\left(-0.01 * 1/d_{ij}\right)\}$, (2) inverse of distance $\mathbf{W}_2 = \{1/d_{ij}\}$, and (3) inverse of square of distance $\mathbf{W}_3 = \{1/d_{ij}^2\}$, all with a 25[th] percentile cutoff, i.e., the neighbors of a particular country are only the closest 25% of all countries in terms of distance. Countries with distance beyond the cutoff have a weight of zero. The use of a percentile cutoff instead of an absolute distance cutoff reduces the effect of country area size.

(2) Spatial Durbin Model

The spatial Durbin model (SDM) is implemented to account for the spatial spillover effect in the production function of country i in the form of the weighted average of

[3] In a spatial weight matrix, the extent to which a location is interconnected with all other locations is imposed a priori. Thus, the spatial weight matrix should not be treated as something to be estimated, but as exogenous. As such, geography-based (e.g. contiguity- and distance-based) weights that are free of the endogeneity issue have been widely used. This paper also follows this traditional concept of a spatial weigh matrix that requires to be exogenous. However, interconnectedness can be represented by economic distance such as trade flows and there have been many attempts to address an endogenous spatial weight matrix in the recent spatial econometrics literature. Authors leave this issue to our future research agenda.

[4] This study follows an approach commonly used in the literature to compute the distance between two countries. It is calculated by first plotting the country centroids using a Geographic Information System (GIS) country shapefile, then spherical distance functions were used to compute the distance in kilometers between the centroids.

the regressors, in addition to the weighted average of the of the output of neighbors, given by the equation:

$$y_{it} = \beta_0 + \beta_1 k_{it} + \beta_2 h_{it} + \mathbf{z}_{it}\boldsymbol{\eta} + \sum_{j=1}^{n} w_{ij}\mathbf{x}_j'\boldsymbol{\theta} + \rho\sum_{j=1}^{n} w_{ij} y_{jt} + \mu_i + \gamma_t + \varepsilon_{it} \tag{6}$$

where $\mathbf{x}$ is a pool of regressor variables deemed as a source of spatial spillover effects with its corresponding coefficient vector $\boldsymbol{\theta}$.

(3) Average direct and indirect impacts

The expected values of y's in the SDM can be written in a matrix form:

$$E(\mathbf{Y}_t) = (\mathbf{I} - \rho\mathbf{W})^{-1}[\mathbf{X}_t\boldsymbol{\beta} + \mathbf{W}\mathbf{X}_t\boldsymbol{\theta}] \tag{7}$$

where $\mathbf{Y}_t$ is a $n \times 1$ vector of response variable of each cross-section unit, $\mathbf{X}_t$ is an $n \times p$ matrix of regressor variables with an $p \times 1$ coefficient vector $\boldsymbol{\beta}$, $\mathbf{X}_t = [\mathbf{x}_{1t}\ \mathbf{x}_{2t} \cdots \mathbf{x}_{pt}]$, $\mathbf{X}_t\boldsymbol{\beta} = \sum_{k=1}^{p} \beta_k \mathbf{x}_{kt}$, $\boldsymbol{\theta}$ is an $p \times 1$ spatial coefficient vector of the regressors, and $\mathbf{X}_t\boldsymbol{\theta} = \sum_{k=1}^{p} \theta_k \mathbf{x}_{kt}$.

The average direct effect is given by:

$$\overline{Direct} = \frac{1}{n}\sum_{i=1}^{n} \frac{\partial E(y_{it})}{\partial x_{ki,t}} = n^{-1} tr\big((\mathbf{I} - \rho\mathbf{W})^{-1}(\beta_k \mathbf{I}_n + \theta_k \mathbf{W})\big) \tag{8}$$

The average total effect is given by:

$$\overline{Total} = \frac{1}{n}\sum_{i=1}^{n}\sum_{j=1}^{n} \frac{\partial E(y_{jt})}{\partial x_{ki,t}} = n^{-1}\mathbf{1}_n'(\mathbf{I} - \rho\mathbf{W})^{-1}(\beta_k \mathbf{I}_n + \theta_k \mathbf{W})\mathbf{1}_n$$

The average indirect effect is estimated from the difference of the average total effect and the average direct effect.

IV. Data[5]

The variables were primarily taken from the dataset in Calderón et al. (2015) which spans only from 1960 to 2000 and we extended it up to 2014. Two new ICT infrastructure variables, mobile and fixed broadband subscriptions, were added. In the final dataset, we have a panel data for 78 countries covering years 1960 to 2014 except for mobile and broadband subscriptions that are available from 1995 to 2014.[6]

The dependent variable, per capita income, is computed by dividing the output-side real GDP at chained PPPs (in million 2011 US $) by the population. Both variables are from the Penn World Table 9.0 (PWT). The data for capital stock at constant 2011 national prices (in million 2011 US $) is also from the PWT.

Six types of infrastructure variables are used separately under two broader categories for analysis:

- Transport and energy (TRE) infrastructure variables: length of total roads (in km), length of rails (in route-km), and electricity generating capacity (in million Kw)
- ICT infrastructure variables: fixed-telephone subscriptions, mobile-cellular telephone subscriptions, and fixed broadband subscriptions[7]

Roads and rails data are from the World Road Statistics (WRS) of the International Road Federation (IRF), and electricity generating capacity from the U.S. Energy Information Administration (EIA).[8] Data for telephone and mobile subscriptions are from the International Telecommunication Union (ITU), and fixed broadband subscriptions from the World Development Indicators (WDI).

[5] More details on the data and variable are presented in Appendix 1.

[6] The final dataset includes 15 countries in Asia and the Pacific: (East Asia) PRC, Japan, Korea, Rep.; (South Asia) Bangladesh, India, Nepal, Sri Lanka; (Southeast Asia) Indonesia, Malaysia, Philippines, Singapore, Thailand; (Central and West Asia) Pakistan; (Pacific) Australia, New Zealand

[7] The exact definitions of each ICT infrastructure variable are as follows: (1) fixed-telephone subscriptions: the sum of active number of analogue fixed-telephone lines, (2) mobile-cellular telephone subscriptions: the number of subscriptions to a public mobile-telephone service that provide access to the public switched telephone network (PSTN) using cellular technology, and (3) fixed broadband subscriptions: fixed subscriptions to high-speed access to the public Internet.

[8] The quality of infrastructure such as the length of highways and express railways determines the efficiency of the infrastructure, thus in turn affects growth. However, the variables for infrastructure quality were generally unavailable or limited to only a small number of countries so this it was not feasible for this cross-country study to utilize such variables.

