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Economic Impacts of Transportation Infrastructure Investments

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16. Abstract

The purpose of this research project for the Pennsylvania Department of Transportation and the Center for Integrated Asset Management for MultiModal Transportation Infrastructure Systems is to quantify the impact of transportation investments on economic activity at the county-level within the Commonwealth of Pennsylvania. Specifically, the project identifies optimal transportation investment strategies that maximize the economic returns for the entire Mid-Atlantic region, considering both traditional and technological investments.

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ECONOMIC IMPACTS OF TRANSPORTATION INFRASTRUCTURE INVESTMENTS

FINAL REPORT

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1. INTRODUCTION

Infrastructure investments – specifically capital-intensive systems and facilities, such as roads, bridges, and water treatment facilities (Stupak, 2018) – can significantly influence the economic growth of a region and its neighbors (Macdonald, 2012). Economic growth of a country – often measured by its gross domestic product, personal income, and unemployment rates (Agbelie, 2013) – is dependent on the collective contributions from all kinds of infrastructure (e.g., roads, highways, railroads, airports, seaports, electricity, telecommunications, water supply, and sanitation). Infrastructure investment leads to higher economic output in the short term by stimulating demand and in the long term by increasing overall productivity (Stupak, 2018). Well-designed infrastructure also enables private businesses and services to operate efficiently by saving time and resources that can be utilized to achieve additional economic output, reduces the production input costs (Mamatzakis, 2008), and improves worker productivity (Agénor and Moreno-Dodson, 2012). Further, infrastructure investments have a great impact on energy consumption, the environment, and socioeconomic activities (Nijkamp, 1986). Transportation infrastructure has received specific attention in the literature due to its significant impact on economic growth. Investment in transportation infrastructure contributes to an increase in the gross domestic product (GDP) of a country, enhances mobility, increases business and work opportunities, and results in significant economic growth (Bonakdarpour et al., 2021). It also improves a country's production through reduction in transportation costs, travel time, and congestion (Sinha and Labi, 2007). Reduction in travel cost even has significant implications in international trade (Ando and Kimura, 2013).

The purpose of this research project for the Pennsylvania Department of Transportation and the Center for Integrated Asset Management for MultiModal Transportation Infrastructure Systems is to quantify the impact of transportation investments on economic activity at the county-level within the Commonwealth of Pennsylvania. Specifically, the project identifies optimal transportation investment strategies that maximize the economic returns for the entire Mid-Atlantic region, considering both traditional and technological investments.

The rest of the document is organized as follows. First, a summary of past literature on key economic performance indicators and their potential relation to transportation infrastructure is presented. Next, the data gathering process to model economic impacts of transportation investments in Pennsylvania for this study is discussed. These data were comprised of four components including: (1) economic performance indicators, (2) socio-demographics, (3) transportation investments, and (4) existing transportation infrastructure and use. Following the data collection, the models developed to predict economic performance indicators as a function of transportation infrastructure investments and other factors are described. Next, model interpretations are provided, along with a forecast of the economic returns associated with different investments (bridges, safety improvement projects, and traffic signals) for two different policy scenarios. The first scenario is the baseline scenario that assumes transportation investments are made only considering direct returns. This is representative of a single-tier county-level transportation infrastructure investment plan that only considers potential economic returns only in the county where the investment is being made. The second scenario considers the inter-dependency of economic performance indicators across county lines and thus should provide a more robust indication of the true impacts of these investments. Finally, concluding remarks are provided.

2. LITERATURE REVIEW

The literature review first discusses the different types of transportation infrastructure investments considered, followed by the economic indicators used to understand their impact. Next, the observed economic impacts of infrastructure investments in the literature are presented along with a discussion of the methodologies used to make such conclusions. Literature that has considered the spatial dependency of the economic impacts of infrastructure investment is presented, and finally some gaps in the literature are identified.

Transportation infrastructure investments considered

Transportation infrastructure spans a wide range of modes including surface transportation, air transportation, and water transportation. The economic impacts of investment in these varying types of transportation infrastructure have been investigated in the past, as they are large projects that often involve a significant fraction of a region's economy. A list of all literature that have considered the economic impacts of transportation infrastructure investment can be found in Table A1 in the Appendix. Many studies have considered the economic impact of existing large infrastructure, such as highways and bridges (Gutiérrez et al., 2010); (Agbelie, 2013); (Bell and McGuire, 1997); (Bonakdarpour et al., 2021); (Wan and Zhang, 2017); (Owusu-Manu et al., 2019), railways (Agbelie, 2013); (Bonakdarpour et al., 2021); (Chen and Haynes, 2015); (Ismail and Mahyideen, 2016), public transit (Bonakdarpour et al., 2021); (Chen and Haynes, 2015), airports (Moreno and López-Bazo, 2003); (Cantos et al., 2005), ports/ harbors (Moreno and López-Bazo, 2003); (Cantos et al., 2005); (Cohen and Monaco, 2008), and waterways (Yu et al., 2013). However, since these projects tend to be large in spatial scale and impact, most studies tend to focus on larger regions – country or state level.

Based on findings from a vast range of studies, there is a general consensus among researchers that transportation infrastructure investments have positive economic impacts (Banister and Berechman, 2001). Such consensus has influenced countries to undertake mega projects to improve their transportation systems. Thus, the impacts of new infrastructure investments have also become of interest for researchers. Some of the worldwide known transportation infrastructure improvement projects include China's Belt and Road Initiative (BRI), Japan's Kyushu bullet train, and India's Railroads of the Raj. BRI was undertaken in 2013 to promote regional economic growth and integration through an interconnected infrastructure system and involved numerous countries from Asia, Europe, and Africa (Zhang, 2018). (Chen and Li, 2021) investigated the impact of BRI on trade cost using data from 42 Eurasian countries that are the primary members of this mega project, while (Mukwaya and Mold, 2018) studied the impact of BRI on East Africa's trade and welfare. (Yoshino and Abidhadjaev, 2018) examined the impact of Kyushu bullet train for three different periods – construction period, operation period without connectivity, and operation period after connectivity. (Donaldson, 2018) investigated the extent of improvement in the economy in 235 Indian districts due to India's Railroads of the Raj. (Beguy et al., 2015) investigated impact of a dam project in Niger on key macroeconomic variables.

While the impacts of large transportation infrastructure investments are apparent from these studies, some countries have also focused on smaller-scale transportation infrastructure, such as investments in bicycle and pedestrian infrastructure. For example, (Liu and Shi, 2018) investigated the impact of three sets of bicycle accessibility measures (BAM) – distance-based BAM, destination-based BAM, and low-stress network BAM. Several studies have specifically focused on the impact of bicycle and pedestrian infrastructure improvements on local business. For a review of these studies, see (Volker and Handy, 2021).

A summary of the different types of infrastructure investment considered in the literature can be found in Table 1. The table organizes the studies by the type of infrastructure investment considered and the spatial scale of the analysis. Notice that most studies use a fairly large spatial scale (county or state), whereas relatively few focus on smaller scales (e.g., census tracts of counties).

Table 1. Summary of Infrastructure Investments Considered

Infrastructure Investment	Reference	Spatial Scale
Highways and roadways	(Gutiérrez et al., 2010)	Region
	(Agbelie, 2013)	Country
	(Bell and McGuire, 1997)	State
	(Bonakdarpour et al., 2021)	Sector and State
	(Wan and Zhang, 2017)	Firm
	(Chen and Haynes, 2015)	Region
	(Snieska and Simkunaite, 2009)	Country
	(Moomaw et al., 1995)	State
	(Ismail and Mahyideen, 2016)	Country
	(Owusu-Manu et al., 2019)	Country
	(Looney and Frederiksen, 1981)	State
	(Yu et al., 2013)	Province
	(Delgado and Álvarez, 2007)	Province
	(Xie et al., 2016)	City
	(Moreno and López-Bazo, 2003)	Province
	(Cantos et al., 2005)	Region
	(Cohen and Monaco, 2008)	State
	(Richaud et al., 1970)	Country
	(Vlahinić Lenz et al., 2018)	Country
Railways	(Agbelie, 2013)	Country
	(Bonakdarpour et al., 2021)	Sector and State
	(Chen and Haynes, 2015)	Region
	(Ismail and Mahyideen, 2016)	Country
	(Owusu-Manu et al., 2019)	Country
	(Yu et al., 2013)	Province
	(Moreno and López-Bazo, 2003)	Province
	(Cantos et al., 2005)	Region
	(Vlahinić Lenz et al., 2018)	Country
Public transit	(Bonakdarpour et al., 2021)	Sector and State
	(Chen and Haynes, 2015)	Region
Airport	(Ismail and Mahyideen, 2016)	Country
	(Moreno and López-Bazo, 2003)	Province
	(Cantos et al., 2005)	Region
Ports, Harbors	(Ismail and Mahyideen, 2016)	Country
	(Moreno and López-Bazo, 2003)	Province
	(Cantos et al., 2005)	Region
	(Cohen and Monaco, 2008)	State
Waterways	(Yu et al., 2013)	Province
Dam	(Beguy et al., 2015)	Country
Bicycle	(Liu and Shi, 2018)	Census block
Overall transportation infrastructure	(Palei, 2015)	Country
	(Khan et al., 2020)	Country
Specific projects		
New Silk Road Economic Belt	(Li et al., 2017)	Province
Kyushu high-speed rail line	(Yoshino and Abidhadjaev, 2018)	Region
China's Belt and Road Initiative (BRI)	(Mukwaya and Mold, 2018)	Country
India's Railroads of the Raj	(Donaldson, 2018)	District

Economic indicators

Numerous indicators have been used in the literature to measure the economic impact associated with transportation infrastructure investments. Numerous economic factors are influenced by transportation infrastructure such as regional competitiveness, income inequality, output, labor productivity, and the environment (Bristow and Nellthorp, 2000). Many past studies have focused on a single economic performance indicator – for example, gross domestic product (GDP) (Snieska and Simkunaite, 2009; Looney and Frederiksen, 1981), gross metropolitan product (GMP) (Chen and Haynes, 2015), private sector production (Delgado and Álvarez, 2007), and public capital stock (i.e., government-owned assets (Moomaw et al., 1995)).

