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Global evidence on productivity effects of road infrastructure incorporating spatial spillover effects

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ABSTRACT

This paper empirically analyzes the productivity effects of road infrastructure incorporating spatial spillover effects using a global database, which was originally developed in 2010 at a grid-cell scale of 0.1-degree covering all land areas in the world by integrating national-level statistical socio-economic data with available global data sources of nighttime lights imagery, global population database, and global road network. A macroscopic Hicks-neutral Cobb-Douglas production function, containing input factors of capital stock, labor force, and road infrastructure is estimated with the global dataset of 14,565 aggregated grids at 1.0-degree grid-cell scale, using ordinary least squares, spatial error model, spatial lag model, and spatial Durbin model (SDM). The statistical tests suggest that there is significant spatial dependence particularly in the error term and the overall results of the model estimations indicate that the SDM outperforms other models. The estimates of SDM further show that the direct impact of road infrastructure is significantly negative, spatial spillover effect is significantly positive, and overall effect is positive but insignificant.

1. Introduction

Investments in road infrastructure have risen significantly globally in the last few decades. By 2050, the total road length worldwide is expected to increase by 60% over the 2010 level (Dulac, 2013). This global road rush has been driven by population growth in developing regions, and increasing urbanization and demand for motorized mobility, mainly in emerging countries (Schafer and Victor, 2000). Developing countries are currently spending approximately US$ 1 trillion each year for road development. International organizations, such as the Global Infrastructure Facility established by the World Bank, have been helping to meet this increased infrastructure demand in those countries (World Bank, 2014).

One reason for the significant growth in road infrastructure is that road development is expected to bring about positive productivity impacts and economic growth. Many governments believe road infrastructure plays a vital role in enhancing regional economic output. This has been justified by empirical studies, including the pioneering works of Aschauer (1989) and Munnell (1990a). However, along with the emergence of new economic geography and spatial economics, studies have also reported the negative impacts of road infrastructure (Puga, 2002; Arbués et al., 2014). As pointed out by Deng (2013), whether the economic impacts of transportation infrastructure are positive or negative is highly dependent on local/regional contexts. Although many studies have reported empirical results through case studies in specific regions or nations, few studies have attempted to report empirical evidence from around the world.

Road infrastructure is also believed to have spatial spillover effects. As road development has significant effects on the spatial redistribution of input factors, better road connections between two regions could lead to better connectivity but could also harm the lagging regions due to the removal of trade barriers and lead to extreme gaps in economic performance or "core-periphery" structure (Krugman, 1991). From the viewpoint of international development, road infrastructure, often called spatially connective infrastructure, is an essential element in achieving inclusive development globally because the connectivity of landlocked nations to the global trading system is critical for their trading (World Bank, 2009; Arvis et al., 2010). Although many studies have demonstrated the spatial spillover effects of transportation infrastructure (Cohen and Morrison Paul, 2004; Joseph and Ozbay, 2006; Tong et al., 2013), some have also provided empirical evidence by way of case studies on the potential impact of transportation infrastructure

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investment on regional economies in remote areas (Tanabe et al., 2016; Li et al., 2017; Shibasaki et al., 2020). To the best of our knowledge, no study has shown evidence for spatial spillover effects of transportation infrastructure on a global scale.

This study attempts to fill this gap by empirically examining the economic impact of road infrastructure incorporating spatial spillover effects on a global scale. It hypothesizes that road infrastructure has a positive association with regional economic productivity globally. The productivity effects are estimated with a global dataset using a simple macroscopic production function that follows the Cobb-Douglas specification and is assumed to contain factors of capital stock, labor force, and road infrastructure. The production function is empirically estimated with spatial dependence models to incorporate spatial interaction effects, using the global dataset, which was initially organized into a gridded spatial scale resolution of 0.1-degree using a satellite image and geographic information system. This study covers 178 countries using a global mapping database (TM_WORLD_BORDERS-0.3) in ArcGIS. One of the uniqueness of this study is to present global evidence about the association of road infrastructure with its productivity effect, using a global dataset. Existing empirical studies have limited geographical scopes, typically within a single country or region. In contrast, this study offers evidence based on an unlimited scope, the world, enabling us to determine the average productivity effect of road infrastructure on a global scale. Another uniqueness of this study is an empirical analysis that uses grid-based data. Due to data availability constraints, most of the past empirical studies have been inevitably affected by the size or shape of existing administrative units. In comparison, our analysis is independent of administrative borders as it employs satellite data with a geographical information system. This enables us to estimate the less biased effect from road infrastructure. However, this study has a critical limitation in the cross-sectional analysis. Although the endogeneity issue is addressed by introducing an instrument, the findings from this study indicate the correlation, rather than the causal effect, between road infrastructure and regional productivity. Nevertheless, our evidence should be unique, and useful for policymakers in helping them to devise better economic strategies related to road infrastructure.

The remainder of this paper is organized as follows. Section 2 reviews the literature on the economic effects of transportation infrastructure and its spatial spillover effects. Section 3 describes the models used for empirical analysis, followed by specific details on data acquisition and dataset development. Section 4 presents the results of the model estimation, and Section 5 presents the discussions. The final Section 6 concludes the paper.

2. Literature review

In theory, transportation infrastructure is widely believed to be one of the critical factors influencing private output. Economic theories and regional science research submit that transportation has some impact on the economy. Classical urban economic theory proposes that transportation cost is a determinant of the location of economic activities (Alonso, 1964; Muth, 1969; Mills, 1972). New economic geography highlights transportation cost as a location factor typically under a theoretical framework of monopolistic competitive markets (Krugman, 1991; Fujita et al., 1999; Fujita and Thisse, 2002), and growth theory often hypothesizes transportation investment as a change in factor input, or a change in technology (Aschauer, 1989; Munnell, 1990a, 1990b). Generally, infrastructure can affect regional output in two ways: (1) directly, through an additional input in the production process in other sectors (for instance, improving road infrastructure directly reduces travel cost and enhances accessibility such as shorter trip distance, lower traffic congestion, and faster travel speed, which contributes to lower capital and labor costs, creates jobs, stimulates trade, and increases private investment); and (2) indirectly, through raising economic productivity by reducing transaction costs, allowing more efficient use of other inputs for production, and even inducing agglomeration economies (Graham, 2007; Crafts 2009; Chatman and Noland, 2011; Faber, 2014). For instance, transportation infrastructure could stimulate innovative activities through better inter-regional communication among workers and increased participation of individuals in innovative activities in business clusters, both of which could lead to increased total factor productivity (de Groot et al., 2009; Wetwitoo and Kato, 2017).

Another important effect of transportation infrastructure investment is the so-called "spatial spillover effect" (Rietveld, 1994; Holtz-Eakin and Schwartz, 1995; Boarnet, 1998). Spatial spillover is the effect spread beyond the geographical boundary. Road development can enlarge the market in its own region while spreading its impact to neighboring regions. Hu and Liu (2010) summarize the positive geographical externalities of transportation into: (1) opening up of the export market, (2) spatial movement of labor, (3) reduction in wealth gap and improved social welfare, and (4) economies of scale, which can only be achieved when development of transportation makes the spatial expansion of the market possible. In contrast, as some studies have shown, an economic increase in one area can cause an economic decrease in another area through the flow of capital, human, and production factors along the transportation infrastructure (Li et al., 2017).

Several empirical studies have attempted to estimate the economic productivity effect of infrastructure since the 1970s. Early studies attempted to measure the effects of aggregated public capital on economic productivity with a simple macroeconomic regional production function (Mera, 1973; Costa et al., 1987; Aschauer, 1989; Munnel, 1990a, 1990b). For instance, Aschauer (1989) estimated a Cobb-Douglas production function using time-series data from 1949 to 1985 and concluded that output elasticity with respect to public capital is 0.39. This was confirmed by Munnell (1990a), who showed that elasticity is 0.33. Other studies also supported the positive elasticity, although with smaller effects (Garcia-Mila and McGuire, 1992; Holtz-Eakin and Schwartz, 1995; Fernald, 1999). Meanwhile, some studies have shown insignificant or negative elasticity (Andrews and Swanson, 1995; Evans and Karras, 1994; Holtz-Eakin, 1993; Garcia-Mila et al., 1996). This debate was examined in the World Development Report (World Bank, 1994) in a literature review of a wide range of empirical results. These studies stimulated further investigations into the relationship between economic productivity and specific sectors of infrastructure. Subsequent studies introduced more sophisticated econometric techniques for identifying the economic impact of transportation infrastructure. In the 1990s, empirical studies have incorporated the idea of spatial spillover effects into infrastructure productivity analysis. Munnell (1992) was one of the earliest to indicate the possible existence of regional spatial spillover effects of road infrastructure. However, some researchers have debated this result (Holtz-Eakin and Schwartz, 1995; Ozbay et al., 2007; Sloboda and Yao, 2008). Boarnet (1998) hypothesized that road infrastructure influences economic activity by spatially shifting its location, and is different from the idea of spatial spillover effects. Berechman et al. (2006) investigated the spatial spillover effects of highway infrastructure at different geographical levels and concluded that spatial spillover effects can be observed at the municipal level but not at a larger regional scale. Aside from the cases in the United States, Cantos et al. (2005) confirmed the existence of spatial spillover effects of road infrastructure in 17 regions in Spain. The late 1990s onwards, along with further development in spatial econometrics (Anselin, 1988a; LeSage and Pace, 2009), various advanced econometric models have been employed to capture the spatial externalities from road infrastructure (Moreno and Lopez-Bazo, 2007; Cohen, 2010; Arbués et al., 2015; Álvarez et al., 2016). These studies integrated spatial effects into the Cobb–Douglas production function by adding a spatial lag, which represents the effect of neighboring regions. Kelejian and Robinson (1997) was one of the first to incorporate spatial lag into the Cobb-Douglas production function and suggested the conditions under which the spatial lag can be ignored. Soon after, the spatial lag was introduced into other studies as well. In the United States, Cohen

(2010) considered spatial effects as dependent variables and reported positive elasticity of highway capital, and Tong et al. (2013) applied spatial lag into both dependent and independent variables to explain agriculture output from road infrastructure investment. Del Bo and Florio (2012) also measured the productivity of motorways and other roads using a similar model in European regions, finding that motorways do not show spillover effects, but other roadways show positive spillover effects.