For the variable for human capital, we use average years of secondary schooling by country obtained from Barro and Lee (2013). The Barro and Lee dataset only provides average years of secondary schooling every 5 years from 1950-2010. To have complete annual data from 1960 to 2014, the available data for year i was used from year i to year $i + 4$ (i.e., 1960 data was used until year 1964; 1965 data used until 1969; and so on). All variables but human capital are used in per capita terms in the model.

It is common in the literature using cross-country data to include infrastructure variables as explanatory variables in addition to total capital in regression models. It is, however, worth noting that the capital stock variable commonly used in the literature including this study is comprehensive in coverage. In other words, total capital includes all asset classes of gross fixed capital formation (GFCF) in the public and private industrial sectors of the National Accounts: residential and non-residential buildings, machinery and equipment, and civil engineering works.[9]

A few papers attempted to address this issue of total capital and infrastructure capital stocks being included together in empirical models. Those studies are mainly national or subnational-level analyses where more detailed data on capital stock or investments are available or specific types of capita stock are estimated using the perpetual inventory method based on data and/or assumptions on service life, disposal patterns, and depreciation rates. Berndt and Hansson (1991; for Sweden) and Canning and Bennathan (1999) made a note of caution in the interpretation of the coefficients. As a robustness check, Égert et al. (2009) use private investment instead of *total* investment as an explanatory variable together with infrastructure to show such an issue is less of a serious problem. Yu et al. (2013) use provincial data in the PRC that distinguishes public investment, private sector investment, and transport investment separately, from which stocks were calculated based on the perpetual inventory method. Álvarez-Ayuso and Delgado-Rodriguez (2012) follow a similar approach, using investment in high-capacity highways as their infrastructure variable to account for inter-city spillovers in Spain. For the states in the United States, Tong et al. (2013) use state-level administrative data to estimate capital stock for each asset type.

[9] To our inquiry about whether the capital stock in the latest PWT dataset includes both private and public infrastructure, one of the coauthors in Feenstra et al. (2015) confirmed that "Total investment across all assets adds up to gross fixed capital formation from the National Accounts, so anything included in that concept (according to the System of National Accounts each country adhered to two years ago) will be covered in PWT data. That certainly covers civil engineering works and these are economy-wide figures, so cover both private and public investments."

Given the fact that the large shares of infrastructure stock contained in the total capital stock highly vary by country, it is important to address potential risks of misinterpretation in a cross-country analysis where data on detailed capital stock by asset are limited.[10] As only total capital stock in value and a few proxies for infrastructure capital stock in quantity by type are available, we attempt to extract non-infrastructure capital stock from the total capital stock variable using a statistical method by regressing total capital stock on infrastructure variables, and using the residuals as a proxy for non-infrastructure variable (see Appendix 2 for more discussion).

It should also be noted that the original data sources include many missing values for less developed countries; these omissions prevent us from running the spatial panel model due to missing information on neighbors. Thus, the data are collapsed from an annual frequency to a five-year frequency by averaging non-missing values only. As a result, the missing value problem is significantly reduced by taking non-overlapping 5-year moving averages. For the missing cells even after taking averages, the midpoint of the preceding and succeeding years are taken instead as estimates of the missing values. For cases where missing data occurs at the beginning (or at the end) of each series, the values at the succeeding (or preceding) years were used as estimates instead. As a robustness check, we provide, in Appendix 3, the estimation results when yearly data with missing values are used in the non-spatial models.

V. Results

1. Exploratory Analysis: Spatial Autocorrelation

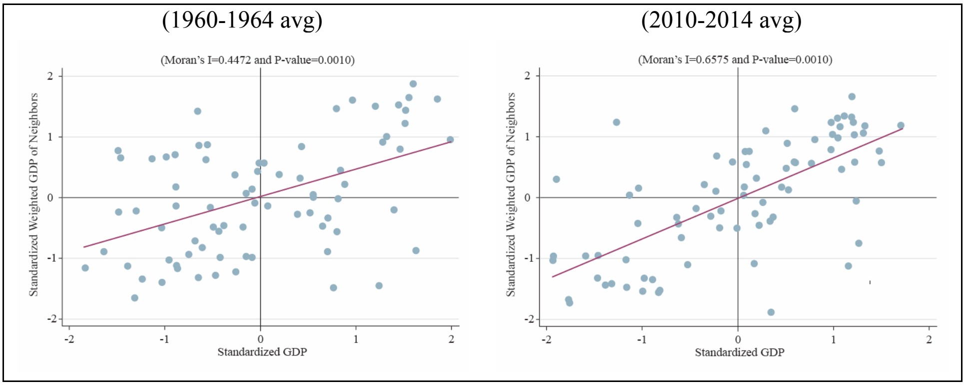
Moran's *I*, a measure of spatial autocorrelation at a point in time, for the dependent variable suggest that national income is positively correlated with neighboring countries' incomes.[11] Furthermore, the statistics trending upwards indicate that national

[10] ADB (2017a; Box 3.4) suggests that infrastructure as % of general government GFCF widely vary by country, from 40% (Pakistan) to 70% (Fiji). In general, national account statistics are not disaggregated enough to identify infrastructure investments (ADB, 2017a). Costs for even collecting disaggregated information publicly available from central and local governments (e.g. budget data) at the national level may be prohibitive. Moreover, infrastructure investments in the private sectors and public-private partnership projects will require other data sources.

[11] Moran' I is defined by $I = \frac{\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}(y_i-\bar{y})(y_j-\bar{y})}{N^{-1}\sum_{i=1}^{N}(y_i-\bar{y})^2 \sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}}$ where N is the number of observational units; W = {wij}

economies have increasingly been interconnected over the four decades (Figure 2). Positive and significant spatial dependence indicates that countries with similar income levels are clustered and this spatial correlation of income is known to be very persistent over time (Acemoglu and Robinson, 2012). Positive spatial autocorrelations increasing over time are found in all other variables. These findings are consistent regardless of the choice of the spatial weight matrix.

Figure 2. Moran's Scatter Plot for y



Note: $W_1 = \{\exp(-0.01*d)\}$ is used; x axis is log(capita GDP); y axis is weighted average of neighboring countries log(per cap GDP)

2. Estimation Results: Average Direct and Indirect Impacts[12]

Along with the non-spatial panel models, the spatial Durbin models are estimated using maximum likelihood estimation, with various combination of infrastructure variables and spatial weight matrices.[13]

[12] Statistical tests point to no spurious relationship among the variables in the model. The unit root tests for our panel data suggest that all variables are non-stationary, and the panel cointegration tests indicate that the variables are cointegrated. This implies that national income, total capital, human capital, and infrastructure variables in levels (logged) are in a stable long-run relationship. Estimations results for non-spatial and spatial panel models with and without the estimated variable for non-infrastructure stock are presented in Appendix 3.