However, without a holistic analysis of multi-dimensional economic performance indicators (i.e., using multiple indicators simultaneously) the true impact of a transportation investment may be obscured (Cohen and Paul, 2004). For this reason, some studies have measured the impact of transportation infrastructure on multiple economic indicators. The economic impact of transportation infrastructure on global competitiveness of 124 different countries was studied using data from the *Global Competitiveness Report-2012* (Palei, 2015). Many variables – including goods market efficiency, labor market efficiency, financial market development, technological readiness, market size, the macroeconomic environment, health and primary education, higher education, and training – were considered in that work. Another study investigated the impact of transportation, energy, internet & communication technology, and finance infrastructure on 30 economic indicators – including GDP growth, foreign direct investment (FDI), and inflation – using data from South Asia (Khan et al., 2020). (Beguy et al., 2015) investigated the impact of the Kandaji Dam project in Niger on key macroeconomic variables such as consumption, government spending, imports, GDP, and the GDP deflator.

Several studies have calculated new economic indicators using existing indicators. For example, (Chen and Li, 2021) investigated the impact of China's Belt and Road Initiative (BRI) mega project on the change in trade cost, estimated from trade cost elasticities and individual investment in transportation, of 42 Eurasian countries. (Donaldson, 2018) investigated the extent of improvement in India's economy due to the Railroads of the Raj in terms of trade costs reduction, interregional price gaps reduction, and trade flows increase. Due to the lack of other strong economic indicators, some studies have also used tax revenue as their economic performance indicators (Yoshino and Abidhadjaev, 2018; Beguy et al., 2015).

Table 2 provides a summary of all economic indicators used in the literature to quantify the impact of infrastructure investment, along with the spatial scale of the measurements.

Table 2 Summary of Economic Indicators

Economic Indicator	Reference	Spatial Scale
GDP	(Agbelie, 2013)	Country
	(Chen and Li, 2021)	Country
	(Bell and McGuire, 1997)	State
	(Beguy et al., 2015)	Country
	(Bonakdarpour et al., 2021)	Sector and State
	(Snieska and Simkunaite, 2009)	Country
	(Khan et al., 2020)	Country
	(Ismail and Mahyideen, 2016)	Country
	(Owusu-Manu et al., 2019)	Country
	(Looney and Frederiksen, 1981)	State
	(Yu et al., 2013)	Province
	(Li et al., 2017)	Province
	(Vlahinić Lenz et al., 2018)	Country
Income	(Bell and McGuire, 1997)	State
	(Bonakdarpour et al., 2021)	Sector and State
	(Richaud et al., 1970)	Country
Employment	(Bell and McGuire, 1997)	State
	(Bonakdarpour et al., 2021)	Sector and State
	(Liu and Shi, 2018)	Census block
	(Cohen and Monaco, 2008)	State
Public and private capital stock	(Cohen and Paul, 2004)	State
	(Bell and McGuire, 1997)	State
	(Bonakdarpour et al., 2021)	Sector and State
	(Chen and Haynes, 2015)	Region
	(Moomaw et al., 1995)	State
Trade, Trade cost, Import, Export	(Chen and Li, 2021)	Country
	(Mukwaya and Mold, 2018)	Country
	(Donaldson, 2018)	District
	(Ismail and Mahyideen, 2016)	Country
	(Richaud et al., 1970)	Country
Manufacturing production, Private production	(Cohen and Paul, 2004)	State
	(Bonakdarpour et al., 2021)	Sector and State
	(Delgado and Álvarez, 2007)	Province
	(Cantos et al., 2005)	Region
Labor and logistics cost	(Wan and Zhang, 2017)	Firm
	(Moreno and López-Bazo, 2003)	Province
Private cost saving, Investment savings	(Cohen and Paul, 2004)	State
	(Mukwaya and Mold, 2018)	Country
GMP	(Chen and Haynes, 2015)	Region
Travel time	(Gutiérrez et al., 2010)	Region
Property value	(Liu and Shi, 2018)	Census block
Competitiveness	(Palei, 2015)	Country
Tax revenue, Government revenue	(Bonakdarpour et al., 2021)	Sector and State
	(Yoshino and Abidhadjaev, 2018)	Region

Impacts of infrastructure investment

As previously mentioned, most researchers have found significant positive relationships between infrastructure investments and economic indicators (Aschauer, 1989; Kavanagh, 1997; Munnell, 1990). For example, the impact of transportation infrastructure investment and existing highway and railway infrastructure across countries in Asia, Australia, Europe, North America and South America was investigated using historical data between 1992 and 2010 (Agbelie, 2013). The results suggested that: (1) a 10% increase in highway infrastructure investment can increase economic output (measured in real GDP per capita) by 2.58% to 3.81%; (2) a country with 10% larger highway infrastructure density can observe an increased economic output by 2.27% to 5.90%; and, (3) a 10% increase in railway investment can increase economic output by 0.23% to 0.94%. A study to understand the impact of investment in highway, bridges, and public transit on GDP, employment, income, and capital stock found that the nonfarm productivity index increased by 0.03% from highway and bridge investments and by 0.01% from public transit investments (Bonakdarpour et al., 2021). Further, a $1 million investment in infrastructure created 21 jobs on average and increased disposable income per household per year by $232.

Investigating the impact of investment in public surface transportation modes suggested that a 1% increase in highway investment per capita results in a 0.154% increase in gross metropolitan product (GMP) per capita, and a 1% increase in private railroad investment per capita results in a 0.405% increase in gross metropolitan product (GMP) per capita (Chen and Haynes, 2015). Attempts to quantify the impact of transportation capital stock of roads, ports, airports, and railways considering their aggregated impact and individual impact suggested that the impact is heterogeneous for different types of transportation systems, and that transportation infrastructure has a statistically significant impact on the agriculture sector with an elasticity of 0.072 (Cantos et al., 2005). The direct and indirect impact of transportation infrastructure were separated in a study that investigated firm-level data from 440,490 firms in the China Industrial Enterprise Database (CIED) over the period 2002–2007 (Wan and Zhang, 2017). The results suggested that roadway infrastructure have a positive impact on firm productivity both directly and indirectly.

Only a few studies conducted economic impact analyses considering data from all states in the United States (e.g., Cohen and Paul, 2004, Bell and McGuire, 1997). The most comprehensive study was conducted as part of the National Cooperative Highway Research Program (Report 389) to better estimate the value of the public and private capital transportation stock in the United States. (Bell and McGuire, 1997). This study collected a vast amount of data, including private-sector data (e.g., Gross State Product, personal income, employment, private capital stock estimates), public-sector data (e.g., infrastructure spending, infrastructure capital stock estimates, total receipts of all highways from the Federal Highway Administration), and network characteristics (e.g., road mileage, condition, transit mileage, total number of airport flights). Production functions of the gross state product for eight industries, private nonfarm, durable manufacturing, nondurable manufacturing, TCPU (transportation, communication and public utilities), wholesale trade, retail trade, FIRE (finance, insurance and real estate) and Services were estimated considering highway capital as an input. The results suggest that in the United States, highway capital-only impacts the output of three out of the eight industries considered, which are TCPU, retail trade, and services. Further, the findings suggest that increasing public infrastructure has little impact on per-capita income.