Many studies have shown empirical evidence on the output elasticity of road infrastructure, with mixed results. Deng (2013) conducted an extensive literature survey highlighting the contribution of transportation infrastructure to productivity and economic growth and provided many reasons for the contentious results, including research period, geographical scale, different types of transportation infrastructure, and different ways of measuring. Melo et al. (2013) also conducted a meta-analysis of the empirical evidence on the output elasticity of transportation infrastructure, and showed that the existing estimates of the productivity effect of transportation infrastructure, which can vary across main industry groups, tend to be higher for the US economy than for European ones, and are higher for roads compared to other modes of transportation. Roberts et al. (2020) also showed the results of a quantitative meta-analysis on the wider economic benefits from transportation corridor investment. It should be noted that many studies have focused on developed economies, of North America and Europe for instance, whereas only a few have analyzed developing economies. Some studies have attempted to cover developing regions (for instance, Canning, 1999; Canning and Bennathan, 2000; Calderón and Servén, 2004; Boopen, 2006); however, their scope is often limited to a regional or national scale. Additionally, most of the empirical studies covering developing regions did not apply the idea of spatial spillover effects, although such effects of road infrastructure should be particularly important for those countries because their public finances are highly constrained (Boopen, 2006).

Finally, theoretical approaches have been recently explored, by economists such as Donaldson and Hornbeck (2016), to estimate the causal effects of highways on regional output and population. In contrast to conventional econometric analyses, this study employs an approach, based on the model proposed by Eaton and Kortum (2002), which explicitly accounts for general equilibrium effects, and estimates the economic impacts of transportation infrastructure in a reduced form. A similar approach is also employed by Tombe and Zhu (2019), and Alder (2019); however, as Baum-Snow et al. (2016) pointed out, the price of an explicit model of general equilibrium effects is high.

3. Method

3.1. Models

This study follows a general approach to investigate the association of road infrastructure with economic output, using a production function with two input factors: labor and capital. We assume that road infrastructure is a technological factor and employ the following production function with Hicks-neutrality as:

$$Y_i = f(X_i) \cdot g(T_i) \tag{1}$$

where Y_i denotes the private output of region i; $f(\cdot)$ represents production technology, including a vector of direct input factors X_i; and $g(\cdot)$ represents a Hicks-neutral shift factor containing road infrastructure stock T_i. The direct input factors are private capital (K_i) and labor force (L_i). The above equation assumes that road infrastructure is a frontier shifter that increases the efficiency of other production inputs (Boarnet, 1998; Tong et al., 2013). An empirical model is often specified with a log-linear Cobb–Douglas production function as:

$$lnY_i = \beta_0 + \beta_K lnK_i + \beta_L lnL_i + \beta_T lnT_i + \varepsilon_i \tag{2}$$

where β_0 is the intercept and β_m ($m = K, L$, and T) is the coefficient of the independent variables, and ε_i is an error component. β_T represents the productivity effect of road infrastructure, our main concern. This model is an ordinary least squares (OLS) model. Note that other types of specifications, such as a trans-log function, have also been used (Pinnoi, 1994), but this study uses the Cobb-Douglas function for simplicity. The model shown in eq. (2) does not consider the spatial impacts of road infrastructure and is formulated as if the roads are not used by the corresponding economic agents in the neighboring regions.

Previous studies suggest that spatial dependence be considered when handling spatial effects (Anselin, 1988a, 1988b; Anselin and Bera, 1998). Spatial dependence represents a correlation between the values of a random variable at its own location and the values of the same variable at neighboring locations, while geographically closer implies a greater impact. There are many reasons why a model would exhibit spatial autocorrelation. One reason is possible omitted variables that vary spatially or common shocks that spill across geographic boundaries; for example, decision makers in a given region are potentially influenced by the decisions taken in other regions. Ignoring spatial dependence could cause biased estimation results, which motivates the use of spatial models rather than a simple OLS-based Cobb-Douglas production function.

Elhorst (2013) shows that there are three types of spatial interaction effects that explain spatial dependence between observations: (1) the interaction effects of error terms, where the error term of location i depends on the error term of location j, and vice versa; (2) endogenous interaction effects, where the dependent variable of a particular location i depends on the dependent variable of another location j, and vice versa; and (3) exogenous interaction effects, where the explanatory variable of location i depends on the explanatory variable of location j, and vice versa.

Departing from an OLS model, which can be regarded as the most restricted form of a spatial dependence model, the spatial error model (SEM) allows spatial interaction in error terms to be specified as follows:

$$lnY_i = \beta_0 + \beta_K lnK_i + \beta_L lnL_i + \beta_T lnT_i + \varepsilon_i,\ \varepsilon_i = \lambda \sum_{j=1}^{N} w_{ij}\varepsilon_j + \mu_i \tag{3}$$

where $\sum_{j=1}^{N} w_{ij}\varepsilon_j$ are the interaction terms among error components ε, w_{ij} is an element of the row-standardized spatial weight matrix that describes the degree of spatial relatedness, N is the number of neighboring regions, and λ is a spatial autocorrelation coefficient. SEM suggests that spatial dependence exists only in the error term and assumes that spatial dependence is due to omitted spatially correlated variables or the boundaries of spatial regions not coinciding with actual behavior units (Zhang et al., 2009). This specification is appropriate when the concern is to correct the potential influence of spatial autocorrelation caused by using spatial data.

Similarly, the spatial lag model (SLM) can be specified by including the endogenous interaction effects as

$$lnY_i = \rho \sum_{j=1}^{N} w_{ij} lnY_j + \beta_0 + \beta_K lnK_i + \beta_L lnL_i + \beta_T lnT_i + \varepsilon_i \tag{4}$$

where $\sum_{j=1}^{N} w_{ij} lnY_j$ are the interaction terms among the dependent variable Y and ρ is the spatial autocorrelation coefficient. This model illustrates that the dependent variable at a location is influenced not only by explanatory variables at one location but also by the dependent variable at neighboring locations. In a cross-sectional data analysis, SLM can be interpreted as the equilibrium outcome of the spatial or social interaction process, in which the dependent variable for one economic agent is jointly determined with that of the neighboring agents (Brueckner, 2003).

To account for the exogenous interaction effects, Boarnet (1998) incorporated the stock of road infrastructure in neighboring regions as an additional production input factor. This can be specified by transforming Eq. (2) into:

$$lnY_i = \beta_0 + \beta_K lnK_i + \beta_L lnL_i + \beta_{Tl} lnT_i^l + \beta_{Tn} lnT_i^n + \varepsilon_i \tag{5}$$

where T_i^l denotes the local road infrastructure stock and T_i^n represents the neighboring regions' road infrastructure stock. Boarnet (1998) defines T_i^n this as $\sum_{j=1}^{N} w_{ij}T_j$.

Some models that partially combine the above three effects have also been proposed. The spatial Durbin model (SDM) is one such model, which incorporates the endogenous and exogenous interaction effects as:

$$lnY_i = \rho \sum_{j=1}^{N} w_{ij} lnY_j + \beta_0 + \beta_K lnK_i + \beta_L lnL_i + \beta_T lnT_i$$

$$+\theta_K \sum_{j=1}^{N} w_{ij} lnK_j + \theta_L \sum_{j=1}^{N} w_{ij} lnL_j + \theta_T \sum_{j=1}^{N} w_{ij} lnT_j + \varepsilon_i \tag{6}$$

where θ_X is the spatial autocorrelation coefficient ($X = K, L, T$). SDM is useful because it captures the contribution of explanatory variables both in and outside of a given location to the dependent variable, which can be translated into spatial spillover effects (Del Bo and Florio, 2012; Tong et al., 2013; Yu et al., 2013). Moreover, SDM is the only model that produces an unbiased estimator in all possible spatial data modeling (LeSage and Pace, 2009). The omitted variable problem is also less likely to be observed because of including spatial lags in the explanatory variables, which means that this model is the most appropriate for this study.

It should be noted that a model incorporating all types of spatial effects takes the form

$$lnY_i = \rho \sum_{j=1}^{N} w_{ij} lnY_j + \beta_0 + \beta_K lnK_i + \beta_L lnL_i + \beta_T lnT_i$$

$$+\theta_K \sum_{j=1}^{N} w_{ij} lnK_j + \theta_L \sum_{j=1}^{N} w_{ij} lnL_j + \theta_T \sum_{j=1}^{N} w_{ij} lnT_j + \varepsilon_i$$

$$\varepsilon_i = \lambda \sum_{j=1}^{N} w_{ij} \varepsilon_j + \mu_i \tag{7}$$

This is the most general spatial dependence model, often called the Manski (1993) model. Elhorst (2010) summarized seven linear spatial dependence models, where other models can be derived from the Manski model by imposing restrictions on one or more spatial parameters. Although the Manski model enables the incorporation of spatial lags into all variables, Elhorst (2010) found that the parameter estimates of the endogenous and exogenous interaction effects are biased when all spatial spillover effects are considered. Estimating with the Manski model is technically feasible, but it is impossible to separately identify the interaction effects from the corresponding estimated parameters (Elhorst, 2010). To overcome this, LeSage and Pace (2009) proposed the exclusion of interaction effects in the error term, taking SDM as a general model. Elhorst (2010) pointed out that the cost of ignoring spatial dependence in the disturbances is less serious than that of ignoring spatial dependence in the dependent and/or independent variables, because the former only causes a loss of estimation efficiency. Additionally, the spatial Durbin model enables the production of unbiased coefficient estimates. This study also follows their proposal; hence, we use SEM, SLM, and SDM models in our empirical analysis.