[13] To address possible endogeneity between output and infrastructure capital stock, we also performed instrumental variables regression estimation for non-spatial and spatial models using the first lags of the infrastructure variable as instruments. The results are broadly similar to those from the ML estimation and are available upon request.

By the infrastructure type, the two main models are identified: transport and energy infrastructure including roads, rails, and electricity generating capacity (TRE); and ICT infrastructure including telephone, mobile, and broadband. In addition, models using either total capital stock or non-infrastructure capital stock are also estimated. For the spatial models, three types of weight matrices are used, namely, exponential decay (**W1**), inverse distance (**W2**), and square of inverse distance with a cutoff (**W3**), all with a 25th percentile cutoff. The main findings are summarized in Table 1, Tables 2, and 3 present direct and indirect effects estimated from the non-spatial and spatial models with the non-infrastructure capital stock estimate include as one of the explanatory variables.

Table 1. Summary of Average Direct and Indirect Impacts on Output: Output Elasticity

1% increase in: (+1yr for Human capital)	%ΔOutput in		1% increase in: (+1yr for Human capital)	%ΔOutput in	
	Own country	Neighbors		Own country	Neighbors
TRE: Roads	(0.10*–0.11*)	(-0.13–0.02)	ICT: Telephone	(0.00–0.03)	(0.07–0.26)
TRE: Rails	(0.15*–0.17*)	(0.04–0.46*)[a]	ICT: Mobile	(0.07–0.02)	(-0.03–0.02)
TRE: Energy	(0.20*–0.22*)	(0.10–0.23)	ICT: Broadband	(0.02–0.03*)[b]	(0.03*–0.11*)
Human capital	(0.09*–0.14*)	(0.13*–0.26*)	Human capital	(0.10*–0.13*)	(-0.09–0.04)
Non-TRE infra	0.03*	(0.02–0.04)	Non-ICT infra	0.03*	(0.00–0.07)

TRE = transport and energy, ICT = information and communication technology

[a] For W_2 (inverse distance weight matrix) only

[b] For W_1 (exponential decay weight matrix) and W_3 (square of inverse distance matrix with a cutoff) only

* = significant at the 90% or higher levels

It is noticeable in Table 2 that direct effects (or effects on own countries) of roads, rails, and energy infrastructure on growth are positive and significant regardless of the presence of neighborhood effects. This is consistent with what the literature on the role of transport and energy infrastructure finds in promoting economic growth. It is also worth highlighting that the direct impact of human capital on economic growth is highly robust across the board. A 1-year increase in years of schooling is expected to lead to an increase of output in own counties by 0.09-0.14%.

Table 2 shows that the direct output elasticity of roads, rails and energy infrastructure are 0.10-0.11, 0.15-0.17, and 0.20-0.22, respectively, slightly varying by the choice of a spatial weight matrix. Our direct output elasticity estimates for transport & energy infrastructure are mostly within the range of those found in the literature although they widely vary by the choice of infrastructure variables, geographical units, and methodologies (Guild, 2000).

Table 2. Direct and Indirect Effects for Transportation & Energy (TRE)

On Per cap GDP	Non-Spatial (1)	Spatial; W1 (2)	Spatial; W2 (3)	Spatial; W3 (4)
(Direct Effect)				
Non-TRE Infra	0.0318**	0.0327**	0.0276*	0.0285*
	(0.0155)	(0.0155)	(0.0158)	(0.0160)
Human capital	0.1919***	0.1436***	0.0902**	0.1058**
	(0.0452)	(0.0343)	(0.0435)	(0.0414)
TRE: Roads	0.1034*	0.1004**	0.1097**	0.1023**
	(0.0554)	(0.0486)	(0.0513)	(0.0493)
TRE: Rails	0.1815***	0.1670***	0.1468**	0.1578***
	(0.0623)	(0.0563)	(0.0652)	(0.0585)
TRE: Energy	0.2509***	0.2177***	0.1978***	0.2036***
	(0.0603)	(0.0587)	(0.0509)	(0.0583)
(Indirect Effect)				
Non-TRE Infra	-	0.0175	0.0415	0.0229
		(0.0147)	(0.0409)	(0.0241)
Human capital	-	0.1293***	0.2555***	0.2084***
		(0.0361)	(0.0852)	(0.0563)
TRE: Roads	-	0.0174	-0.1303	-0.0635
		(0.0581)	(0.2567)	(0.1325)
TRE: Rails	-	0.0377	0.4608**	0.1654
		(0.0722)	(0.1796)	(0.1277)
TRE: Energy	-	0.0339	0.2321	0.0984
		(0.0450)	(0.1880)	(0.0881)
(Total Effect)				
Non-TRE Infra	0.0318**	0.0502	0.0690	0.0514*
	(0.0155)	(0.0234)	(0.0424)	(0.0292)
Human capital	0.1919***	0.2729***	0.3457***	0.3143***
	(0.0452)	(0.0358)	(0.0795)	(0.0511)
TRE: Roads	0.1034*	0.1177	-0.0206	0.0388
	(0.0554)	(0.0850)	(0.2756)	(0.1580)
TRE: Rails	0.1815***	0.2047**	0.6077***	0.3232**
	(0.0623)	(0.0804)	(0.1817)	(0.1305)
TRE: Energy	0.2509***	0.2515***	0.4298**	0.3020***
	(0.0603)	(0.0652)	(0.2053)	(0.1026)

Notes: Figures in parenthesis are robust standard errors; W1 = {exp(-0.01*d)}; W2 = {1/d}; W3 = {$1/d^2$} with, all a 25^{th} percentile cutoff; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Furthermore, the non-TRE infrastructure also shows significant, but smaller output impact compared to the TRE infrastructure. When it comes to indirect impacts (or impacts on neighboring countries) of the TRE infrastructure, only the coefficient on rail infrastructure under the spatial weight matrix, **W2**, is significant, suggesting that total output effects of rail infrastructure further rise when the neighboring effects are taken into account along with own country effects. However, this should be not interpreted as no cross-border externalities of road and energy infrastructure since the infrastructure data used in this study are mostly based on national capital stock which may not fully reflect cross-border infrastructure stock such as cross-border road network and power grid.