A few studies have investigated the impacts of large projects on economic indicators, specifically related to trades, and found that often transportation infrastructure positively affects economic growth through reducing trade costs (Khan et al., 2020). The impact of BRI on the international trade cost was investigated using data from 42 Eurasian countries that are the primary members of this mega project (Chen and Li, 2021). The result showed that the economic impact – in terms of GDP and economic welfare – in these countries is quite uneven, and the intra-regional trade cost is different for each pair of countries. While trade cost reduction seems to generally lead to economic improvement, several countries in Central and West Asia and non-EU countries in Eastern Europe were found to be negatively influenced by the reduction in intra-regional trade cost. The impact of BRI on East Africa's trade and welfare was also studied, and it was found that an overall increase in GDP in these countries due to reduced trade margins (Mukwaya and Mold, 2018). Specifically, Kenya was found to experience the highest gains (+1.2%) while Uganda was found to experience the lowest benefits (+0.4%) in GDP. The extent of economic improvement due to the reduced trading distance from India's Railroads of the Raj compared to other travel modes was also investigated (Donaldson, 2018). Such reduction in distance facilitated business, which in return improved trading environment and increased the real agricultural income by approximately 16%. The impact of both hard (physical infrastructure such as roads, airports, ports, and rail) and soft (non-physical infrastructure such as transport efficiency in terms of time and cost, cost and time of export and import, and business regulations and transparency) infrastructure was quantified on trade volume for exporters and importers (Ismail and Mahyideen, 2016). The results suggest that all kinds of transportation systems – road network, air transport, railways, and ports – increase trade flows of a study region mainly due to reduced transaction costs because of shorter travel distances. The impact of the Kyushu bullet train on the economic performance of Japan was investigated and it was found that even cities without any connection to the railway increased their tax revenue during the construction period (Yoshino and Abidhadjaev, 2018). However, the tax revenue of the connected regions became much higher after construction.

A few studies suggest that infrastructure investment may not always have a positive economic impact due to many reasons – such as cost overruns, poor implementation quality, inadequate operational and maintenance capacity (Beguy et al., 2015). The risk is even greater for large-scale projects that could potentially impact macroeconomic stability due to project related debt dynamics and long-term operational and maintenance costs. For example, (Liu et al., 2015) found that transportation infrastructure investment might cause businesses to agglomerate in an urban region and as a result have a negative impact on production costs. Moreover, the impact of infrastructure depends on its operational quality. Inefficient and outdated railway infrastructure was found to have a negative impact on the GDP of a country (Vlahinić Lenz et al., 2018).

The impacts of smaller transportation investments, such as bicycle or pedestrian facilities, have not been investigated much in the literature. One such study considered investment in bicycle infrastructure and found that it improved bicycle travel safety and developed a well-connected network for the whole transportation system (Liu and Shi, 2018). They also found that greenway facilities increased the ease of access to different important destinations including employment, retail, service, and parks/recreation destinations. Other studies found that bicycle facilities might have a negative impact on auto-centric businesses, but they do have some impact on local retail and food service businesses (Volker and Handy, 2021).

Methodologies used to determine economic impact

Production functions have been widely used to determine the economic impacts of transportation infrastructure. The Cobb-Douglas (CD) function (Cobb and Douglas, 1928) is the most commonly used production function, which is widely used in theoretical and empirical economic modeling due to the ease of interpreting the coefficients as output elasticity. This function has also been used in different forms, such as translog to investigate the economic impact of public surface transportation modes (Chen and Haynes, 2015). However, the CD model has its limitations; for example, it imposes an arbitrary level for substitution possibilities between inputs (Reynès, 2011) and also assumes a constant share of labor in output. Hence, researchers have investigated numerous other modeling approaches to address and account for these limitations.

A few of these studies have tried to address the inherent endogeneity of the relationship between economic growth and development that can make the modeling difficult (Mukwaya and Mold, 2018). One study used a pooled mean group (PMG) estimator that offers better estimates of the parameters compared to fixed-effect models (Khan et al., 2020). Another used a two-stage-least squares estimation model to estimate the parameters of four series of equations to account for the presence of endogeneity (Richaud et al., 1970). Other work have considered the use of autoregressive distributed lag models (Owusu-Manu et al., 2019), Solow's growth accounting framework combined with CD (Wan and Zhang, 2017), and augmented-gravity model with random effects with a PMG estimator (Ismail and Mahyideen, 2016). Numerous studies have used computable general equilibrium (CGE) models for investigating the true impact of BRI project of China studies, see (Chen and Li, 2021).

A summary table of the different methodologies considered in the literature can be found in Table 3.

Consideration of spatial spillover of economic impact of transportation infrastructure

The studies discussed above have examined the economic impact of transportation infrastructure at an aggregated geographic resolution (e.g., states or municipalities) limiting the ability of these studies to inform investment strategies for local governments (e.g., counties or zones). The impact of infrastructure differs when considering disaggregated versus aggregated geographic regions. For example, when estimating the impact of public capital for individual states, rather than average impact for all states, it was found that elasticity varies significantly (ranging from 0.0 in Connecticut to 0.26 in New York) (Moomaw et al., 1995). Another geographic concern is ignoring the impact of investment in regions with different levels of industrialization (Agbelie, 2013). If the geographic focus is too narrow, the impact of transportation infrastructure is generally underestimated (Munnell, 1992). The improvement in one region may have significant impact – positive or negative – on the adjacent regions (e.g., cross-region productivity leakage often occurs). This spatial dependency is particularly important for integrated regions that have free movement of goods and factors (Owyong and Thangavelu, 2001). Such findings influenced researchers to analyze the impact of transportation infrastructure investments at a smaller geographic scale.

The impact of change in infrastructure in one region on the economy of another region is generally termed as "spatial spillover". A positive spillover occurs when a region benefits the neighboring regions through improving connectivity. For example, infrastructure in one area can attract labor and capital from neighboring areas through high-quality or low-cost infrastructure (Bell and McGuire, 1997). On the other hand, improvement in one region can lead to negative spillover, e.g., by drawing away potential business form adjacent undeveloped regions. It was postulated that general public infrastructure benefits only the region in which it is located, while transportation infrastructures benefit both the region in which they are located and also adjacent areas (Moreno and López-Bazo, 2003). However, in general the spillover effect tends to decrease as the distance from the infrastructure investment increases (Gutiérrez et al., 2010).

Many studies have considered the spatial spillover effect of transportation infrastructure and generally found positive spillover effects. The intra as well as inter-state impact of public infrastructure was considered using U.S. manufacturing sector data (specifically capital, production, and nonproduction labor and materials) between 1982 to 1996 (Cohen and Paul, 2004). The results showed significant positive cross-state impact of public infrastructure on manufacturing production. Railroads in colonial India were found to have a negative impact on the neighboring regions without any connection to the railroads (Donaldson, 2018). Both the infrastructure and the GDP of a country were found to have significant impact on exports of neighboring countries in African countries – a 1% increase in roads per capita in a country resulted in 1.18% increase in GDP per capita in that country and 0.41% increase in GDP per capita in an adjacent country over a two-year period (Richaud et al., 1970). That study concluded that if a neighboring country were to contribute to the cost of the project in proportion to their individual benefits, both countries would have an incentive to invest in the project. The presence of spillover effect of port and highway infrastructure on the manufacturing industry was considered and it was found that there is a negative spillover effect of ports (i.e., a state's manufacturing cost increased by 0.129% due to port infrastructure in neighboring states) (Cohen and Monaco, 2008). That work concluded that large port structures in a state may draw away productive resources from adjacent states. A stochastic frontier model was established and it was found that a high-capacity road (HCR) has a positive impact on production sectors (agriculture, industry, energy, construction, and business sector services) in Spain in both their own province and neighboring provinces (Delgado and Álvarez, 2007). A specialized spatial weight matrix using data from China from 2005 to 2014 was developed and a positive spillover effect was found (Li et al., 2017).

Other studies found that negative spillover effects could also arise. The Durbin model was used to try to quantify the presence of spatial spillover for transportation infrastructure in China (Yu et al., 2013). Due to the connectivity characteristics, that work found a positive spatial spillover at the national level. At the regional level, however, that work found both positive and negative spillover with high variability over time. A negative spillover effect was found using a log-linear Cobb-Douglas aggregate production function that used public capital stock data from 50 Spanish provinces between 1965 to 1997 (Moreno and López-Bazo, 2007). That work concluded that the cost and labor migration from a province with low levels of infrastructure to a province with high levels of infrastructure counteracts the benefits connectivity benefits.

A summary table of literature that considers spatial dependency and the methodology used in each is provided in Table 3.

Table 3. Summary of Methodologies

Methodology	Reference	Spatial dependency
Production function, CD production function, Translog production function	(Agbelie, 2013)	N/A
	(Bell and McGuire, 1997)	N/A
	(Wan and Zhang, 2017)	N/A
	(Moomaw et al., 1995)	N/A
	(Khan et al., 2020)	N/A
	(Owusu-Manu et al., 2019)	N/A
	(Looney and Frederiksen, 1981)	N/A
	(Yu et al., 2013)	Spatial Durbin Model
	(Delgado and Álvarez, 2007)	Stochastic frontier framework
	(Moreno and López-Bazo, 2003)	Inclusion of spillover variable
	(Cantos et al., 2005)	Total factor productivity approach
	(Chen and Haynes, 2015)	Spatial panel approach with fixed effects
Cost function	(Cohen and Paul, 2004)	Spatial autoregressive (SAR) model
	(Cohen and Monaco, 2008)	First order spatial autocorrelation
GIS mapping	(Gutiérrez et al., 2010)	Spillover matrix (Economic potential)
Global Trade Analysis Project (GTAP)	(Chen and Li, 2021)	N/A
	(Mukwaya and Mold, 2018)	N/A
Computable general equilibrium (CGE)	(Chen and Li, 2021)	N/A
	(Mukwaya and Mold, 2018)	N/A
IHS Markit's US Macroeconomic Model	(Bonakdarpour et al., 2021)	N/A
Correlation analysis	(Liu and Shi, 2018)	Spatial equity analysis
	(Snieska and Simkunaite, 2009)	N/A
Graph theory algorithm	(Donaldson, 2018)	N/A
Regression analysis	(Liu and Shi, 2018)	N/A
	(Snieska and Simkunaite, 2009)	N/A
	(Palei, 2015)	N/A
	(Yoshino and Abidhadjaev, 2018)	Difference-in-difference approach
	(Li et al., 2017)	Spatial Lag model and Spatial Tobit model
	(Vlahinić Lenz et al., 2018)	N/A
Pooled mean group estimation (PMGE)	(Ismail and Mahyideen, 2016)	N/A
Autoregressive distributed lag (ARDL)	(Ismail and Mahyideen, 2016)	N/A
	(Menegaki, 2019)	N/A
	(Owusu-Manu et al., 2019)	N/A
Cluster analysis	(Looney and Frederiksen, 1981)	N/A
Two-stage least square	(Looney and Frederiksen, 1981)	N/A
	(Richaud et al., 1970)	N/A
	(Wan and Zhang, 2017)	N/A
Growth equation Mankiw et al (1992)	(Richaud et al., 1970)	Inclusion of spillovers indicators
Spatial Durbin model	(Xie et al., 2016)	Spatial Durbin model