3.2. Data

3.2.1. Data acquisition

This study employs a gridded dataset covering the world to estimate spatial spillover effects. Although recent technological developments have enabled us to access various kinds of global gridded databases, they are not directly applicable to our estimation. Our empirical analysis processes the data of nighttime lights imagery, global population database, and global road database with national-level socio-economic data for preparing the global gridded dataset. Table 1 summarizes the sources of data used to construct our dataset.

The study used the following sources for the data and imagery. First, the socio-economic data contains gross domestic product (GDP), GDP composition by sector, physical capital stock, and labor force as of 2010. Labor force is defined as the population aged 15 years and older. GDP and physical capital stock are sourced from Penn World Table Version 9.0 (Feenstra et al., 2015), and are expressed in purchasing power parity (PPP) units to account for exchange rate biases. GDP composition by sector and labor force is mainly sourced from the World Bank's World Development Indicators data, where some countries' data are complemented by the CIA World Fact Book (Central Intelligence Agency). Figs. 1–4 illustrate the geographical distribution of GDP, capital stock, agriculture to GDP share, and labor force, respectively.

Second, nighttime lights imagery is used to spatially distribute the commercial/industrial economic activities and physical capital stock to grid cells. Defense Meteorological Satellite Program Operational Linescan System (DMSP OLS) nighttime lights imagery was obtained from the US National Geographical Data Center (NDGC) of the National Oceanic and Atmospheric Administration (NOAA). DMSP OLS has the unique ability to capture weak light imaging at night worldwide with a spatial resolution of 30 arc-seconds (approximately equal to 0.86 sq. kms at the equator). The data are produced from a series of cloud-free nighttime light observations for a unit time period with ephemeral lights, such as fires removed from the observation. However, the biggest problem with DMSP OLS stable lights imagery is that the recorded nighttime lights are saturated in the bright cores of city centers and other lit areas because of its six-bit quantization (0–63 digital number), which limits the dynamic range. To overcome this, NOAA NDGC developed a product with no sensor saturation by combining three different images collected at different fixed grain settings. Fig. 5 illustrates the worldwide geographical distribution of nighttime lights with calibrated radiance. We assume that the nighttime lights imagery of 2010 is represented by the average observations from January 11 to December 9, 2010.

Third, the LandScan Global Population Database of 2010 is used to spatially distribute agricultural economic activity and labor population to grid cells. The data were obtained from the Oak Ridge National Laboratory of the US Department of Defense. LandScan, initially developed for the purpose of estimating the ambient population at natural disaster risk, is a global population distribution database with a spatial resolution of 30 arc-seconds and represents the ambient population. That is, it provides a population estimation of not only where people sleep but also of the movement of people for work and travel during the day. It uses a dasymetric spatial modeling approach that distributes the best available census counts to grid cells based on likelihood coefficients estimated from road proximity, slope, land cover, and nighttime lights (Dobson et al., 2000). Fig. 6 illustrates the worldwide geographical distribution of the LandScan Global Population.

Fourth, the Global Roads Open Access Data Set (gROADS) version 1, obtained from the National Aeronautics and Space Administration's (NASA) Socioeconomic Data and Applications Center, hosted by the Center for International Earth Science Information Network at Columbia University, was used for the global road dataset. The gROADS database represents a complete and updated dataset of road infrastructure on a global scale, combining the best available public road data by country. All road networks have been joined topologically at the borders into the

Table 1
Data sources in dataset development.

Name	Acquisition Year	Source	Data Type	Spatial Resolution	Format/Pixel Type and Depth	Spatial Reference	Spatial Coverage
Socio-economic statistical data							
GDP	2010*	Feenstra et al. (2015)	GDP (mn. US$) 2011 data	National scale	–	–	Global
Physical capital stock	2010*	Feenstra et al. (2015)	Physical capital stock (mn. US$) 2011 data	National scale	–	–	Global
GDP composition by sector	2010*	The World Bank/CIA	Structure of GDP by sector (%)	National scale	–	–	Global
Labor force	2010*	The World Bank/CIA	Labor force (labor population count) data	National scale	–	–	Global
Raster and Vector data							
Nighttime light imagery	2010	US NOAA National Geophysical Data Center	Radiance calibrated nightlights intensity, continuous raster	30-arc seconds	Geo-tiff/flt32	WGS 1984	Global
Global population database	2010	Oak Ridge National Laboratory	Global population count, continuous raster	30-arc seconds	Geo-tiff/flt32	WGS 1984	Global
Global roads database	1980–2010	Center for International Earth Science Information Network	Global deployed road map, categorical vector	Computable to 30-arc seconds	GDB database	WGS 1984	Global
Geographical data (Instrumental Variables)							
Surface roughness (Standard deviation of elevation)	1996	US Geological Survey's Center for Earth Resources Observation and Science	Global digital elevation model, continuous raster	30-arc seconds	–	WGS 1984	Global
Coastal Distance	2009	NASA's Ocean Biology Processing Group	Distance from the nearest coast, continuous raster	0.04-degree	Geo-tiff/flt32	WGS 1984	Global

Note 1: *For some countries, data acquisition years are different from 2010 due to data availability.
Note 2: GDP—Gross Domestic Product; NOAA—National Oceanic and Atmospheric Administration; CIA—Central Intelligence Agency; GDB—Geodatabase in ArcGIS Pro 2.2.3; WGS, World Geodetic System; NASA, National Aeronautics and Space Administration.

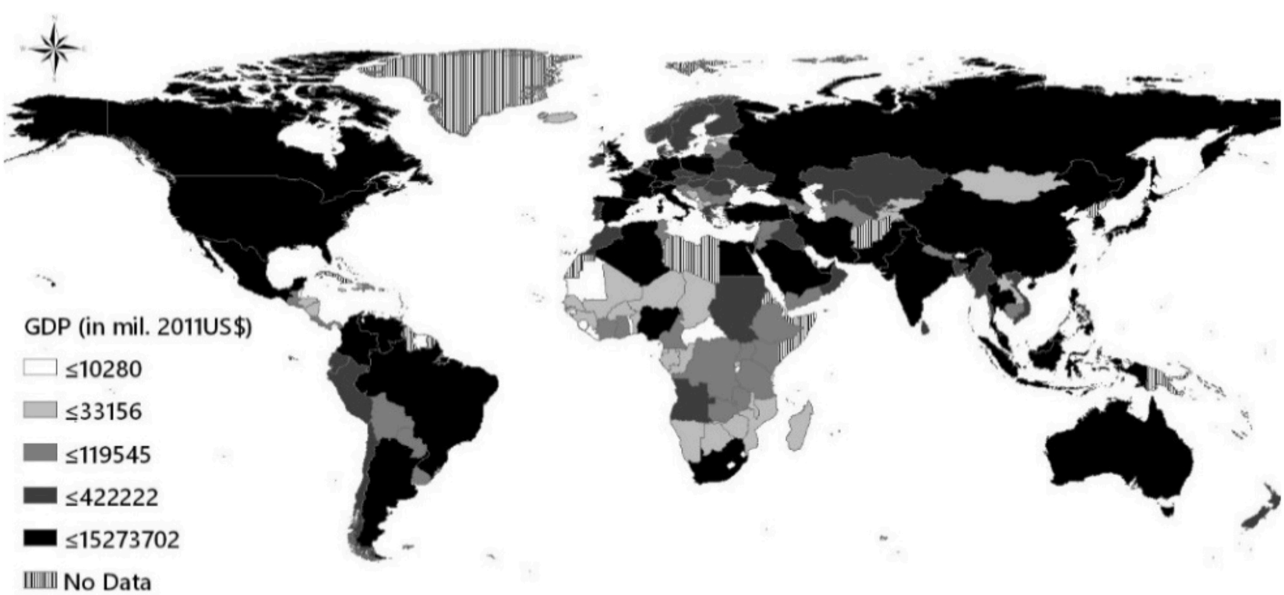

Fig. 1. Worldwide geographical distribution of GDP

global road coverage. Fig. 7 illustrates the worldwide geographical distribution of roads in this database. This database highlights long-distance road networks between settlements. Its availability in the public domain allows for various global studies, particularly in environmental research, where the potential impact of road investment on the natural environment is assessed (Laurence et al., 2014; Venter et al., 2016; Strano et al., 2017). However, this dataset has several shortcomings. First, the roads in the gROADS database are classified into highway, primary, secondary, tertiary, local/urban, trail, private, and unspecified, but the classification is inconsistent across countries (Nelson et al., 2006). Additionally, qualitative attributes, such as carriageways, surface type, and surface conditions, are available for only a few roads. Second, as the road data are compiled from multiple sources, such as vector map level 0, the timing of data collection varies from the 1980s to 2010 across countries. This means that the quality of road data also varies significantly across nations, while short and unofficial roads are not included. Given the rapid growth of road construction in many regions in recent years, this database highly underestimates the actual extent of the global road network. Although road types, such as highways, motorways, or rural roads could affect economic performance, it is not considered in this study because poor consistency in road classification and limited data availability do not enable us to analyze it with sufficient quality.