Table 3. Average Direct and Indirect Effects for ICT

On Per cap GDP	Non-Spatial (1)	Spatial; W1 (2)	Spatial; W2 (3)	Spatial; W3 (4)
(Direct Effect)				
Non-ICT infra	0.0262	0.0291*	0.0291*	0.0291*
	(0.0162)	(0.0171)	(0.0158)	(0.0167)
Human capital	0.0883	0.1289**	0.0986**	0.1125**
	(0.0597)	(0.0516)	(0.0496)	(0.0520)
ICT: Telephone	0.0325	-0.0004	0.0123	0.0049
	(0.0560)	(0.0475)	(0.0486)	(0.0493)
ICT: Mobile	0.0150	0.0073	0.0173	0.0069
	(0.0163)	(0.0241)	(0.0256)	(0.0305)
ICT: Broadband	0.0171	0.0299***	0.0155	0.0236**
	(0.0109)	(0.0112)	(0.0107)	(0.0112)
(Indirect Effect)				
Non-ICT infra	-	0.0027	0.0730*	0.0116
		(0.0188)	(0.0409)	(0.0354)
Human capital	-	0.0429	-0.0872	0.0278
		(0.0405)	(0.1144)	(0.0798)
ICT: Telephone	-	0.0663	0.2643	0.1343
		(0.0697)	(0.2459)	(0.1522)
ICT: Mobile	-	0.0223	-0.0268	0.0114
		(0.0355)	(0.0575)	(0.0523)
ICT: Broadband	-	0.0292**	0.1121***	0.0512***
		(0.0141)	(0.0213)	(0.0192)
(Total Effect)				
Non-ICT infra	0.0262	0.0317	0.1022***	0.0407
	(0.0162)	(0.021)	(0.0371)	(0.0322)
Human capital	0.0883	0.1718**	0.0114	0.1403
	(0.0597)	(0.0692)	(0.1357)	(0.1075)
ICT: Telephone	0.0325	0.0659	0.2766	0.1392
	(0.0560)	(0.0802)	(0.2552)	(0.1602)
ICT: Mobile	0.0150	0.0296	-0.0095	0.0184
	(0.0163)	(0.0189)	(0.0442)	(0.0317)
ICT: Broadband	0.0171	0.0591***	0.1276***	0.0748***
	(0.0109)	(0.0113)	(0.0199)	(0.0172)

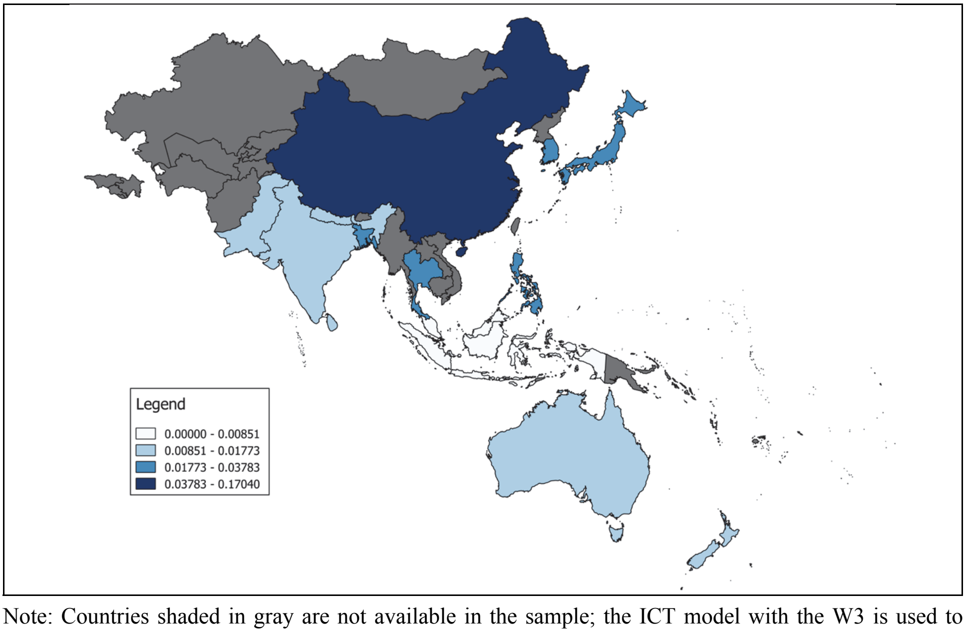
Notes: Figures in parenthesis are robust standard errors; W1 = {exp(-0.01*d)}; W2 = {1/d}; W3 = {$1/d^2$}, all with a 25^{th} percentile cutoff; * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Table 3 shows that among the three types in the ICT infrastructure, broadband shows not only positive direct impact, but also indirect impact on output, while telephone and mobile phone infrastructure are found to have no significant output impact on own countries and neighboring countries. The spillover effect of access to the Internet on neighboring countries' output (0.03-0.11) is estimated to be much larger than that of the direct effect on the own countries (0.02-0.03). The positive spillover of broadband is robust to the choice of the spatial weight matrix. This finding is in line with a strand of the literature (see Lin et al., 2017, for example) that provides supporting evidence of the spillover effect of the Internet as a medium of knowledge exchanges.

3. An Illustration of Cross-border Spillover of Infrastructure

To illustrate how a positive shock in access of the Internet propagates across space, we assume a scenario of a 10% increase in broadband subscription in PRC using the

Figure 3. Long-term Spillover Effects of a 10% Increase in access to the Internet in PRC



Note: Countries shaded in gray are not available in the sample; the ICT model with the W3 is used to estimate the spillover effects; Boundaries are not necessarily authoritative.

ICT model with the **W3** weight matrix. The resulting total effects are presented on the map of the countries in Asia and the Pacific in Figure 3. It should be noted that the total effects differ by the choice of a country from which a shock originates because every country has different neighbors. The results indicate that a 10% positive shock in broadband subscriptions in PRC leads to an increase in its own income by 0.1704% in the long run. Potential knowledge spillover through higher access to the Internet in PRC also have positive income shock on its neighboring countries (a total of 0.2420%), whose magnitude decreases with distance as assumed in the spatial weight matrix.

VI. Conclusions

This paper estimates direct benefits and cross-border spillover effects of transport (road and rail) & energy and ICT infrastructure (telephone, mobile, and broadband). Using the spatial panel regression models, we find a highly positive and significant impact of infrastructure, particularly transport & energy, on own countries. Furthermore, the positive externalities of rail, broadband, and human capital are found, and these results are robust in particular for broadband and human capital regardless of the choice of the spatial weight matrices.

Our finding on spillover effects of rail infrastructure provides support for the key role of other countries' transport infrastructure on own country's economies. The quality of infrastructure of trading partners is often highlighted as one of the major determinants that facilitate bilateral trade. For example, using the gravity model, Grigoriou (2007) finds that the infrastructure of neighboring countries is essential due to the transit effect in the landlocked Central Asian countries whose main modes of transportation to trade are road and rail.

It is worth highlighting that the cross-border spillover effect of broadband infrastructure is estimated to be larger than its within-country effect. This implies that increased access to the Internet can benefit not only own country's economic growth, but also other neighboring economies to a higher extent. A positive link between higher Internet access and economic growth is also found in the literature (for example, Choi and Yi, 2009 and Pradhan et al., 2014).