Gaps in the literature

The literature reviewed here shows that the impact of transportation infrastructure investment is different for each location, each project, and each sector. For example, most of the studies found either a positive or negative impact of infrastructure investment on the study area and adjacent regions. However, some studies also found that infrastructure investment does not have any role in the economic growth of a country (Holtz-Eakin, 1994; Hulten and Schwab, 1991). Investment in motor infrastructure was found to improve the economy of urbanized regions but it did not favor the development of rural regions (Rephann and Isserman, 1994). As more urbanized regions were connected through improved infrastructure, rural regions were even more neglected. Such differences in findings result from differences in research questions, approaches used, and the types of data employed (Bell and McGuire, 1997). Hence, analysis of the economic impacts of transportation investment for Pennsylvania is expected to reveal unique insights. Such findings can help better allocate transportation infrastructure funds.

3. DATA ASSEMBLY

The research team collected data on four different categories: (1) Economic performance indicators, (2) socio-demographics, (3) transportation investments, and (4) existing transportation infrastructure in PA and their use. Multiple different data sources, including PennDOT's web-based GIS mapping application, OneMap (https://onemap.penndot.gov), the Pennsylvania Spatial Data Access (PASDA), the Federal Aviation Administration (FAA), the American Public Transportation Association (APTA), the Bureau of Transit Statistics (BTS), the Bureau of Economic Analysis, and the American Community Survey Census. The data collection for the four different categories is discussed next, and Table 4 provides a summary of the relevant data items and their sources. Each data element is collected at the county scale (i.e., a single value associated for each county within Pennsylvania) for each year in the period from 2010 through 2020, inclusive.

Economic Performance Indicators

The economic performance indicators were obtained directly from the Bureau of Economic Analysis. The available data include information on the GDP of a county, also broken down by industry, and the income and employment levels of the population.

Socio-demographic Indicators

Socio-demographic indicators were directly obtained from the American Community Census Survey. These data include information on population (by age groups), incomes (for average households, families and individuals), average travel time to work, employment (across different industries), and families under the poverty line. The age categories were chosen to represent younger (younger than 15) and older (older than 65 and 75) categories.

Transportation Investments

Transportation investment data were obtained from PennDOT's web-based GIS mapping application, OneMap (https://onemap.penndot.gov). Transportation improvement projects were obtained from the Multi-modal project Management System inventory, which is used to create official reports that are submitted to the Federal Highway Administration, Federal Transit Administration and the Pennsylvania State Transportation Commission, as well as for tracking project delivery. Many unique improvement types (78) were observed in this database; to better facilitate the modeling in the next task, these were grouped into five categories: infrastructure, safety, operations, multimodal, and other. The detailed list of improvement type, the number of times it was observed, and the category to which it was assigned is provided in Table A2 in Appendix 2.

Existing Transportation Infrastructure and Use

Available information on the existing transportation infrastructure and its use was collected for the road transportation, public transportation, and aviation systems. The data on the road transportation system were obtained from both the Pennsylvania Spatial Data Access (PASDA) system that provides open GIS data and also the PennDOT Onemap System. The data obtained from PASDA includes the total length of PA state roads, total vehicle miles traveled, and total truck miles traveled. The total vehicle (truck) miles traveled was calculated as the segment length in miles times the corresponding average annual daily traffic (average daily truck traffic) of that segment summed for the entire county.

Data on the public transportation infrastructure were collected from the National Transit Database (NTD) maintained by The American Public Transportation Association (APTA). These data include the number of transit maintenance facilities, total bus-lane miles, and total train miles.

Data on the aviation infrastructure were collected from the Federal Aviation Administration and include the annual passenger boarding at airports and annual landed weights of cargo at airports.

Summary of Data Assembly and Missing Data

All the critically important datasets for analyzing the economic impacts of transportation infrastructure investments for Pennsylvania were obtained in the data collection task. A few variables that were not available to the research team at the time of conclusion of this task are:

1) Estimated costs of operating the 511 system,
2) Locations of fiber optic cables in PA, along with the year in which they were installed,
3) CAV hotspots report, and
4) Freight commodity flow information.

The unavailability of this data did not significantly impact the modeling process.

Table 4. Summary of data collection

Category	Description	Source
Economic performance indicator	Total GDP (all industries)	Bureau of Economic Analysis
	Total GDP (only trade)	
	Total GDP (transportation and utilities)	
	Total GDP (transportation and warehousing)	
	Personal income	
	Total employment	
	Total employment in construction industry	
	Total employment in wholesale industry	
	Total employment in retail industry	
	Total employment in transportation and warehouse industry	
Socio-demographics	Total population	The American Community Survey Census
	# of population under age 15	
	# of population over age 65	
	# of population over age 75	
	# of households	
	# of families	
	Mean household income	
	Mean family income	
	Mean personal income	
	Median household income	
	Median family income	
	Aggregated travel time to work	
	Mean travel time to work	
	# of employed population	
	# of workers who did not work at home	
	% of families below poverty level	
	# employed in agriculture, forestry, fishing and hunting, and mining	
	# employed in construction	
	# employed in manufacturing	
	# employed in wholesale trade	
	# employed in retail trade	
	# employed in transportation and warehousing, and utilities	
	# employed in information	
	# employed in finance and insurance, and real estate and rental and leasing	
	# employed in professional, scientific, and management, and administrative and waste management services	
	# employed in educational services, and health care and social assistance	

	# employed in arts, entertainment, and recreation, and accommodation and food services	
	# employed in other services, except public administration	
	# employed in public administration	
Transportation investments	Total cost of road and bridge infrastructure improvement projects deployed	PennDOT Onemap
	Total cost of safety infrastructure improvement projects deployed	
	Total cost of operations improvement projects deployed	
	Total cost of other improvement projects deployed	
	Total cost of multimodal transportation infrastructure improvement projects deployed	
Existing transportation infrastructure and use	Annual passenger boarding at airports	The Federal Aviation Administration
	Annual landed weights (lbs) of cargo at airports	
	Total public transportation vehicle miles travelled	The American Public Transportation Association
	Accumulated distance ridden by passengers on public transportation	
	Total train miles travelled	
	Facilities used for inspecting, servicing, and performing light maintenance work upon revenue vehicles	
	# of adaptive traffic signals	PennDOT Onemap
	# of bridges	
	# of detectors	
	# of Dynamic Message Signs	
	# of highway advisory broadcast radios	
	# of traffic cameras	
	# of traffic signals	
	# of PennDOT's Traffic Signal Asset Management System projects deployed	
	Daily Truck Vehicle Miles Traveled	PASDA
	Daily Vehicle Miles Traveled	
	Total length (in feet) of PA state roads	

4. MODEL DEVELOPMENT

This section provides details on methodological formulations that have been used to establish a relationship between economic performance indicators and exogenous factors.

A linear regression model was first developed to explore the relationships between economic performance indicators and various county-level features. This was done to identify those features that have a significant impact on economic performance. Then, more complex models were developed that consider spatial dependency among neighboring counties on economic activity within a given county. The results from both models were then compared.

Several GDP-based performance indicators were available for this study: total GDP from all industries, GDP from trade industries only, GDP from transportation and utilities industries, and GDP from transportation and warehousing industries. As activities from all industries are dependent on transportation infrastructure, any improvement on such infrastructure was expected to benefit all industries. Hence, the total GDP from all industries was selected as the economic performance indicator for this analysis. A wide range of exogenous variables have also been collected in this study; see Table 4. Factors that can potentially impact the GDP, including socio-economic factors (such as personal income and employment), demographic variables, vehicular movements, and the existing transportation infrastructure were all considered. The following specific variables were considered to understand the impact of transportation infrastructure investments on the GDP of a county: percentage of adaptive traffic signals, number of new traffic signals, and total cost of safety and other infrastructure improvement projects.