Finally, two geographical variables, surface roughness and distance from the nearest coast, are introduced to instrument the road infrastructure. GTOPO30, a global digital elevation model with a spatial

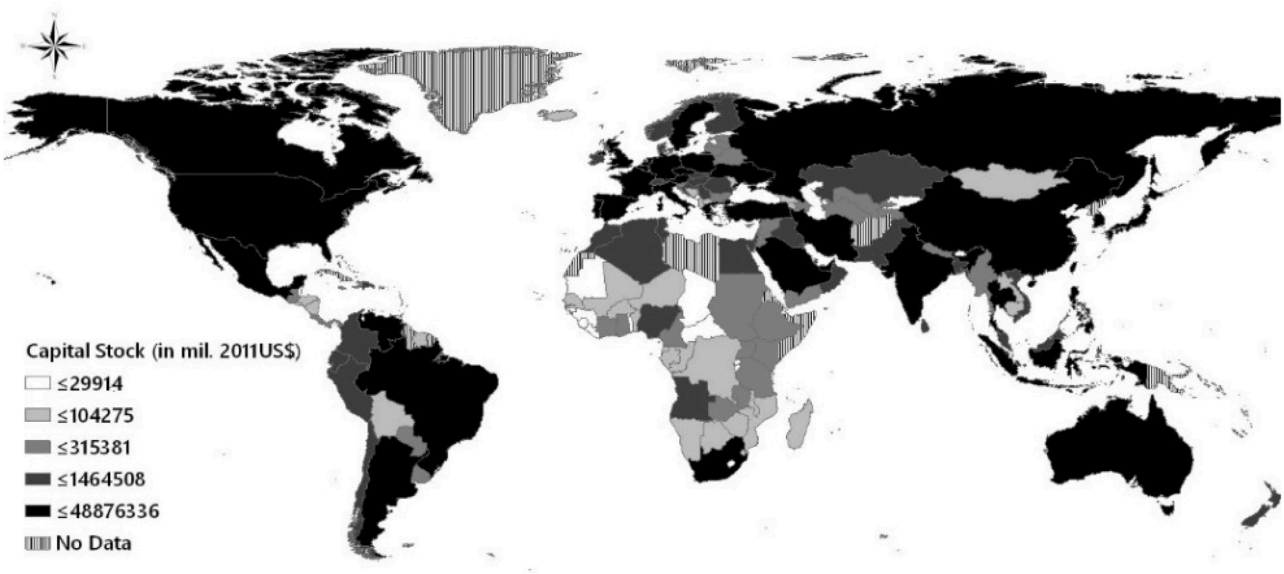

Fig. 2. Worldwide geographical distribution of capital stock.

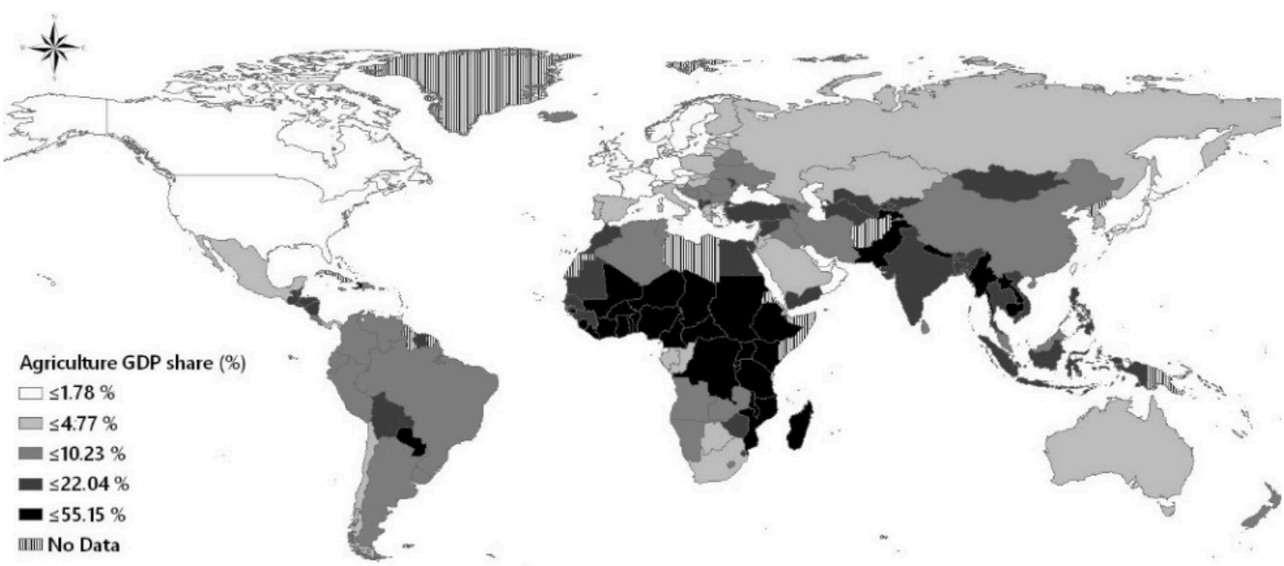

Fig. 3. Worldwide geographical distribution of agriculture to GDP share (%).

resolution of 30 arcseconds, developed by the United States Geological Survey, was used to compute the standard deviation of elevation from the slope. A global dataset of distances from the nearest coastline, with a spatial resolution of 0.04-degree, was obtained from NASA's Ocean Biology Processing Group.

3.2.2. Dataset development

We estimate the private output data at the grid-cell level, using national-level data and the intensity of DMSP OLS nighttime light imagery as a proxy for economic statistics at various geographical scales under the assumption that all consumption and investment activities in the night require lighting. Many studies have applied a similar approach, including Elvidge et al. (1997), Sutton and Costanza (2002), Sutton et al. (2007), Henderson et al. (2012), and Bundervoet et al. (2015). Doll et al. (2000) created the first global disaggregated GDP map at 1.0-degree spatial resolution based on a log-linear relationship between lit urban areas and official PPP converted GDP using a composite stable light image for 1994–95. They also acknowledged that the use of radiance calibrated nighttime lights imagery and the consideration of agricultural economy are important for better results. Hence, Doll et al. (2006) investigated the relationship between radiance calibrated nighttime lights and regional GDP in European countries and the United States and found that radiance calibrated nighttime lights are a good proxy for regional GDP, where industry and service sectors comprise over 90% of the economy. As pointed out by several researchers, such as Keola et al. (2015), nighttime lights have a weaker linkage with non-illuminated sectors, particularly the agricultural sector. For example, Africa is the world's most dimly lit area since a significant share of its GDP originates from unlit agriculture. To overcome this, Ghosh et al. (2010) proposed a method that accounts for non-lit agricultural GDP by the grid population data from LandScan, under the assumption that agriculture does not emit any observable nighttime lights. We follow Ghosh et al. (2010) and compute grid-based GDP under the assumption that the economic activities attributed to the agricultural sector are proportionally distributed in the LandScan global population, while those attributed to the nonagricultural sectors are proportionally distributed in the radiance

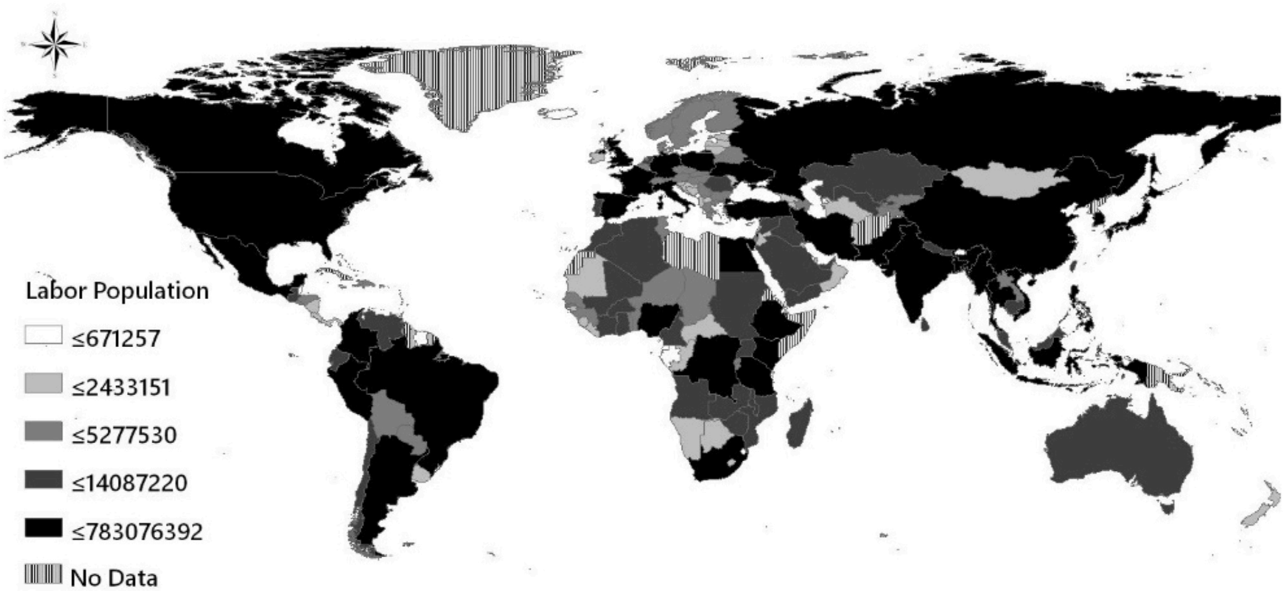

Fig. 4. Worldwide geographical distribution of labor force.