Human capital also shows positive cross-border spillover effects on growth. Human capital activities involve not only transmission of available knowledge, but also the production of new knowledge which is the source of innovation and technical change

(Mincer, 1981). Human capital positively affects productivity and thus educated labor has a much higher marginal product (Fleisher et al., 2008).

In sum, our empirical results confirm positive *direct* contributions of infrastructure, broadband infrastructure, and human capital on economic growth. More importantly, we find that their impacts are going even further beyond more than one country. This implies that transport network, access to Internet, and education show the nature of regional public goods since the benefits can be shared by public users across borders, contributing to regional growth. In particular the Internet, more broadly ICT has a large potential for Asia's inclusive development, for example, by raising the equity, quality, and efficiency of education through ICT-enabled teaching and learning (ADB, 2017b).

REFERENCES

Acemoglu, D. and J. A. Robinson. 2012. *Why Nations Fail: The Origins of Power, Prosperity and Poverty*. New York, NY: Crown Publishers.

Álvarez-Ayuso, I. C. and M. J. Delgado-Rodriguez. 2012. "High-capacity Road Networks and Spatial Spillovers in Spanish Regions," *Journal of Transport Economics and Policy*, vol. 46, no. 2, pp. 281-292.

Asian Development Bank (ADB). 2017a. *Meeting Asia's Infrastructure Needs*. Abd.org eBook. <http://dx.doi.org/10.22617/FLS168388-2> (accessed December 21, 2020)

________. 2017b. *Innovative Strategies for Accelerated Human Resource Development in South Asia: Information and Communication Technology for Education—Special Focus on Bangladesh, Nepal, and Sri Lanka*. Abd.org eBook. <http://dx.doi.org/10.22617/TCS179 080> (accessed December 21, 2020)

Anselin, L. 2003. "Spatial Externalities, Spatial Multipliers, and Spatial Econometrics," *International Regional Science Review,* vol. 26, no. 2, pp. 156-166.

Barro, R. J. and J. W. Lee. 2013. "A New Data Set of Educational Attainment in the World, 1950-2010," *Journal of Development Economics,* vol. 104, pp. 184-198.

Batey, P. W. and P. Friedrich. 2000. *Regional Competition*. Berlin: Springer.

Berndt, E. R. and B. Hansson. 1991. Measuring the Contribution of Public Infrastructure Capital in Sweden. NBER Working Paper, no. 3842.

Bhattacharyay, B. N. 2010. Estimating Demand for Infrastructure in Energy, Transport, Telecommunications, Water and Sanitation in Asia and the Pacific: 2010-2020. ADBI Working Paper Series, no. 248.

Boarnet, M. G. 1998. "Spillovers and the Locational Effects of Public Infrastructure," *Journal of Regional Science*, vol. 38, no. 3, pp. 381-400.

Calderón, C., Moral-Benito, E. and L. Servén. 2015. “Is Infrastructure Capital Productive? A Dynamic Heterogeneous Approach,” *Journal of Applied Econometrics,* vol. 30, no. 2, pp. 177-198.

Canning, D. and E. Bennathan. 1999. The Social Rate of Return on Infrastructure Investments. World Bank Policy Research Working Papers, no. 2390.

Choi, C. and M. H. Yi. 2009. “The Effect of the Internet on Economic Growth: Evidence from Cross-country Panel Data,” *Economics Letters,* vol. 105, no. 1, pp. 39-41.

Cohen, J. and K. Monaco. 2007. “Ports and Highways Infrastructure: An Analysis of Intra- and Inter-state Spillovers,” *International Regional Science Review,* vol. 31, no. 3, pp. 257-274.

Égert, B., Kozluk, T. and D. Sutherland. 2009. Infrastructure and Growth: Empirical Evidence. OECD Economics Department Working Papers, no. 685.

Feenstra, R. C., Inklaar, R. and M. P. Timmer. 2015. “The Next Generation of the Penn World Table,” *American Economic Review*, vol. 105, no. 10, pp. 3150-3182.

Fleisher, B. M., Li, H. and M. Q. Zhao. 2008. Human Capital, Economic Growth, and Regional Inequality in China. IZA Discussion Paper, no. 3576. <https://www.econstor.eu/bitstream/10419/34981/1/573334765.pdf> (accessed December 21, 2020)

Guild, R. L. 2000. “Infrastructure Investment and Interregional Development: Theory, Evidence, and Implications for Planning,” *Public Works Management & Policy*, vol. 4, no. 4, pp. 274-285. <http://doi:10.1177/1087724X0044002> (accessed October 21, 2020)

Grigoriou, C. 2007. Landlockedness, Infrastructure and Trade: New Estimates for Central Asian Countries. World Bank Policy Research Working Paper, no. 4335. <https://openknowledge.worldbank.org/handle/10986/7294> (accessed December 21, 2020)

Hu, Z. and S. Luo. 2017. “Road Infrastructure, Spatial Spillover and County Economic Growth,” *IOP Conference Series: Materials Science and Engineering*, vol. 231. <https://iopscience.iop.org/article/10.1088/1757-899X/231/1/012028> (accessed December 22, 2020)

International Road Federation (IRF). n.d. <https://www.irf.global/statistics/> (accessed October 21, 2020)

International Telecommunication Union (ITU). n.d. <https://www.itu.int/en/ITU-D/Statistics/Pages/default.aspx> (accessed October 21, 2020)

LeSage, J. and R. K. Pace. 2009. *Introduction to Spatial Econometrics*. Boca Raton: CRC Press.

Lin, J., Yu, Z., Wei, Y. D. and M. Wang. 2017. “Internet Access, Spillover and Regional Development in China,” *Sustainability*, vol. 9, no. 6. <https://doi.org/10.3390/su9060946> (accessed December 22, 2020)

Mincer, J. 1981. Human capital and economic growth. NBER Working Paper, no. 803.

Moshiri, S. 2016. “ICT Spillovers and Productivity in Canada: Provincial and Industry Analysis,” *Economics of Innovation and New Technology,* vol. 25, no.8, pp. 801-820.

O’Mahony, M. and M. Vecchi. 2005. “Quantifying the Impact of ICT Capital on Output Growth: A Heterogeneous Dynamic Panel Approach,” *Economica*, vol. 72, no. 288, pp. 615-633.

Organisation for Economic Co-operation and Development (OECD). 2002. *Measuring the Information Economy*. OECD eBook. <https://www.oecd.org/sti/ieconomy/1835738.pdf> (accessed December 22, 2020)

Pradhan, R. P., Arvin, M. B., Norman, N. R. and S. K. Bele. 2014. “Economic Growth and the Development of Telecommunications Infrastructure in the G-20 Countries: A Panel-VAR Approach,” *Telecommunications Policy,* vol. 38, no. 7, pp. 634-649.