Next, the computation of average elasticity effects that indicate the percentage change in economic indicators for unit percentage change in transportation investments across all counties is presented to aid the interpretation of the models. Three types of elasticity are estimated: (1) direct elasticity (change in economic performance indicators of a county due to change in transportation investment in the same county), (2) indirect elasticity (change in economic performance indicators of neighboring counties due to change in transportation investments in a specific county), and (3) total elasticity (combination of both direct and indirect elasticity).

Linear Regression

As previously mentioned, linear regression was used as the initial model type used to explore relationships between economic activity and potential explanatory features. The form of the linear regression model is described in this section.

Let $s = 1,2, \dots, S$ denote the index of counties where S is the total number of counties in the study area. Additionally, for each county s, the set of independent variables that influence the economic performance indicator is denoted $\{x_{s,j}\}$ where j is an index for each individual explanatory variable. Note that GDP is the only dependent variable considered in this study. The relationship between economic performance indicator and exogenous factors is assumed to obey the following linear relationship:

$$y_s = \sum_j x_{s,j} \times \beta_j + \epsilon_s, \tag{1}$$

where y_s is the magnitude of economic performance indicator (i.e., GDP), β_j model coefficients estimated in the statistical model to predict economic performance indicator, and ϵ_s is normally distributed random error term. Due to this error term, there is always a non-zero probability of outcome of the regression model to be a negative value, which is counterintuitive for the GDP metric. To account for this issue, a natural logarithmic transformation is conducted on the response variable. This log-linear model takes the following relationship:

$$\log(y_s) = \sum_j x_{s,j} \times \beta_j + \epsilon_s, \tag{2}$$

The resulting model is referred to as "Log-linear regression (LLR)" model in the results section.

The most common way of fitting this regression is the ordinary least square (OLS) technique, which determines the optimum $\{\beta_j\}$ such that errors between the predicted and observed values is the least. Specifically, the OLS technique minimizes the sum of square error (SSE), which is given by:

$$SSE = \sum_{s=1}^{S} (y_s - \widehat{y_s})^2 \tag{3}$$

where $\widehat{y_s}$ denotes the predicted magnitude of economic performance indicator.

Linear Regression with Spatial Dependence

The traditional log-linear regression model described in Equation (2) assumes that the GDP of a given county is independent of neighboring counties. To introduce spatial dependence across counties, Equation (2) is modified to include a spatial dependence term as follows:

$$\log{(y_s)} = \sum\nolimits_j x_{s,j} \times \beta_j + \rho \sum_{s'=1}^{S} w_{ss'} y_{s'} + \epsilon_s \tag{4}$$

where ρ denotes the strength of spatial dependence that is estimated within the model, and $w_{ss'}$ denotes the spatial dependency of county s to s', which is an input to the model. A common way to define spatial dependency is as the inverse of the geographic distance between the counties. In that case, a positive value of ρ would suggest that GDP growth in neighboring counties will have a larger positive impact on GDP growth in a county compared to that from counties located further away. This study further explores whether this spatial dependency is contingent upon the counties being geographic neighbors (i.e., sharing a physical border) and/or having some sort of major transportation connection (in this case, an interstate highway connection). In summary, this study considers five specifications (separately and combined) of the $w_{ss'}$ measure:

i. Log distance (natural logarithm of geographical distance from the corresponding county)
ii. Inverse distance (inverse of geographical distance from the corresponding county)
iii. Neighbor (all counties within 50 miles of the corresponding county)
iv. Adjacent (all counties sharing the border of the corresponding county)
v. Interstate connection (all counties having an interstate connection with the corresponding county)

The resulting model is referred to as "Spatial Dependency (SD)" model in the results section. The specifications of three spatial dependency models are discussed below:

SD Model 1:

This specification aims to find out whether GDP in neighboring counties with a major transportation connection (specifically, interstate connection) impacts the GDP in a corresponding county. The form of this relationship is defined as follows:

$$y_s = \sum\nolimits_j x_{s,j} \times \beta_j + \rho \sum_{s'=1}^{S} (Interstate\ connection \times Neighbor) y_{s'} + \epsilon_s \tag{5}$$

SD Model 2:

This specification aims to find out whether GDP in neighboring counties with interstate connections impacts the GDP in a corresponding county. Moreover, it also captures whether this impact on GDP varies with distance.

$$\begin{aligned} y_s = \sum\nolimits_j x_{s,j} \times \beta_j \\ + \rho \sum_{s'=1}^{S} (Interstate\ connection \times Neighbor \times Inverse\ Distance) y_{s'} \\ + \epsilon_s \end{aligned} \tag{6}$$

SD Model 3:

This specification aims to find out whether GDP in neighboring counties impacts the GDP in a corresponding county. Moreover, it also captures whether this impact on GDP varies with distance.

$$y_s = \sum\nolimits_j x_{s,j} \times \beta_j + \rho \sum_{s'=1}^{S} (\log(Distance) \times Neighbor) y_{s'} + \epsilon_s \tag{7}$$

Elasticity

Elasticity is generally defined as the relative change in a response variable (i.e., economic performance indicators) with respect to a unit change in an explanatory variable (i.e., transportation infrastructure investments). It is usually quantified as the percentage change in the magnitude of response variable with respect to a one percent change in magnitude of the explanatory variable. Three categories of elasticity effects are considered here: direct elasticity, indirect elasticity, and total elasticity.

Direct elasticity

Direct elasticity is the change in economic performance indicators of a given county due to a transportation investment in that county. The impact of investment or economic changes in other counties and spatial dependency are not considered in this calculation.

The direct elasticity associated with exogenous variable x_j is given by:

$$e_{direct,\ x_{s,j}} = \frac{\%\ change\ in\ y_s}{\%\ change\ in\ x_{s,j}} = \frac{dy_s/y_s}{dx_{s,j}/x_{s,j}} \tag{8}$$

Recall that in our analysis the response variable is the natural logarithm of total GDP. The relationship between log (y_s) and explanatory variables was prescribed as in Equation 2.

Taking a derivative of log (y_s) with respect to $x_{s,j}$ in Equation 2, we get:

$$\frac{d}{dx_{s,j}}\log(y_s) = \frac{d}{dx_{s,j}}\left(\sum_j x_{s,j} \times \beta_j\right)$$

or, $\frac{dy_s}{dx_{s,j}}\frac{1}{y_s} = \beta_j$

or, $\frac{dy_s/y_s}{dx_{s,j}/x_{s,j}} = \beta_j x_{s,j}$

Hence, for continuous variables, the formula of direct elasticity is given by:

$$e_{direct,\ x_{s,j}} = \beta_j x_{s,j} \tag{9}$$

A point estimate of the direct elasticity of a variable can be obtained from Equation (9) by taking the average over all counties. This results in:

$$e_{direct,\ x_j} = \beta_j \overline{x_j} \tag{10}$$

where $\overline{x_j}$ is the mean magnitude of variable x_j over all counties.

For explanatory variables that are included in the statistical model using a logarithmic transformation, the derivative of log (y_s) with respect to $x_{s,j}$ simplifies to:

$$e_{direct,\ x_j} = \beta_j \tag{11}$$

Indirect elasticity

Indirect elasticity is referred to as the change in economic performance of neighboring counties due to a change in transportation investment in a given county. Through spatial dependence consideration, any improvement in a county has an impact on its neighboring counties. Hence, for this analysis, the indirect elasticity is calculated as the percentage change in GDP in neighboring counties associated with a one percent increase in a specific variable in a given county. The relationship between log $(y_{s,i})$ and explanatory variables considering this spatial dependency was established as in Equation (4). In this equation, the derivative of the response variable cannot be directly calculated, since y_s is dependent on the economic activity in neighboring counties (the set of values $y_{s'}$). Hence, a numerical procedure is used instead to estimate this indirect elasticity. The steps to calculate indirect elasticity are provided below:

Step 1: For a specific county of interest with index c, calculate the GDP in each neighboring county, $y_s \forall s \in N_c$ where N_c, is the set of counties that are neighbors to county c, using Equation (4). Note that Equation (4) must be repeated for all neighbors using the baseline input vector, $\{x_{s,j}\}$. The total GDP of all the neighbors of county c is calculated as the sum of their individual GDPs as follows:

$$Total\ GDP, y_{c,neighbor} = \sum_{s \in N_c} y_s \tag{12}$$

Step 2: Increase the magnitude of variable $x_{c,j}$ by Δx.

Step 3: Calculate the new GDP in the county of interest as $\log(y_{c,new}) = \log(y_c) + \Delta x \times \beta_j$.

Step 4: Calculate the new GDP in each neighboring county, $y_{s,new}$, by using the $y_{c,new}$ calculated in Step 3 as the input for Equation (4).

$$Total\ new\ GDP, y_{c,neighbor,new} = \sum_{s \in N_c} y_{s,new} \tag{13}$$

Step 5: Calculate the indirect elasticity using the following formula:

$$e_{indirect,\ x_{c,j}} = \frac{y_{c,neighbor,new} - y_{c,neighbor} / y_{c,neighbor}}{\Delta x / x_{c,j}} \tag{14}$$

Step 6: Repeat Step 1 through Step 5 for each year and for all 67 counties.