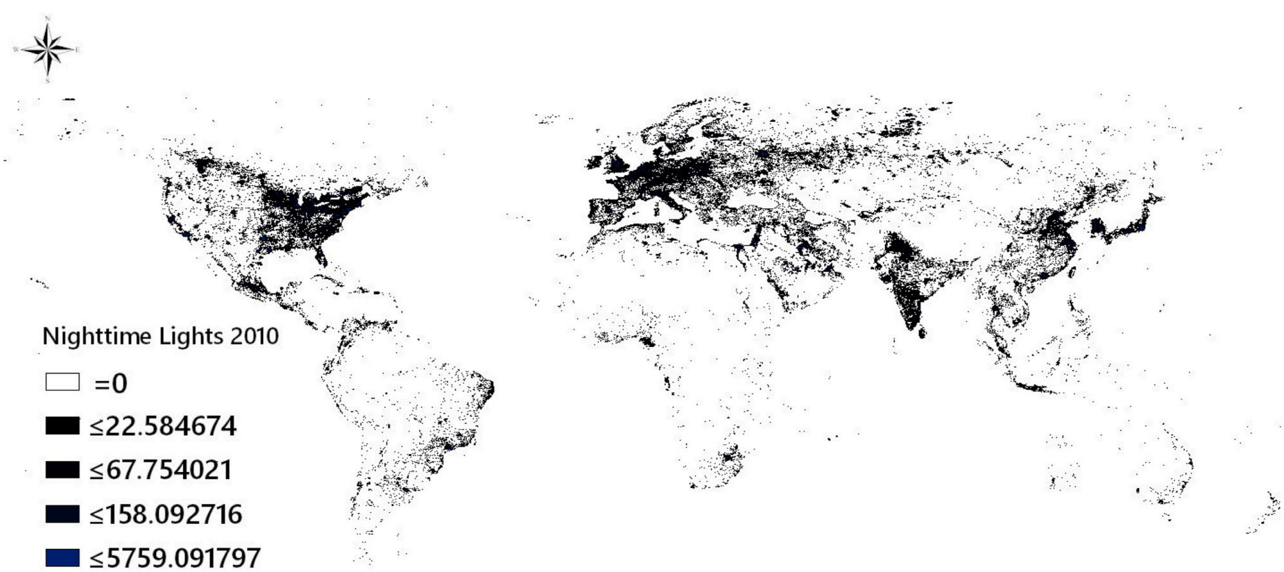

Fig. 5. Radiance calibrated nighttime light imagery.

calibrated nighttime lights sum. This is formulated as:

$$Y_i = AGDP_{c_i} \times \frac{P_i}{\sum_{j \in c_i} P_j} + NAGDP_{c_i} \times \frac{NL_i}{\sum_{j \in c_i} NL_j} \tag{8}$$

where Y_i denotes the private output at grid cell i; $AGDP_{c_i}$ denotes the GDP of the agricultural sector of the country c_i to which grid-cell i belongs, P_i denotes the LandScan global population at grid cell i, $NAGDP_{c_i}$ denotes the GDP of the nonagricultural sector of country,c_i and NL_i denotes the radiance calibrated nighttime lights sum at grid cell i.

Physical capital stock data are also estimated at the grid-cell level, using national-level data and nighttime lights imagery as a proxy. The rationale behind the use of nighttime lights is that the sources of man-made illumination are associated with physical capital stock, such as offices, retail shopping areas, factories, residences, and street lighting. These sources can be classified into several types of physical capital, such as buildings, infrastructure, and vehicles. Recent studies support this assumption, indicating a positive association between physical capital stock and nighttime lights imagery, as shown by Addison and Stewart (2015). Moreover, remote sensing data enables the disaggregation of data at a substantially higher degree of spatial resolution than traditional data. For these reasons, the national-level capital stock is disaggregated using nighttime lights imagery as a proxy, as shown below:

$$K_i = K_{c_i} \times \frac{NL_i}{\sum_{j \in c_i} NL_j} \tag{9}$$

where K_i is the capital stock at grid-cell i, and K_{c_i} is the capital stock of country c_i to which the grid-cell i belongs.

Labor force is estimated at the grid-cell level using the LandScan global population database under the assumption that the ratio of labor population to total population is constant in each country for simplicity. This is expressed as:

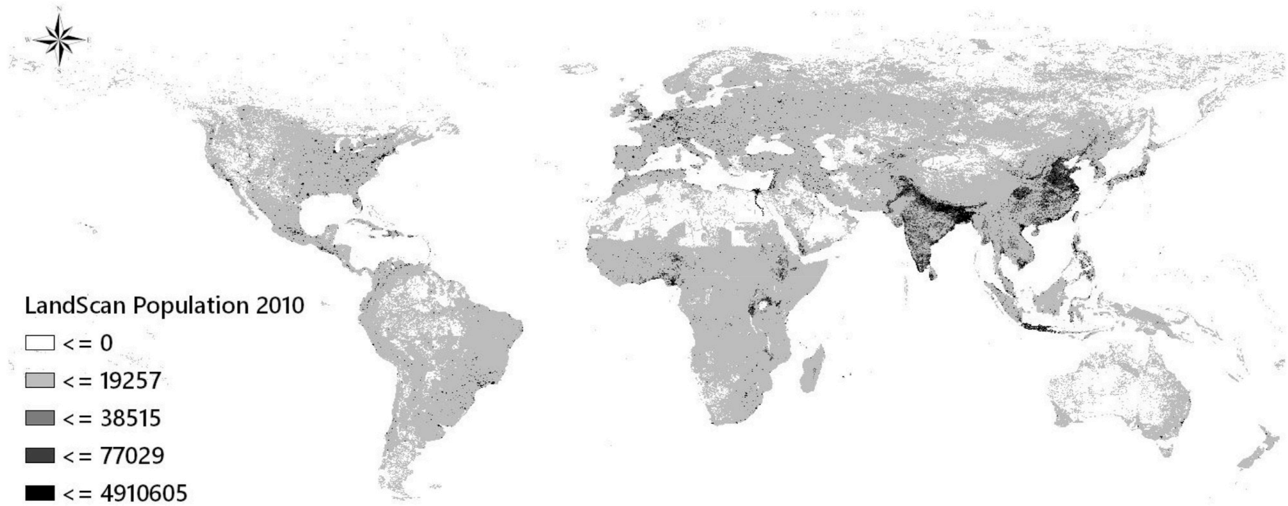

Fig. 6. LandScan population grid.

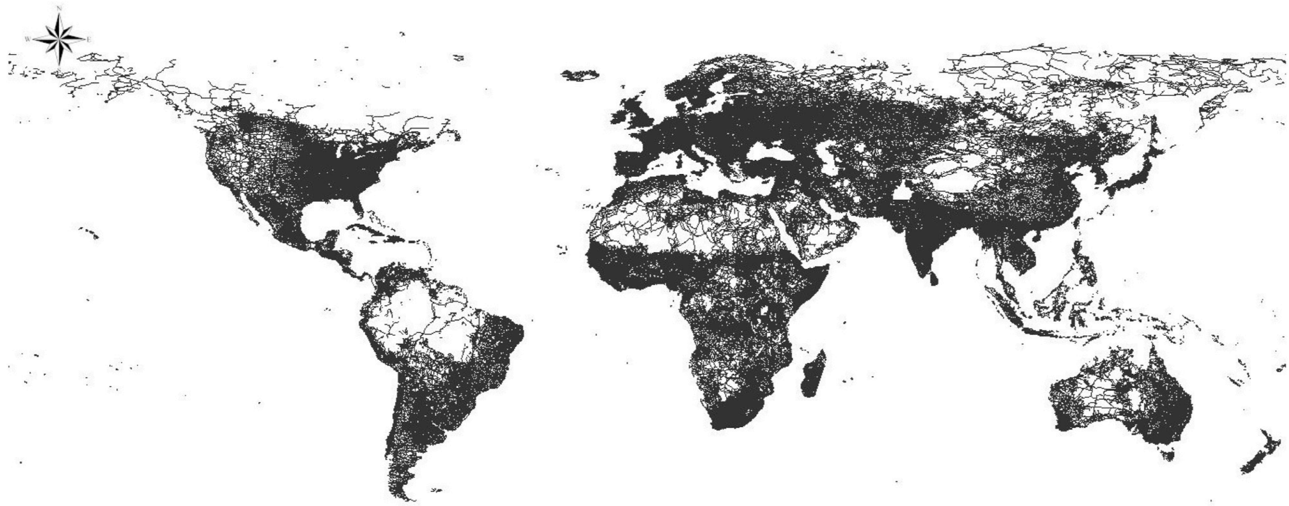

Fig. 7. Global roads open access data set.

$$L_i = L_{c_i} \times \frac{P_i}{\sum_{j\in c_i} P_j} \tag{10}$$

where L_i is the labor population at grid-cell i, and L_{c_i} is the labor population of country to which the grid-cell i belongs.

Finally, road infrastructure at the grid-cell level is represented by the total length of roads in each grid cell, which is computed using ArcGIS Pro 2.2.3 with a latitude and longitude coordinate system.

The proposed method assumes that population and nighttime lights sum are used for estimating both input and output factors. Although there could be an endogeneity effect, factors other than population and nighttime lights, such as national-level share of GDP from the agricultural sector and national-level labor population/capital stock could also affect the estimation; hence, we expect the endogeneity effect to be negligible. However, our method is so heuristic that its validity is unclear. Hence, we tested the reproducibility of our dataset estimated using the above method with an available exogenous dataset. Table 2 summarizes the correlation coefficients of the estimated data from the above process that are aggregated into administrative units with the official statistical data of the same administrative units for six countries where the official statistical data is available at the sub-national level. This shows that the estimated results reproduce the official statistical data in administrative units quite well.

4. Results

4.1. Preparation for model estimation

First, we examine the areal unit of analysis, which is called the modifiable areal unit problem (MAUP), since levels of aggregation in grid cells could significantly influence empirical results (Openshaw, 1984). MAUP typically deals with two aspects of areal unit problems: one is a scale effect, showing analytical differences depending on the size of units used and the other is an aggregation effect, showing differences depending on how the study area is divided. The scale effect could matter in our study because the spatial resolution of regular lattice grids can be arbitrarily changed from 0.1-degree to a coarser resolution. We decided to conduct the model estimations using an areal unit of 1.0-degree in latitude and longitude mainly because data reproducibility cannot be guaranteed if the areal units have too high or too low geographical resolution. For instance, because the dataset contains many areas without economic activities, if the grid scale is too small, the model estimates could be seriously biased. Additionally, a larger spatial dataset requires more computation time, which could constrain the flexibility of our analysis in practice, although it is technically computable. Meanwhile, if the grid scale is too large, spatial spillover effects will rarely be observed because most road users do not travel

Table 2
Reproducibility of estimated data for empirical analysis.