Sandler, T. 2006. “Regional Public Goods and International Organizations,” *The Review of International Organizations,* vol. 1, no. 1, pp. 5-25.

Shahiduzzaman, M., Layton, A. and K. Alam. 2015. “On the Contribution of Information and Communication Technology to Productivity Growth in Australia,” *Economic Change and Restructuring,* vol. 48, no.3-4, pp. 281-304.

Skorupinska, A. and J. Torrent-Sellens. 2015. “The Role of ICT in the Productivity of Central and Eastern European Countries: Cross-Country Comparison,” *Revista de Economía Mundial,* vol. 39, pp. 201-222. <http://sem-wes.org/sites/default/files/revistas/07_TORRENT.pdf> (accessed December 22, 2020)

Sloboda, B. W. and V. W. Yao. 2008. “Interstate Spillovers of Private Capital and Public Spending,” *The Annals of Regional Science,* vol. 42, no. 3, pp. 505-518.

Tong, T., Yu, T.-H., Cho, S.-H., Jensen, K. and D. D. Ugarte. 2013. “Evaluating the Spatial Spillover Effects of Transportation Infrastructure on Agricultural Output across the United States,” *Journal of Transport Geography,* vol. 30, pp. 47-55.

U.S. Energy Information Administration (EIA). n.d. <https://www.eia.gov/tools/> (accessed October 21, 2020)

van Leeuwen, G. and H. van der Wiel. 2003. Spillover Effects of ICT. CPB Report, no. 2003/3. <https://pdfs.semanticscholar.org/8e50/d4245c1b1d241d04f135e5ece2235ec51ab5.pdf> (accessed December 21, 2020)

Wamboye, E., Adekola, A. and B. Sergi. 2016. “ICTs and Labour Productivity Growth in Sub-Saharan Africa,” *International Labour Review*, vol. 155, no. 2, pp. 231-252.

Yu, N., de Jong, M., Storm, S. and J. Mi. 2013. “Spatial Spillover Effects of Transport Infrastructure: Evidence from Chinese Regions,” *Journal of Transport Geography,* vol. 28, pp. 56-66.

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APPENDIX 1. DATA DESCRIPTION

Variable	Description	Source
y_output	Output-side real GDP at chained PPPs (in mil. 2011US$)	Penn World Table 9.0
pop	Population (in millions)	Penn World Table 9.0
secondary	Average years of secondary schooling	Barro & Lee (2013) dataset
rkna	Capital stock at constant 2011 national prices (in mil. 2011US$)	Penn World Table 9.0
troads	Total roads (in km)	International Road Federation (IRF)
rails	Total rail lines (in route-km)	World Bank's World Development Indicators (WB-WDI)
tlines	Fixed-telephone subscriptions (thousands)	International Telecommunication Union (ITU)
mobile	Mobile-cellular telephone subscriptions (thousands)	International Telecommunication Union (ITU)
broadband	Fixed broadband subscriptions from the World Bank's World Development Indicators	World Bank's World Development Indicators (WB-WDI)
egc	Electricity generating capacity (Million Kw)	U.S. Energy Information Administration (EIA)

List of Countries (78)

Africa (25)			
Algeria	Kenya	Morocco	Tanzania
Benin	Lesotho	Mozambique	Togo
Cameroon	Liberia	Niger	Tunisia
Congo, Rep.	Malawi	Rwanda	Uganda
Egypt, Arab Rep.	Mali	Senegal	Zambia
Gabon	Mauritania	South Africa	Zimbabwe
Ghana			
Asia and the Pacific (15)			
Australia	Korea, Rep. of	Pakistan	Philippines
New Zealand	Bangladesh	Sri Lanka	Singapore
People's Rep. of China	India	Indonesia	Thailand
Japan	Nepal	Malaysia	

Europe (17)			
Austria	Germany	Netherlands	Spain
Belgium-Luxemburg	Greece	Norway	Sweden
Denmark	Ireland	Portugal	Switzerland
Finland	Italy	Romania	United Kingdom
France			
South America (19)			
Argentina	Costa Rica	Honduras	Paraguay
Bolivia	Dominican Republic	Jamaica	Peru
Brazil	Ecuador	Mexico	Uruguay
Chile	El Salvador	Nicaragua	Venezuela
Colombia	Guatemala	Panama	
North America (2)			
Canada	United States		

APPENDIX 2. CONSTRUCTION OF NON-INFRASTRUCTURE CAPITAL STOCK

Conceptually, the total capital stock K_{it}^{T} (in constant dollars; **observed**) of country i at time t can be written as:

$$K_{it}^{T} = K_{it}^{I} + K_{it}^{N} = \sum_{g=1}^{G} P_{i,g}^{I} Q_{it,g}^{I} + \sum_{h=1}^{H} P_{\mathrm{i},h}^{N} Q_{it,h}^{N} \qquad \text{(A9)}$$

where

- K_{it}^{I}= total infrastructure capital stock in constant dollars (unobserved); K_{it}^{N}= total non-infrastructure capital stock in constant dollars (unobserved)
- $Q_{it,g}^{I}$= infrastructure capital stock in quantity for type g (**observed**); $P_{i,g}^{I}$= the unit price of $Q_{it,g}^{I}$ in the base year (unobserved)
- $Q_{it,h}^{N}$= non-infrastructure capital stock in quantity for type h (unobserved); $P_{\mathrm{i},h}^{N}$= the unit price of $Q_{it,h}^{N}$ in the base year (unobserved)

For simplicity, we assume that the unit prices reflect the depreciation of each capital stock item.

For each country, we regress the total capital stock on the infrastructure capital stock in quantity without a constant:

$$K_{it}^{T} = \beta_{i1} Q_{it,1}^{I} + \beta_{i2} Q_{it,2}^{I} + \cdots + \beta_{iG} Q_{it,G}^{I} + \varepsilon_{it} \tag{A10}$$

where the β's can be seen as the unit prices of each infrastructure type. From the estimated equation, we can write:

$$\widehat{\varepsilon_{\iota t}} = K_{it}^{T} - \sum_{g=1}^{G} \widehat{P_{\iota,g}^{I}} Q_{it,g}^{I} = K_{it}^{T} - \widehat{K_{\iota t}^{I}} = \widehat{K_{\iota t}^{N}} \tag{A11}$$

where $\widehat{P_{\iota,g}^{I}} \equiv \widehat{\beta_{\iota g}}$.

This leads us to express non-infrastructure capital as the residuals in Equation A11.