After Step 6, an indirect elasticity value is available for each of 67 counties for each year in the analysis period (2010 to 2020). We then take the mean of the elasticity estimates for a given county across all years in the analysis period to yield 67 estimates of elasticity values for that independent variable, one for each county. Summary statistics (mean, standard deviation, minimum, and maximum value) of indirect elasticity are then presented to illustrate the elasticity distribution for any given independent variable.

Total elasticity

The total elasticity is referred to as the change in economic performance indicators in all counties due to changes in transportation investments performed in a specific county. Note that any investment in a given county will change the GDP of that county (direct effects) and will impact the GDP of neighboring counties as well (indirect effects). Thus, the total elasticity captures both of the effects previously described. The total elasticity is provided as the percent change in GDP across all affected counties associated with a one percent change in investment in that specific county.

Similar to the indirect elasticity, the point estimate of total elasticity cannot be theoretically calculated. Rather, it is calculated using the same steps described for the indirect elasticity calculation, with one difference: for total elasticity, both the neighboring counties as well as the county in which the investment is made are considered.

5. RESULTS

Results of Model Estimation

Table 5 provides estimation results from the best LLR model and three best spatial dependency models. Note that numerous model specifications were investigated as a part of this task; however, the results presented here represent the models that demonstrate the best statistical fit and with relationships that make the most intuitive sense.

Each model includes a constant term and ten year-specific variables (Year 2011 to Year 2020). Year 2010 is kept as the base year in all models. These year-specific variables capture annual variation in economic activity across the state. Apart from these, a total of ten exogenous variables are found to be statistically significant across all models.

Table 5. Summary of modeling results

Variables	LLR Model	SD Model 1	SD Model 2	SD Model 3
Constant	1.6095**	1.6018**	1.6629**	1.7439**
Year 2011	0.0183**	0.0183**	0.0192**	0.0215
Year 2012	0.0235**	0.0229**	0.0240**	0.0269
Year 2013	0.0539**	0.0529**	0.0545**	0.0594**
Year 2014	0.0819**	0.0800**	0.0819**	0.0885**
Year 2015	0.0637**	0.0625**	0.0653**	0.0711**
Year 2016	0.0612**	0.0603**	0.0635**	0.0689**
Year 2017	0.0856**	0.0848**	0.0888**	0.0946**
Year 2018	0.0849**	0.0844**	0.0895**	0.0953**
Year 2019	0.1100**	0.1091**	0.1139**	0.1195**
Year 2020	0.0800**	0.0776**	0.0817**	0.0863**
Natural logarithm of number of bridges	0.0893**	0.0875**	0.0809**	0.1014**
Natural logarithm of personal income	0.3776**	0.3767**	0.3611**	0.3492**
Percentage of people employed	1.7520**	1.7614**	1.7483**	1.7142**
Natural logarithm of total number of people	0.5950**	0.6026**	0.6269**	0.6402**
Total cost of safety infrastructure improvement projects deployed	0.0041**	0.0041**	0.0039**	0.0040**
Total cost of other improvement projects deployed	0.0014**	0.0013**	0.0014**	0.0016**
Natural logarithm of total number of crashes	-0.0852**	-0.0947**	-0.1047**	-0.1127**
Total number of traffic signals adjusted using MPMS Improvement type: New traffic signal	0.0002**	0.0002**	0.0002**	0.0001**
Daily Vehicle Miles Traveled	0.0573**	0.0276**	0.0359**	0.1379**
ρ_i	--	0.00025**	0.0019**	-0.00027**
Goodness-of-fit statistics				
Sum of square error	14424.43	14272.54	14161.14	13833.87
Pseudo R^2	0.9902	0.9909	0.9899	0.9901
MAPE	0.1176	0.1187	0.1199	0.1155

Significance code: At 90% confidence interval '', at 95% confidence interval '**'*

It is apparent from Table 5 that the signs of the coefficients from all models are consistent and the magnitude of the coefficients are also comparable. A review of the parameter estimates suggests that they are reasonable and generally match with engineering expectation.

- Number of bridges: The positive coefficients associated with the number of bridges in a county suggest that an economic activity increases with the number of bridges in the subject county. This is reasonable, as the number of bridges is associated with higher transportation connectivity within a county, and economic activity should increase with increased transportation connectivity.
- Personal income: Individual income is suggestive of the prosperity in a county, and higher average income is expected to be associated with increased GDP within a county. In line with our intuition, the coefficients associated with natural logarithm of personal income are found to be positive.
- Employment: The percentage of people employed is a measure of the human capital within a given county that can contribute to economic activity. Hence, this factor is found to have a positive relationship with the GDP of a county.
- Population: With more people in a county, economic activity is expected to be higher. In line with our intuition, the coefficient of the natural logarithm of total number of people is found to be positive.
- New traffic signals: Installation of new traffic signals is usually associated with improvement in intersection control in a county. With better control, vehicular movement is also improved, which in return gives rise to more economic activities.
- Infrastructure investment: This study aims to find out whether investment in infrastructure results in growth in GDP. The results suggest that more expense in safety infrastructure improvement and other improvement projects are associated with increase in GDP. Coefficients associated with both of the variables are found to be positive. Moreover, it is also apparent that spending in safety infrastructure results in three times growth in GDP, compared to spending in other infrastructure improvement.
- Traffic crashes: Traffic crashes are both devastating to communities and individuals and can create non-recurring travel delays that decrease transportation system reliability. The models suggest that counties with more crashes are thus associated with decreased economic activity.
- Vehicle movement: As most of the economic activities are based on vehicles (such as car, bus, and truck), more vehicle movement is indicative of more economic activities. Hence, the coefficient associated with vehicle miles traveled is found to be positive.

Further, all three models have a high accuracy in predicting the GDP, as can be seen from the high R^2 values and low mean absolute percent errors (MAPE) on the order of 10%. The latter suggest that individual predictions are off by less than 10% on average, which suggests strong model predictive performance. To further understand the model accuracy, Figure 1 plots the predicted GDP value for each year for each county against the observed value for all four models considered. As can be seen from this plot, the predictions of the GDP of a county are accurate and mostly lie along the line with slope 1. However, for counties/years with larger GDP values, there appear to be more errors in prediction. Regardless, the model can identify low and high GDP values accurately.

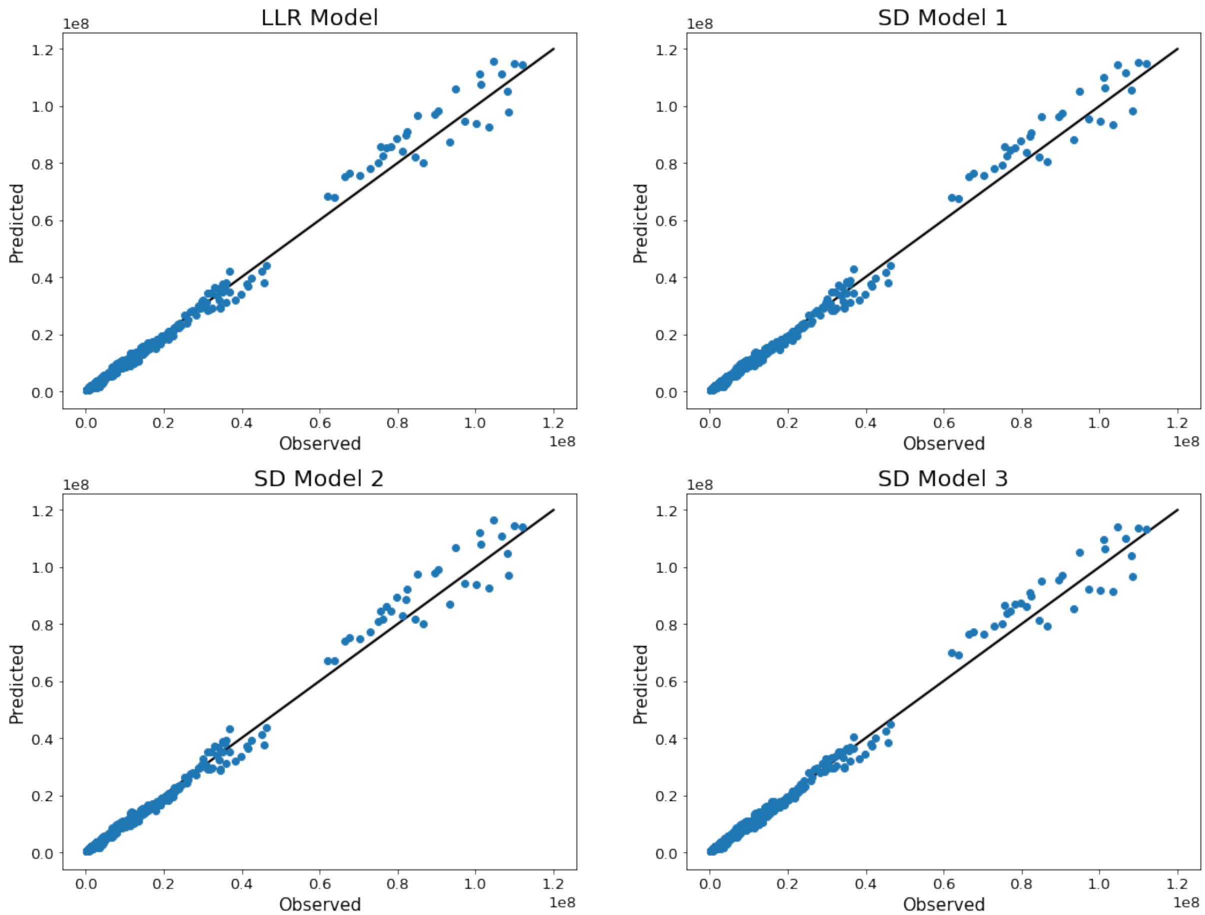

Figure 1. Observed vs. predicted GDP value for all models considered

Spatial dependency

SD Model 1 specifies $w_{ss'}$ as an indicator variable, which represents neighboring counties with interstate connections. Hence, ρ_i is associated with the impact of GDP growth in neighboring counties that have good connectivity with the corresponding county. The positive coefficient suggests that a county's GDP is improved with GDP growth in neighboring counties, especially those having interstate connection with the county.