Country	Variables	Correlation coefficient	Administrative Units	Sources of official statistical data
Cambodia	Output	0.8967	22	Institute of Developing Economies, Japan External Trade Organization
China	Output	0.9208	31	China Statistical Yearbook 2011
	Capital	0.8822		
	Labor	0.9963		
Japan	Output	0.8961	47	Cabinet office of Japan
	Capital	0.8933		
	Labor	0.9970		
Myanmar	Output	0.9024	51	Institute of Developing Economies, Japan External Trade Organization
Thailand	Output	0.9044	76	Institute of Developing Economies, Japan External Trade Organization
United States	Output	0.8227	51	Bureau of Economic Analysis

across the borders of grids. We also believe that the areal unit should be comparable with the regional scale because it enables us to compare the estimates with previous empirical studies on road productivity at the regional/national scale. As for the aggregation effect, we apply a grid pattern for simplicity, although other types of geographical space could be applicable. Examination of the aggregation effect is one of the issues for further study.

Next, we specify the spatial weight matrix for the spatial models. Previous studies on spatial productivity effects of road infrastructure have applied the spatial weight matrix in different ways. Various ways to specify the weight matrix have been proposed. For instance, Holtz-Eakin and Schwartz (1995) assume three kinds of weight matrices: (1) the total sum of neighboring regions' roads, (2) average of neighboring regions' roads, and (3) weighted average of neighboring regions' roads, where the weights are inversely proportional to the area of the neighboring regions. Another method employs physical contiguity with binary weights and assigns a weight of 1 to regions sharing a border and 0 otherwise (Cohen, 2010; Tong et al., 2013; Yu et al., 2013). Alternatively, inverted distance and trade-flow-based weight matrices have also been specified (Arbués et al., 2015; Álvarez et al., 2016). We use a row-normalized first-order binary contiguity matrix for two reasons. First, it enables us to reflect the direct physical connectivity between the grids. This could be critical in the context of road infrastructure because regions isolated by oceans are expected to have poorer spillover effects. Second, the first-order contiguity-based weight matrix has been empirically demonstrated to be better than the inverse distance weight matrices (Stakhovych and Bijmolt, 2009). It should be noted that the choice of weight matrix is still the biggest issue in spatial econometric models, although the estimates could be very sensitive to the matrix, and there is no consensus regarding which weight matrix is the best for analysis (Anselin, 1988; LeSage and Pace, 2014).

Then, we define the geographical scope of our empirical analysis. We first exclude the regions where no labor force is observed from our analysis because no production can be expected without people. We also ignore isolated grids that have no adjacent neighboring grid, mainly due to the technical difficulties in defining the spatial weight matrix. Finally, we use 14,565 grids in our empirical analysis.

Table 3 summarizes the descriptive statistics of our dataset and the scatter plot matrix between each statistic. It shows that the dataset includes zero values for physical capital stock and road length. Of the 14,565 grids in total, there are zero values for capital stock and road infrastructure in 3560 grids and 1816 grids, respectively, while 1235 grids have zero values for both. In theory, production activities without physical capital stock and/or road infrastructure are unrealistic. One of the potential reasons for zero observations of capital stock in some grids is that the Penn World Table covers only produced capital while excluding natural capital, such as crops and subsoils. For zero observations of road infrastructure, the global road database covers only long-distance roads, excluding short-distance streets. Figs. 8 and 9 illustrate the worldwide geographical distribution of zero-level capital stock and road infrastructure, respectively.

Table 3
Descriptive statistics of global dataset (N = 14,565).

Variable	GDP	Physical Capital Stock	Labor Force	Road Length
Unit	Million US$ (2011)	Million US$ (2011)	population	km
Mean	5,870.59	19,801.50	219,455.60	564.44
Standard Deviation	19,266.77	70,416.07	683,068.30	817.07
Minimum	0.000527	0.000	0.325	0.000
Maximum	697,082.50	2,621,57	16,262,50	31,616.41

Several studies have addressed the solutions for this zero-value issue. The first is resampling proposed by Moss (2000), where all zero values are bootstrapped or substituted with 0.1, 0.01, and 0.001. Moss (2000) then investigated the accuracy of the estimated Cobb–Douglas production function and suggested using a substitution approach. The second is the Box–Cox transformation (Box and Cox, 1964). One of the most well-known methods is to add a particular value to all observations of the independent variable with a value of 0. However, there is no guideline regarding the appropriate method for Box-Cox transformation. The third example is a dummy variable method in which one explanatory variable has zero input level (Battase, 1997) and a modified Cobb–Douglas production function that can be specified as follows:

$$lnY_i = \beta_0 + (\alpha_0 - \beta_0)D_i + \beta_1 lnX_i^* + \varepsilon_i \quad (11)$$

where $D_i = 1$ if $X_i = 0$ and $D_i = 0$ if $X_i > 0$; and $X_i^* = \text{Max}\,(X_i, D_i)$. We decided to use the third approach after examining all three, because we found that the first and second approaches should lead to significantly biased estimates, depending on the initial input values after our many trials and errors in estimations.

4.2. Estimation results

Table 4 summarizes the results of the models estimated using OLS, SEM, SLM, and SDM. These models are estimated with maximum likelihood method, using the Chebyshev approximation method for computing the Jacobian in the spatial models (Ord, 1975; Pace and LeSage, 2004). First, the estimates of the OLS model show that the estimated output elasticity of road infrastructure is statistically insignificant. Moran's I statistics (Moran, 1950) show that it has positive and significant spatial autocorrelations among the OLS regression residuals. Moran's I takes the value of 0.355, which suggests that there is a strong

Fig. 8. Worldwide geographical distribution of zero-level capital stock.

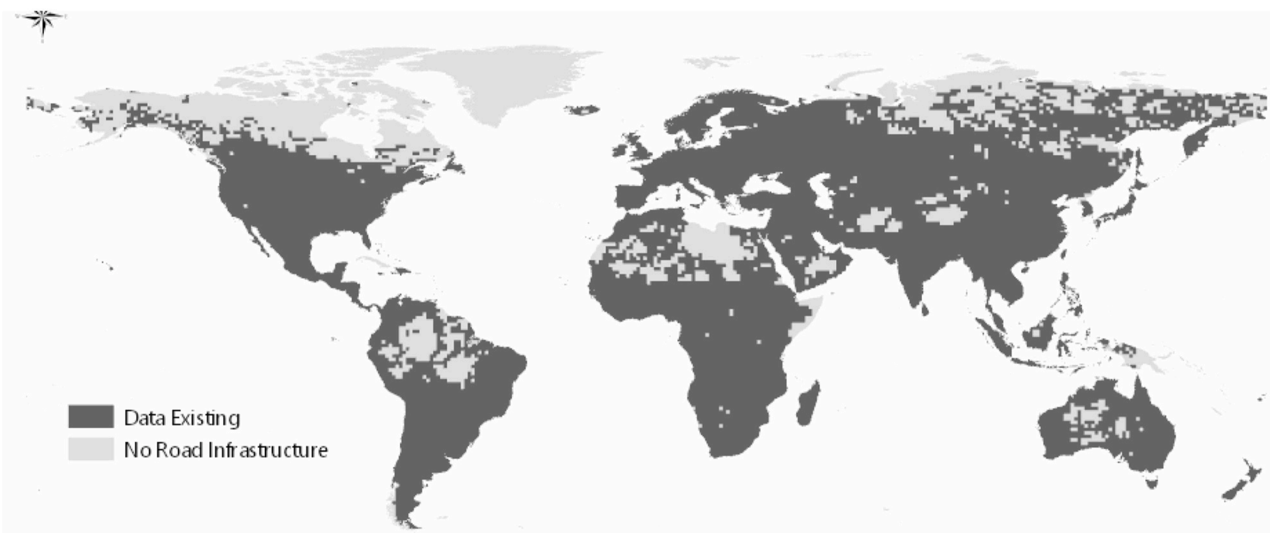

Fig. 9. Worldwide geographical distribution of zero-level road infrastructure.

positive spatial autocorrelation. This means that the OLS estimates could be highly biased. Next, Lagrange multiplier (LM) tests are performed to test whether spatial interaction effects should be considered (Burridge, 1980). Table 4 indicates that both the LM test (Error) and robust LM test (Error) reject the null hypothesis of no spatial error, implying the existence of spatial dependence in the error term. The LM test (Lag) rejects the null hypothesis of no spatial lag, while the robust LM tests (Lag) do not reject the null hypothesis of no spatial lag. This suggests that the spatial models are preferable to the OLS model.

As suggested from the estimates of OLS, the model fitness represented by Pseudo-R^2, log-likelihood, and Akaike Information Criteria is the best in SDM, followed by SEM. Additionally, Table 4 shows that the hypothesis that the SDM can be simplified into SEM or SLM is statistically rejected from the LR tests, which suggests that SDM is preferable to any other spatial dependence model.