For illustration purposes, we assume the Cobb-Douglas production function with infrastructure capital stock, non-infrastructure capital stock, and labor, and with constant returns to scale:

$$Y_{it} = A_{it} {K_{it}^{I}}^{\alpha} {K_{it}^{N}}^{\gamma} L_{it}^{1-\alpha-\gamma} \tag{A11}$$

where Y denotes output, A total factor productivity, K^{I}, K^{N}, and L infrastructure capita stock, non-infrastructure capital stock, and population, respectively. The subscripts *i* and *t* represent country and time. This is a simplified version of Equation (4) without human capital. It is assumed for simplicity that there is only one type of infrastructure and non-infrastructure stock, i.e., $K_{it}^{I} = P_{i}^{I} Q_{it}^{I}$; $K_{it}^{N} = P_{i}^{N} Q_{it}^{N}$; and let $K_{it}^{T} = K_{it}^{I} + K_{it}^{N}$. Equation (A11) is transformed into per-capita term and log-normalized for estimation:

$$\begin{aligned} \log(y_{it}) &= \beta_0 + \beta_1 \log(k_{it}^{I}) + \beta_2 \log(k_{it}^{N}) + \varepsilon_{it} \\ &= \beta_0 + \beta_1 \log(q_{it}^{I}) + \beta_2 \log(k_{it}^{N}) + \eta_i + \varepsilon_{it} \end{aligned} \tag{A12}$$

where k_{it}^{I} and k_{it}^{N} are per capita infrastructure and non-infrastructure stock capital stock in constant dollars, q_{it}^{I} is per capital infrastructure capital stock in quantity; $\eta_i \equiv \beta_1 \log(P_i^I)$; ε_{it} is an error term. The non-infrastructure capital stock in value, k_{it}^{N}, is estimated as described in Equations A10-A11. Therefore, $\widehat{\beta_1}$ is the estimated coefficient of interest, output elasticity of infrastructure capital stock in quantity $((\partial y_{it}/y_{it})/(\partial q_{it}^{I}/q_{it}^{I}))$. This is the approach that this study adopts.

On the other hand, in the case of when both total infrastructure stock and infrastructure stock in value are included, we show that the estimation results should be interpreted with caution as unknown values are part of the elasticity. We estimate:

$$\begin{aligned} \log(y_{it}) &= \beta_0' + \beta_1' \log(k_{it}^{T}) + \beta_2' \log(k_{it}^{I}) + \nu_{it} \\ &= \beta_0' + \beta_1' \log(k_{it}^{N} + P_i^I q_{it}^{I}) + \beta_2' \log(q_{it}^{I}) + \pi_i + \nu_{it} \end{aligned} \tag{A13}$$

where k_{it}^{T} is per capital total capital stock in constant dollars; $\pi_i \equiv \beta_2' \log(P_i^I)$. It can be easily shown that the expected value of output elasticity of infrastructure capital stock in quantity becomes $\frac{\overline{K_i^I}}{\overline{K_i^T}} \beta_1' + \beta_2'$. The term, $\frac{\overline{K_i^I}}{\overline{K_i^T}}$, represents country i's share of infrastructure capital stock in total capital stock and is subject to estimation since this is unobservable. This may cause the computation of direct and indirect impacts of infrastructure capital stock in the spatial Durbin model (described in Section 3.2.4) to be complicated to compute.

APPENDIX 3. ESTIMATION RESULTS FOR NON-SPATIAL AND SPATIAL MODELS

Table A3.1 Estimation Results (Transportation & Energy: TRE) with Non-infrastructure Capital

y=Per cap GDP	Non-Spatial (1)	Non-Spatial[1)] (2)	Spatial; W1 (3)	Spatial; W2 (4)	Spatial; W3 (5)
X					
Non-TRE Infra	0.0318**	0.0201**	0.0304**	0.0259*	0.0267*
	(0.0155)	(0.0083)	(0.0148)	(0.0155)	(0.0156)
Human capital	0.1919***	0.2413***	0.1320***	0.0848*	0.0958**
	(0.0452)	(0.0597)	(0.0376)	(0.0462)	(0.0447)
TRE: Roads	0.1034*	0.0940*	0.0944*	0.1090**	0.1020**
	(0.0554)	(0.0546)	(0.0496)	(0.0521)	(0.0492)
TRE: Rails	0.1815***	0.1288*	0.1647***	0.1363**	0.1505**
	(0.0623)	(0.0771)	(0.0595)	(0.0679)	(0.0612)
TRE: Energy	0.2509***	0.2742***	0.2177***	0.1928***	0.2011***
	(0.0603)	(0.0660)	(0.0643)	(0.0537)	(0.0624)
Wx					
Non-TRE Infra	-	-	0.0077	0.0126	0.0062
			(0.0129)	(0.0275)	(0.0187)
Human capital	-	-	0.0824**	0.1139*	0.1108**
			(0.0387)	(0.0644)	(0.054)
TRE: Roads	-	-	-0.0036	-0.1077	-0.0732
			(0.0491)	(0.1366)	(0.0847)
TRE: Rails	-	-	-0.0072	0.2072*	0.0616
			(0.0696)	(0.1227)	(0.1037)
TRE: Energy	-	-	-0.0224	0.0431	-0.007
			(0.0517)	(0.1038)	(0.0759)
Wy	-	-	0.2179***	0.4300***	0.3478***
			(0.0407)	(0.0814)	(0.0663)
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No
Obs	858	1653	858	858	858
#Years	11	55	11	11	11
#Country	78	78	78	78	78
R2	0.8267	0.8613	0.8324	0.7955	0.8217

Notes: 1) Original annual data with missing values for 1960-2014 are used; the other columns are when all variables are taken 5 year averages and missing values are imputed; 2) All variables are in logs; figures in parenthesis are robust standard errors; 3) W1 = {exp(-0.01*d)}; W2 = {1/d}; W3 = {$1/d^2$}, all with a 25th percentile cutoff; 4) * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Table A3.2 Estimation Results for ICT with Non-infrastructure Capital