SD Model 2 specifies $w_{ss'}$ as inverse of distance from neighboring counties with interstate connections. Hence, ρ_i for a county is associated with the impact of distance from neighboring counties with interstate connection as well as GDP growth in those counties. The positive coefficient suggests that GDP growth in neighboring counties with good interstate connection positively impacts the GDP of a county, and the magnitude of this impact decreases with distance from the counties.

SD Model 3 specifies $w_{ss'}$ as a function of distance from neighboring counties. Hence, ρ_i for a county is associated with the impact of distance from neighboring counties, as well as GDP growth in those counties. The negative coefficient suggests that the impact of the county indicator and the distance variable change the GDP in opposing directions. In other words, if a neighbor has a high

GDP, the county of interest will also have a higher GDP; however, the impact of neighbors further away will decrease this positive impact.

Results of the Elasticity Estimation

Table 6 presents the estimates of the direct elasticity of all variables considered in this study. Elasticity estimates from the log-linear regression (LLR) model – i.e., the model without any spatial dependency considered – are presented in the second column. For each of the three models that consider spatial dependency, elasticity estimates from only the linear part of the models that consider spatial dependency are presented.

Several explanatory variables are used in the models through logarithmic transformation – bridges, personal income, total population, cost of safety and other improvement projects, and total crash counts. For these variables, the elasticity is equal to the estimated coefficient for each variable. The elasticity estimates from the linear part of all three spatial-dependency models are found to be very close to that from the LLR model.

Among the four transportation investments, bridges seem to have the highest return on investment: a 1% increase in bridge count within a county is associated with more than a 0.08% increase in GDP within that county. Investments in traffic signals, safety improvement projects, and other improvement projects follow investments in bridges: a 1% increase in number of traffic signals in a county is associated with more than a 0.03% increase in GDP within that county, a 1% increase in total investment in safety improvement projects is associated with a 0.004% increase in GDP, and a 1% increase in total investment in other improvement projects is associated with a 0.001% increase in GDP. In general, percent employment seems to have the highest impact on GDP in all models (0.9113~0.9181); i.e., a 1% increase in employment is associated with a 0.9% increase in GDP.

For each model considering spatial dependency, the distribution of elasticities across all counties is presented. In terms of mean, minimum, and maximum elasticity, the ranking of the transportation infrastructure investments remains the same. The standard deviation of bridges and the cost of other improvement projects are found to be very low. This suggests that these two types of investments have an almost similar impact on every county, regardless of the dissimilarities among them.

Table 6 Direct Elasticity

Explanatory variable	Variable form	LLR Model	SD Model 1	SD Model 2	SD Model 3
Bridges	Log	0.089	0.0875	0.0809	0.1014
Personal Income	Log	0.378	0.3767	0.3611	0.3492
Percent Employment	Continuous	0.9132	0.9181	0.9113	0.8935
Total Population	Log	0.5950	0.6026	0.6269	0.6402
Cost in Safety Projects	Continuous	0.0041	0.0041	0.0039	0.0040
Cost in Other Projects	Continuous	0.0014	0.0013	0.0014	0.0016
Total crash count	Log	-0.0852	-0.0947	-0.1047	-0.1127
Traffic Signal	Continuous	0.0374	0.0408	0.0390	0.0278
Daily VMT per PA Roads	Continuous	0.0477	0.0230	0.0299	0.1148

Table 7 presents the estimates of indirect elasticity of all variables considered in this study. The LLR model does not have a spatial component; hence, estimation of indirect elasticity is not possible. For each of the three spatial-dependency models, elasticity estimates from the full model are shown through the mean, standard deviation, minimum, and maximum values of the distribution. All three models appear to yield consistent results. The ranking of impact of four transportation infrastructure investments on neighboring counties is found to be investment in other improvement projects, investment in safety projects, bridges, and traffic signals. Investment in other improvement projects seems to have the highest impact in the GDP of neighboring counties: a 1% increase in investments in other projects in a specific county is associated with a 0.2% GDP increase in the neighboring counties. Similar to direct elasticity, percent employment is found to have the highest indirect elasticity. However, the impact on neighboring counties seems to have about half of the impact compared to the county that made the investment.

Table 8 presents the estimates of total elasticity of all variables considered in this study. The LLR model does not have a spatial component; hence, the total elasticity associated with this model should be the same as the direct elasticity. For each of the three spatial-dependency models, elasticity estimates from the full model are shown through the mean, standard deviation, minimum, and maximum values of the distribution. It can be seen that the total elasticities are generally similar in magnitude to the indirect elasticity, indicating that most of the improvement in GDP due to an investment is observed in neighboring counties. In all models, the total elasticity of bridges is found to be in the range of 0.0334~0.0394. This suggests that a 1% increase in bridge count in a specific county is associated with an approximately 0.035% GDP increase experienced across that county and neighboring counties combined. Investment in other improvement projects seems to have the highest impact on the GDP of neighboring counties. The ranking of the four transportation infrastructure investments is investment in other improvement projects, investment in safety projects, bridges, and traffic signals.

Table 7 Indirect Elasticity

	SD Model 1				SD Model 2				SD Model 3			
	Mean	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**
Bridges	0.0361	0.0304	0.0000	0.1567	0.0335	0.0281	0.0000	0.1446	0.0419	0.0354	-0.0001	0.1803
Personal Income	0.1389	0.2247	0.0000	1.3681	0.1332	0.2159	0.0000	1.3140	0.1275	0.2045	-0.0003	1.2425
Percent Employment	0.5220	0.3355	0.0000	1.4288	0.5184	0.3325	0.0000	1.4174	0.5057	0.3245	-0.0009	1.3906
Total Population	0.2167	0.3137	0.0000	2.1843	0.2263	0.3275	0.0000	2.2793	0.2299	0.3302	-0.0006	2.2938
Cost in Safety Projects	0.0737	0.1691	0.0000	0.9242	0.0715	0.1639	0.0000	0.8938	0.0722	0.1648	0.0000	0.8954
Cost in Other Projects	0.2169	0.5317	0.0000	3.4821	0.2310	0.5680	0.0000	3.7332	0.2611	0.6462	0.0000	4.2831
Total crash count	-0.0330	0.0427	-0.2579	0.0000	-0.0366	0.0473	-0.2856	0.0000	-0.0391	0.0502	-0.3025	0.0001
Traffic Signal	0.0224	0.0730	0.0000	0.5609	0.0215	0.0698	0.0000	0.5360	0.0153	0.0499	-0.0001	0.3830
Daily VMT per PA Roads	0.0120	0.0140	0.0000	0.0863	0.0156	0.0182	0.0000	0.1120	0.0602	0.0701	-0.0002	0.4328

Table 8 Total Elasticity

	SD Model 1				SD Model 2				SD Model 3			
	Mean	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**	**Mean**	**S.D.**	**Min**	**Max**
Bridges	0.0394	0.0287	0.0008	0.1567	0.0366	0.0266	0.0007	0.1446	0.0458	0.0334	0.0008	0.1803
Personal Income	0.1496	0.2069	0.0023	1.3681	0.1435	0.1989	0.0022	1.3140	0.1375	0.1883	0.0019	1.2425
Percent Employment	0.5683	0.3110	0.0090	1.4612	0.5645	0.3084	0.0090	1.4498	0.5510	0.3005	0.0082	1.4214
Total Population	0.2366	0.3016	0.0038	2.1843	0.2472	0.3149	0.0040	2.2793	0.2514	0.3175	0.0040	2.2938
Cost in Safety Projects	0.0708	0.1644	0.0000	0.9242	0.0686	0.1593	0.0000	0.8938	0.0693	0.1602	0.0000	0.8954
Cost in Other Projects	0.1895	0.4202	0.0000	2.7001	0.2018	0.4491	0.0000	2.8944	0.2278	0.5096	0.0000	3.3185
Total crash count	-0.0363	0.0401	-0.2579	-0.0007	-0.0402	0.0444	-0.2856	-0.0008	-0.0430	0.0471	-0.3025	-0.0008
Traffic Signal	0.0261	0.0749	0.0000	0.5609	0.0250	0.0716	0.0000	0.5360	0.0178	0.0512	0.0000	0.3830
Daily VMT per PA Roads	0.0133	0.0140	0.0000	0.0863	0.0172	0.0181	0.0001	0.1120	0.0664	0.0700	0.0002	0.4328

6. POLICY SCENARIO

The previous section discussed elasticity, which shows the relationship between investments and changes in GDP. Through elasticity, information is gained on the type of investments that return the most increase in GDP. This section examines where specific investments should be made to get the most benefit in terms of GDP increase. To do this, a sensitivity analysis was conducted using three transportation infrastructure investment variables: bridges, investment in safety improvement projects, and traffic signals. The economic returns under two different policy scenarios are forecasted using the models developed, ignoring and considering spatial dependency.