The above models do not adequately address the potential endogeneity that likely leads to biased results when estimating the impacts of road infrastructure. In order to address the potential endogeneity of road networks, the instrumental variables (IV) method is employed. Past studies used various geographical data for the instrument of road infrastructure such as the original plan of routes (Michaels, 2008), historical road networks (e.g. Duranton and Turner, 2012; Holl, 2012; 2016), least-cost route and Euclidean spanning tree network (Faber, 2014), and straight distance to the lines connecting major places (Banerjee et al., 2012). This study used the standard deviation of elevation, and the distance from the nearest coastline. This is because we assume that road infrastructure is more developed in plain areas than in mountainous ones, and more developed in coastal areas than in land-locked ones. Table 5 summarizes the results of the IV models, estimated with two-stage least squares (2SLS), IV-SEM, IV-SLM, and IV-SDM (see also Table A.1 for the estimation results of first-stage regression). First, the estimates of the 2SLS model show that the estimated output elasticity of road infrastructure is positive and statistically significant. However, both Moran's I statistics and LM tests indicate that the spatial models are preferable to the 2SLS model. In addition, the model fitness represented by the Akaike Information Criteria and the results of the LR tests suggest that IV-SDM is preferable to any other spatial dependence model.

The estimates of SDM in Table 4 and those of IV-SDM in Table 5 indicate that capital stock and labor force are estimated to be

Table 4
Estimated output elasticities with OLS, SEM, SLM, and SDM.

	OLS		SEM		SLM		SDM	
Intercept	−2.346***	(-51.04)	−2.863***	(-62.01)	−2.197***	(-65.86)	−0.777***	(-15.24)
Capital	0.523***	(91.36)	0.465***	(85.02)	0.487***	(104.93)	0.434***	(72.33)
Labor	0.499***	(70.62)	0.607***	(106.36)	0.462***	(111.30)	0.657***	(93.86)
Road Infrastructure	−0.001	(-0.15)	−0.030***	(-3.58)	−0.002	(-1.46)	−0.036***	(-4.00)
Dummy Capital	−1.153***	(-35.25)	−1.094***	(-33.98)	−1.187***	(-37.55)	−1.184***	(-35.88)
Dummy Road	−0.528***	(-9.60)	−0.517***	(-13.09)	−0.494***	(-19.00)	−0.486***	(-11.85)
λ			0.621***	(77.63)				
ρ					0.081***	(20.25)	0.571***	(71.38)
W*Capital							−0.206***	(-22.89)
W*Labor							−0.469***	(-52.11)
W*Road							0.043**	(3.07)
Pseudo R^2	0.954		0.965		0.956		0.966	
Log-likelihood	−18985.60		−17057.53		−18761.95		−16848.77	
Akaike Information Criteria	37985.21		34131.05		37539.89		33723.54	
Breusch-Pagan test	1899.9***							
Jarque Bera test	2044.5***							
Moran's I	0.355***		−0.06		0.288***		−0.05	
LM test (Error)	5451.5***							
Robust LM (Error)	4975.7***							
LM test (Lag)	477.31***							
Robust LM (Lag)	1.48							
LR test (SEM)							419.25***	
LR test (SLM)							3826.40***	

Notes: t-statistics are in parentheses; ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. Robust standard errors are used for taking heteroskedasticity into consideration for OLS.

Table 5
Estimated output elasticity with 2SLS, IV-SEM, IV-SLM, and IV-SDM.

	2SLS		IV-SEM		IV-SLM		IV-SDM	
Intercept	−2.557***	(-25.88)	−2.833***	(-47.74)	−1.727***	(-31.65)	−0.784***	(-12.74)
Capital	0.522***	(117.88)	0.466***	(84.19)	0.483***	(104.10)	0.438***	(70.46)
Labor	0.477***	(45.09)	0.611***	(82.03)	0.502***	(91.18)	0.674***	(70.84)
Road Infrastructure	0.074*	(2.22)	−0.042**	(-2.36)	−0.160***	(-10.92)	−0.090***	(-3.68)
Dummy Capital	−1.153***	(-35.96)	−1.093***	(-33.88)	−1.193***	(-37.94)	−1.173***	(-35.22)
Dummy Road	−0.205	(-1.42)	−0.564***	(-8.18)	−1.162***	(-17.38)	−0.660***	(-7.89)
λ			0.621***	(75.56)				
ρ					0.097***	(24.01)	0.571***	(67.99)
W*Capital							−0.210***	(-24.22)
W*Labor							−0.487***	(-42.52)
W*Road							0.101**	(3.67)
Pseudo R^2	0.954		0.965		0.956		0.966	
Log-likelihood	−18983.14		−17061.9		−18703.54		−16847.62	
Akaike Information Criteria	37980		34140		37423		33721	
Breusch-Pagan test	1899.5***							
Jarque Bera test	2069.2***							
Moran's I	0.354***		−0.06		0.283***		−0.05	
LM test (Error)	5412.1***							
Robust LM (Error)	4886.9***							
LM test (Lag)	582.65***							
Robust LM (Lag)	3.48*							
LR test (SEM)							438.74***	
LR test (SLM)							3711.80***	
Instruments	Surface Roughness and Coastal Distance							

Notes: t-statistics are in parentheses; ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$. Robust standard errors are used to consider the heteroskedasticity for 2SLS.

significantly positive, which is reasonable. Both dummy capital and dummy road are estimated to be significantly negative, as expected. The estimated spatial auto-regressive coefficient ρ is 0.571 in both models, which is statistically significant. Although the spatially lagged regressors provide an idea of interactions among regions, the sign and magnitude of SDM can be estimated more precisely. The direct effect measures the effect on the dependent variable when the independent variable in its own grid is altered, which contains its own effects generated in the given unit and feedback effects that pass through neighboring units and back to their own unit. Meanwhile, the indirect effects measure the effect in the dependent variable in neighboring areas when the independent variable in one's own area is altered. Thus, they can be understood as spillover effects. In OLS or SEM, the direct effect of an explanatory

Table 6
Direct, spillover, and total effects of input factors computed from SDM and IV-SDM.

		SDM		IV-SDM	
Capital	Direct	0.439***	(74.51)	0.443***	(75.57)
	Spillover	0.092***	(8.07)	0.088***	(7.70)
	Total	0.531***	(48.86)	0.531***	(48.40)
Labor	Direct	0.644***	(101.63)	0.659***	(73.85)
	Spillover	−0.206***	(-18.06)	−0.224***	(-15.53)
	Total	0.438***	(40.93)	0.435***	(35.34)
Road	Direct	−0.033***	(-3.68)	−0.083***	(-3.57)
	Spillover	0.049**	(2.44)	0.108***	(2.90)
	Total	0.016	(0.79)	0.024	(0.75)

Notes: t-statistics are in parentheses; ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

variable equals the estimated coefficient of that variable and its spillover effect is zero, while in SLM or SDM, the direct and spillover effects should be estimated with the scalar summary measures. They can be computed with an approximation of the matrix using the traces of the powers of the weight matrix. An inference of these measures is drawn using Bayesian Markov chain Monte Carlo estimation methods, which provide a posterior distribution of the scalar summary measures of impact. The inference is obtained from 2000 simulated draws following Del Bo and Florio (2012).

Finally, Table 6 summarizes the direct, spillover, and total effects of road infrastructure computed from the estimated SDM and IV-SDM. This shows that the direct impact of road infrastructure is significantly negative, while the spatial spillover effects are significantly positive, and in total, the total output elasticity of road infrastructure is positive but insignificant.

5. Discussion

Table 7 shows the elasticities of direct, spillover, and total effects estimated in earlier studies for comparison. This shows that the elasticity of the direct effect of road infrastructure in previous studies varies from −0.058 to 0.912, while that of this study is estimated at −0.083 to −0.033. Many of them showed positive elasticities, but Holtz-Eakin and Schwartz (1995) and Berechman et al. (2006) showed −0.022 and −0.009, respectively, while some studies, such as Garcia-Mila et al. (1996) and Boopen (2006) concluded with insignificant elasticity. Previous studies show that the elasticity of spillover effect from road infrastructure varies from −0.806 to 0.24, while that of this study varies from 0.049 to 0.108. Finally, the elasticity of the total effect from road infrastructure shown in previous studies varies from 0.034 to 0.27, and from 0.016 to 0.024 for this study.

The negative direct impact from road infrastructure estimated from

Table 7
Elasticities of direct, spillover, and total effects from road infrastructure in previous studies.

Authors	Geographical scale	Period	Road infrastructure	Model	Elasticity of direct effect	Elasticity of spillover effect	Elasticity of total effect
Garcia-Mila and McGuire (1992)	US, 48 states	1969–83	Highway capital	CD	[0.044, 0.045]	–	–
Holtz-Eakin and Schwartz (1995)	US, 48 states	1969–86	Highway capital	CD	−0.022	Not Significant	–
Garcia-Mila et al. (1996)	US, 48 states	1970–83	Highway capital	CD	Not Significant	–	
Boarnet (1998)	California counties	1969–88	Street and highway capital	CD	[0.236, 0.300]	[-0.806, 0.125]	–
Canning (1999)	57 countries	1960–90	Paved roads and railroads (km)	CD	Not Significant	–	–
Canning and Bennathan (2000)	67 countries	1960–90	Paved roads (km)	Translog	Low income nations: 0.05 Middle income nations: 0.09 High income nations: 0.04	–	–
Cantos et al. (2005)	Spain, 17 regions	1965–95	Road capital	CD	[Not Significant, 0.286]	–	–
Berechman et al. (2006)	US state, county, and municipality level	1990–2000	Highway capital	CD	State: Not significant, County: 0.042, Municipality: −0.009	State: 0.021, County: 0.022, Municipality: 0.01	State: 0.047, County: 0.045, Municipality: Not significant
Ozbay (2007)	US, 18 counties	1990–2000	Street and highway capital	CD	[Not Significant, 0.057]	[Not Significant, −0.051]	–
Boopen (2006)	38 sub-Saharan and 13 SIDS countries	1980–2000	Road length (km)	CD	Not Significant	–	–
Moreno and López-Bazo (2007)	Spain, 50 provinces	1965–97	Transport capital	CD	[0.039, 0.041]	[-0.106, −0.080]	–
Cohen (2010)	US, 48 states	1996	Highway (monetary value)	SLM	0.106	–	–
Del Bo and Florio (2012)	Europe, 262 regions	2006	Motorways, other roads (physical value)	SDM	Motorways: 0.045; Other roads: −0.058	Motorways: Not significant; Other roads: 0.066	Motorways: 0.034; Other roads: Not significant
Tong et al. (2013)	US, 44 states	1981–2004	Road disbursement	SDM	1st order contiguity matrix: Not Significant, Other matrices: [0.02, 0.03]	2nd order contiguity matrix: 0.24, Other matrices: Not significant	2nd order contiguity matrix: 0.27, Other matrices: Not significant
Arbues et al. (2015)	Spain, 47 provinces	1986–2006	Roads (monetary value)	SDM	[0.043, 0.070]	[0.032, 0.055]	[0.080, 0.119]
Álvarez et al. (2016)	Spain, 47 provinces	1980–2007	Roads used in trade flows (monetary value)	SLM & Spatial autoregressive combined model	[0.026, 0.042]	[0.025, 0.033]	[0.051, 0.075]
Elburz, Z. et al. (2017)	Turkey, 26 regions	2004–2011	Road length (km) Motorway length (km)	CD	Road: [0.278, 0.912] Motorway: [0.058, 0.226]	–	–
Barilla, D. et al. (2020)	Italy, 20 regions	2007–2015	Index of cost competitiveness for transport and warehousing sectors	SDM	–	–	–