y=Per cap GDP	Non-Spatial (1)	Non-Spatial[1)] (2)	Spatial; W1 (3)	Spatial; W2 (4)	Spatial; W3 (5)
X					
Non-ICT infra	0.0262	0.0096	0.0284*	0.0282*	0.0282*
	(0.0162)	(0.0064)	(0.0166)	(0.0157)	(0.0166)
Human capital	0.0883	0.0504	0.1311**	0.1001**	0.1135**
	(0.0597)	(0.0524)	(0.0538)	(0.0507)	(0.0535)
ICT: Telephone	0.0325	0.0593	-0.0030	0.0080	-0.0005
	(0.0560)	(0.0518)	(0.0488)	(0.0490)	(0.0502)
ICT: Mobile	0.0150	0.0877**	0.0074	0.0172	0.0063
	(0.0163)	(0.0367)	(0.0248)	(0.0267)	(0.0324)
ICT: Broadband	0.0171	0.0041	0.0299***	0.0149	0.0225**
	(0.0109)	(0.0152)	(0.0113)	(0.0108)	(0.0114)
Wx					
Non-ICT infra	-	-	0.0034	0.0654*	0.0074
			(0.0191)	(0.0388)	(0.0337)
Human capital	-	-	0.0471	-0.0855	0.0178
			(0.0397)	(0.1000)	(0.0706)
ICT: Telephone	-	-	0.0691	0.2566	0.1315
			(0.0699)	(0.2337)	(0.1410)
ICT: Mobile	-	-	0.0228	-0.0277	0.0095
			(0.0359)	(0.0560)	(0.0522)
ICT: Broadband	-	-	0.0305**	0.1046***	0.0457**
			(0.0139)	(0.0289)	(0.0193)
Wy	-	-	-0.0277	0.0648	0.0857
			(0.0619)	(0.1495)	(0.0901)
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No
Obs	312	523	312	312	312
#Years	4	17	4	4	4
#Country	78	78	78	78	78
R2	0.7209	0.6926	0.8229	0.7708	0.8187

Notes: 1) Original annual data with missing values for 1995-2014 are used; the other columns are when all variables are taken 5 year averages and missing values are imputed; For ICT-TC annual raw data, there are no broadband values for years 1995-1997; 2) All variables are in logs; figures in parenthesis are robust standard errors; 3) W1 = {exp(-0.01*d)}; W2 = {1/d}; W3 = {1/d^2}, all with a 25th percentile cutoff; 4) * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Table A3.3 Estimation Results (Transportation & Energy: TRE) with Total Capital

y=Per cap GDP	Non-Spatial (6)	Non-Spatial[1)] (7)	Spatial; W1 (8)	Spatial; W2 (9)	Spatial; W3 (10)
X					
Total capital	0.5661***	0.5797***	0.5175***	0.4781***	0.4833***
	(0.0696)	(0.0797)	(0.0705)	(0.0833)	(0.0794)
Human capital	0.0671**	0.0840*	0.0894***	0.0426	0.0612*
	(0.0312)	(0.0431)	(0.0315)	(0.0322)	(0.0313)
TRE: Roads	-0.0192	-0.0210	-0.0034	0.0129	0.0106
	(0.0362)	(0.0356)	(0.0357)	(0.0344)	(0.0336)
TRE: Rails	0.0605	-0.0379	0.0494	0.0464	0.0518
	(0.0466)	(0.0658)	(0.0456)	(0.0493)	(0.048)
TRE: Energy	0.0739	0.0634	0.0802	0.0785	0.0836
	(0.0618)	(0.0513)	(0.0623)	(0.0618)	(0.0624)
Wx					
Total capital	-	-	0.0561	0.0517	0.1211
			(0.0899)	(0.1895)	(0.1559)
Non-TRE Infra	-	-	-	-	-
Human capital	-	-	0.0117	0.0419	0.0281
			(0.0355)	(0.0563)	(0.0477)
TRE: Roads	-	-	-0.0335	-0.1039	-0.1213
			(0.0436)	(0.1264)	(0.0834)
TRE: Rails	-	-	-0.0711	-0.0541	-0.1269
			(0.0605)	(0.1242)	(0.1141)
TRE: Energy	-	-	-0.0276	-0.0720	-0.0764
			(0.0527)	(0.1185)	(0.0895)
Wy	-	-	0.0781**	0.3091***	0.1733***
			(0.0364)	(0.0841)	(0.0572)
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No
Obs	858	3369	858	858	858
#Years	11	55	11	11	11
#Country	78	78	78	78	78
R2	0.9082	0.8917	0.9121	0.9103	0.9004

Notes: 1) Original annual data with missing values for 1960-2014 are used; the other columns are when all variables are taken 5 year averages and missing values are imputed; 2) All variables are in logs; figures in parenthesis are robust standard errors; 3) W1 = {exp(-0.01*d)}; W2 = {1/d}; W3 = {$1/d^2$}, all with a 25th percentile cutoff; 4) * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$

Table A3.4 Estimation Results for ICT with Total Capital

y=Per cap GDP	Non-Spatial (6)	Non-Spatial[1)] (7)	Spatial; W1 (8)	Spatial; W2 (9)	Spatial; W3 (10)
X					
Total capital	0.4722***	0.6019***	0.5128***	0.4543***	0.4974***
	(0.1316)	(0.1213)	(0.1290)	(0.1128)	(0.1214)
Human capital	0.0807	0.0684**	0.0954**	0.0876*	0.0939**
	(0.0525)	(0.0327)	(0.0454)	(0.0462)	(0.0465)
ICT: Telephone	-0.0360	0.0249	-0.0564	-0.0548	-0.0605
	(0.0495)	(0.0409)	(0.0458)	(0.0447)	(0.0469)
ICT: Mobile	0.0262*	0.0830***	0.0168	0.0203	0.0129
	(0.0157)	(0.0277)	(0.0232)	(0.0274)	(0.0330)
ICT: Broadband	0.0152	0.0023	0.0220**	0.0138	0.0204*
	(0.0105)	(0.0104)	(0.0107)	(0.0101)	(0.0108)
Wx					
Total capital	-	-	0.0276	0.3986	0.1118
			(0.0926)	(0.2644)	(0.1575)
Non-ICT infra	-	-	-	-	-
Human capital	-	-	-0.0001	-0.2214*	-0.0651
			(0.0328)	(0.1131)	(0.0649)
ICT: Telephone	-	-	0.0219	0.0339	0.0484
			(0.0636)	(0.2232)	(0.1295)
ICT: Mobile	-	-	0.0140	0.0022	0.0146
			(0.0352)	(0.0550)	(0.0509)
ICT: Broadband	-	-	0.0172	0.0594**	0.0208
			(0.0136)	(0.0275)	(0.0181)
Wy	-	-	-0.0497	-0.0847	0.0099
			(0.0669)	(0.1823)	(0.1049)
Country FE	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	No	No	No
Obs	312	1021	312	312	312
#Years	4	17	4	4	4
#Country	78	78	78	78	78
R2	0.9431	0.9548	0.9460	0.9243	0.9387

Notes: 1) Original annual data with missing values for 1995-2014 are used; the other columns are when all variables are taken 5 year averages and missing values are imputed; For ICT-TC annual raw data, there are no broadband values for years 1995-1997; 2) All variables are in logs; figures in parenthesis are robust standard errors; 3) W1 = {exp(-0.01*d)}; W2 = {1/d}; W3 = {$1/d^2$}, all with a 25th percentile cutoff; 4) * $p < 0.1$, ** $p < 0.05$, and *** $p < 0.01$