our study could be caused by the characteristics of our dataset, which contains mainly long-distance trunk road infrastructure rather than short-distance infrastructure, such as urban roads, streets, and avenues. The trunk road infrastructure promotes inter-regional transportation flows, which stimulate economic activities in a wider geographical area, whereas they suppress economic activities in the area through which the inter-regional traffic passes. Such traffic could have negative external impacts on the region, such as local environmental effects of noise and air pollution, and road accidents.

Next, the significantly positive spatial spillover effects from road infrastructure shown in this study are in line with other spatial productivity studies. The construction of an inter-regional road could improve the network by connecting regions efficiently, thus leading to the redistribution of existing resources for production. An improved transportation network can potentially provide a more efficient and integrated road network to the region and, consequently, contribute positively to the economic activities in its spatially related regions. The average positive spillover effects may be suggestive because, as shown earlier, some trade literature theoretically indicate the asymmetric effects of inter-regional transportation infrastructure between periphery and metropolitan regions (Fujita et al., 1999; Baldwin et al., 2003; Combes et al., 2008). For instance, Faber (2014) empirically investigated the national trunk highway system in China, and concluded that large-scale inter-regional transportation infrastructure can lead to a reduction in industrial and total output growth among connected peripheral regions, relative to non-connected ones, rather than diffusing production from metropolitan regions to the periphery. If this holds true across the world, our findings of average positive spillover effects imply that globally, the positive spillover effects in the metropolitan regions are more dominant than the negative spillover effects from the periphery. This may be evidence that is consistent with the theory of agglomeration economies, as shown in many existing studies (Fujita and Thisse, 2002).

Finally, the total effects from road infrastructure are estimated to be positive but insignificant. Theoretically, this is a sum of the direct and spillover effects; thus, the positive total effects mean that the positive spillover effects are greater than the negative direct effects. However, it is estimated to be statistically insignificant, which suggests that the total effects from road infrastructure are not observed on a global scale.

It should be noted that this study assumes a single production function covering the world for simplicity, but production technology could vary across regions. For instance, Hansen (1965) showed that the effect of public capital varies with the characteristics of regions broadly categorized as lagging, intermediate, and congested regions. Canning and Bennathan (2000) estimated the output elasticity of paved roads for 67 countries and found an inverted U-shaped relationship between income per capita and elasticities. This suggests that the estimation of productivity effects by region should be elaborated with our dataset. This is one of our further issues.

6. Conclusion

This study makes two major contributions. First, it proposes practical methods for developing a 2010 global gridded database, containing private output, physical capital stock, labor force, and road infrastructure stock with a spatial resolution of 0.1-degree. It is estimated using national-level statistical data, combined with nighttime lights imagery, global population database, and global road network. Their reproducibility is validated well with officially available statistical data at the regional scale. This enables researchers and policymakers to study the economic impacts of road infrastructure at different geographical levels. Second, using a simple Hicks-neutral Cobb-Douglas production function, this study estimates the productivity effects of road infrastructure, incorporating spatial spillover effects. It estimated OLS, SEM, SLM, and SDM with and without IVs, using the developed gridded global database aggregated at 1.0-degree, and empirically showed that SDM and IV-SDM outperform other models. Additionally, the estimation results of SDM and IV-SDM show that the direct effects of road infrastructure are significantly negative and the spatial spillover effects are significantly positive, while the overall effects are positive but insignificant.

Our findings have valuable implications for policymakers. First, the insignificant total effect of road infrastructure may suggest that a road is not a “silver bullet” (Munnell, 1990a) for improving regional productivity. However, it should be noted that our analysis mainly covers long-distance trunk roads. The effect of road infrastructure could be indirectly enhanced by introducing policies related to trunk road infrastructure. For instance, the positive spillover effects from the trunk road infrastructure may be strengthened by better connecting trunk roads with local/regional road networks. This suggests that the integrated investment in local/regional roads and trunk roads could enhance the positive spatial spillover effects, improving accessibility in first-/last-mile trips to/from the trunk roads. Similarly, the total effect may be increased by reducing the negative external effects from trunk road infrastructure, thereby minimizing the negative direct effects. This may include environmental actions, such as reducing the damage from traffic noise and air pollution; change in transportation policies, such as enhancing traffic safety; and regional development plans, such as introducing strategic land-use planning along the trunk road to capture the wider economic impacts from the interregional traffic. Second, our results could contribute to the debates on international aid strategies for international donor agencies and multilateral development banks. If, as discussed earlier, the road infrastructure leads to less spillover effects in the periphery than in the metropolitan regions, our findings of average positive spillover effects imply that the cross-border corridor projects that improve market accessibility to/from remote areas, could enhance regional productivity in the metropolitan regions. However, considering that they could also worsen the inter-regional disparity between the metropolitan and periphery regions, appropriate redistribution policies, including those related to international aid, should be introduced to compensate for the negative effects of road infrastructure in the periphery. Finally, our results could also provide a benchmark of road productivity effects to local/regional policymakers. Existing studies, such as Canning and Bennathan (2000), showed that the productivity effects of road infrastructure vary across regions, while our study shows the average effects on a global scale. Our findings may enable individual local/regional policymakers to use the average effect as a reference for their decision-making on road investment, based on the local/regional evidence estimated with local/regional data.

Although this study adds new evidence on the productivity effects of road infrastructure using a global dataset, many more issues need to be addressed. First, the dataset development should be further elaborated to improve data accuracy. We assume that the physical capital stock is in proportion to the sum of nighttime light intensity, but in reality, the efficiency of consuming man-made resources for economic activities could vary across the world. Additionally, the satellite remote sensing data, for instance, the DMSP OLS data used in this study, are of insufficient quality due to their coarse spatial and spectral resolution. Note that this has been overcome by the Visible Infrared Imaging Radiometer Suite since 2012. Second, this study performs a cross-sectional analysis, which cannot examine causality. This is partly due to the availability of data for developing the grid-based global dataset. If the global dataset for multiple years were available, a quasi-experimental approach, such as the difference-in-differences method could be employed to examine the causal effects from road infrastructure. Third, the econometric modeling should also be more elaborated. Reverse causality may be controlled using more sophisticated econometric techniques other than the simple IV method, such as the generalized method of moments (Kelejian and Prucha, 2004). Misspecification of the models could also seriously bias the estimates (Melo et al., 2013). The estimates of a simple spatial analysis could show a spurious association of road infrastructure with economic output, as pointed out by many studies, such as Ozbay et al. (2007). Additionally, spatial econometric modeling is often criticized for its poor theoretical foundation (Schafer and Victor, 2000; Corrado and Fingleton, 2012), particularly its assumption of the spatial weight matrix, which is one of its weakest issues. The difficulty of identifying and measuring spatial spillover phenomena has been addressed in many studies (Krugman, 1991; Álvarez et al., 2016). Ideally, more heuristic knowledge of the spatial linkage of road infrastructure networks across regions could enable a better formulation of the weight matrix.

CRediT authorship contribution statement

Akio Konno: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Validation, Visualization, Writing - review & editing. **Hironori Kato:** Conceptualization, Funding acquisition, Methodology, Validation, Project administration, Writing - review & editing. **Wataru Takeuchi:** Methodology, Writing - review & editing. **Riku Kiguchi:** Data curation, Investigation.

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Appendix

Table A.1 summarizes the estimation results of first-stage regression of IV models. The IV models were estimated (the results are presented in Table 5), using the road infrastructure that was obtained from the estimated results of first-stage regression. This regresses the road infrastructure on geographical attributes of the Surface Roughness and the Coastal Distance with all the control variables. The results show that both geographical attributes are significantly correlated to the road network. They also indicate the F-statistic is high and well above the commonly suggested threshold to be considered a relevant instrument, demonstrating that weak-instrument bias is not a problem.

Table A.1
Estimation Results of First-Stage Regression of IV models

Dependent variable: ln (Road)		
Intercept	1.649***	(21.99)
ln (Capital)	0.034***	(7.02)
ln (Labor)	0.278***	(59.84)
Dummy Capital	0.041	(1.11)
Dummy Road	−4.199***	(-138.59)
ln (Surface Roughness)	0.075***	(16.09)
ln (Coastal Distance)	0.145***	(14.26)
R^2	0.836	
Log-likelihood	−19831.03	
Akaike Information Criteria	39678.05	
F-Statistic	16570	

Notes: t-statistics based on the robust standard errors are in parentheses. ***: $p < 0.01$, **: $p < 0.05$, *: $p < 0.1$.

Declaration of interest

None.

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