The expected increase in GDP given an investment in transportation is determined using the equations provided in the model development section. Specifically, it is assumed that the improvements considered are:

- Adding 10 new bridges
- Investing $1,000,000 in safety improvement projects
- Adding 10 new traffic signals

It is assumed that these improvements are applied in different counties, independently, and the change in overall GDP as a function of these investments is determined. Two measurements – percentage increase in GDP and amount increase in GDP – are used to compare the returns from each county.

Without spatial dependency

The first scenario is the baseline scenario that assumes transportation investments are made only considering direct returns (non-spatial model). This scenario is representative of a single-tier, county-level transportation infrastructure investment plan that only considers economic returns of the county where the investment is being made.

Without the interaction among counties, the percentage or amount of increase in GDP is entirely dependent on the initial conditions. For example, counties with the same number of bridges will return the same percentage increase in GDP. Rankings of counties in terms of GDP return from a given increase in bridges were computed, since the number of bridges currently in each county differs significantly. However, there are more than 10 counties with the same number of traffic signals and the same investment in safety projects. Given the percentage increase in those counties being the same, the sensitivity analysis was not able to identify the top 10 counties.

The results from Table 9 show that the estimates obtained from all models for all three improvement projects are consistent. Philadelphia and Allegheny counties contain the largest cities in Pennsylvania. Naturally, these counties have the highest number of bridges, signals, as well as money invested in safety improvement projects. Hence, these two counties are consistently at the top of the list of counties in which investment in transportation infrastructure will return the largest GDP increase.

Table 9 Top 10 counties with highest returns

	SD Model 1			SD Model 2			SD Model 3		
	Bridges	**Safety Projects**	**Traffic Signal**	**Bridges**	**Safety Projects**	**Traffic Signal**	**Bridges**	**Safety Projects**	**Traffic Signal**
% Increase	Cameron	--	--	Cameron	--	--	Cameron	--	--
	Forest	--	--	Forest	--	--	Forest	--	--
	Montour	--	--	Montour	--	--	Montour	--	--
	Elk	--	--	Elk	--	--	Elk	--	--
	Carbon	--	--	Carbon	--	--	Carbon	--	--
	Somerset	--	--	Somerset	--	--	Somerset	--	--
	Fulton	--	--	Fulton	--	--	Fulton	--	--
	Phil.	--	--	Phil.	--	--	Phil.	--	--
	West.	--	--	West.	--	--	West.	--	--
	Tioga	--	--	Tioga	--	--	Tioga	--	--
Amount Increase	Phil.	Phil.	Allegheny	Phil.	Phil.	Allegheny	Phil.	Phil.	Phil.
	Mont.	Mont.	Phil.	Mont.	Mont.	Phil.	Mont.	Mont.	Allegheny
	Allegheny	Chester	Mont.	Allegheny	Chester	Mont.	Delaware	Chester	Mont.
	Delaware	Bucks	Chester	Delaware	Bucks	Chester	Allegheny	Bucks	Chester
	West	Delaware	Bucks	West	Delaware	Bucks	West.	Delaware	Bucks
	Lehigh	Berks	Delaware	Lehigh	Berks	Delaware	Lehigh	Berks	Delaware
	Bucks	Lack.	Lancaster	Bucks	Lack.	Lancaster	Bucks	Lack.	Lancaster
	Chester	Beaver	Dauphin	Chester	Beaver	Dauphin	Chester	Beaver	Lehigh
	Dauphin	Lycoming	Lehigh	Dauphin	Lycoming	Lehigh	Cumberland	Lycoming	Dauphin
	Cumberland	Schuylkill	York	Cumberland	Schuylkill	York	Dauphin	Schuylkill	York

Lack. – Lackawanna; Mont. – Montgomery; Phil. – Philadelphia; West. – Westmoreland

With spatial dependency

The next scenario considers both direct and indirect returns. This scenario is representative of a multi-tier transportation infrastructure investment plan where a regional or state agency makes budget allocations to counties within its jurisdiction and individual counties later utilize the allocated budget depending on their needs. Comparing this scenario with the previous one shows how the lack of a holistic view of economic returns can lead to sub-optimal decision-making.

Considering the interaction among the counties, the total or percent increase in GDP is not entirely dependent on the initial conditions of the county alone. For example, counties with a larger number of bridges will return a larger percentage increase in GDP with a given increase in bridge investment. Simultaneously, this will increase the GDP of its neighboring counties and vice versa. In this way, a poorer county with rich neighboring counties has the potential to have higher impact on GDP increase.

Table 10 shows the top 10 counties in PA to have the highest increase in GDP given improvements in bridges, safety projects, and traffic signals. The results from Table 10 show that the estimates from SD Model 1 and SD Model 3 for all three improvement projects are found to be consistent. Similar to Table 9, Philadelphia and Allegheny counties have the highest increase in GDP, and hence they are consistently at the top of the county list. Other notable counties with higher sensitivity to GDP increase are Montgomery, Delaware, Chester, and Lehigh.

Table 10 Top 10 counties with highest returns

	SD Model 1			SD Model 2			SD Model 3		
	Bridges	**Safety Projects**	**Traffic Signal**	**Bridges**	**Safety Projects**	**Traffic Signal**	**Bridges**	**Safety Projects**	**Traffic Signal**
% Increase	Phil.	Phil.	Allegheny	Potter	Potter	Potter	Phil.	Phil.	Allegheny
	Mont.	Mont.	Phil.	McKean	McKean	McKean	Mont.	Mont.	Phil.
	Allegheny	Chester	Mont.	Cameron	Bradford	Cameron	Delaware	Chester	Mont.
	Delaware	Bucks	Chester	Elk	Cameron	Elk	Allegheny	Bucks	Chester
	West.	Delaware	Bucks	Somerset	Tioga	Somerset	West.	Delaware	Bucks
	Lehigh	Berks	Delaware	Bradford	Somerset	Bradford	Lehigh	Berks	Delaware
	Bucks	Lack.	Lancaster	Tioga	Elk	Tioga	Chester	Lack.	Lancaster
	Chester	Beaver	Lehigh	Cambria	Cambria	Cambria	Bucks	Beaver	Lehigh
	Dauphin	Lycoming	Dauphin	Forest	Indiana	Forest	Cumberland	Lycoming	Dauphin
	Cumberland	Schuylkill	York	Huntingdon	Forest	Huntingdon	Dauphin	Schuylkill	York
Amount Increase	Phil.	Phil.	Allegheny	Potter	Potter	Potter	Phil.	Phil.	Allegheny
	Mont.	Mont.	Phil.	McKean	McKean	McKean	Mont.	Mont.	Phil.
	Allegheny	Chester	Mont.	Cameron	Bradford	Cameron	Delaware	Chester	Mont.
	Delaware	Bucks	Chester	Elk	Cameron	Elk	Allegheny	Bucks	Chester
	West.	Delaware	Bucks	Somerset	Tioga	Somerset	West.	Delaware	Bucks
	Lehigh	Berks	Delaware	Bradford	Somerset	Bradford	Lehigh	Berks	Delaware
	Bucks	Lack.	Lancaster	Tioga	Elk	Tioga	Chester	Lack.	Lancaster
	Chester	Beaver	Lehigh	Cambria	Cambria	Cambria	Bucks	Beaver	Lehigh
	Dauphin	Lycoming	Dauphin	Forest	Indiana	Forest	Cumberland	Lycoming	Dauphin
	Cumberland	Schuylkill	York	Huntingdon	Forest	Huntingdon	Dauphin	Schuylkill	York

Lack. – Lackawanna; Mont. – Montgomery; Phil. – Philadelphia; West. – Westmoreland

7. CONCLUDING REMARKS

This work created models to understand the economic impacts of transportation investments considering spatial dependency. Four different models, one traditional log-linear and three spatially dependent log-linear models, are considered to predict the GDP at the county scale. The results suggest that transportation investments, such as traffic signals, bridges, and also investments in safety projects are associated with increased GDP of a county. Moreover, the results suggest that spending in safety infrastructure results in three times growth in GDP, compared to spending in other infrastructure improvements.

Considering the model fit and interpretation of the models, the *SD Model 1* that aims to find out whether GDP in neighboring counties with a major transportation connection (specifically, an interstate connection) impacts the GDP in the corresponding county slightly outperforms the other specifications. Further, this model provides insights into how investment in neighboring counties can impact the GDP of a given county. Hence, moving forward the team recommends the use of the SD Model 1 specification.

Further, the impact of several transportation infrastructure investments on GDP is quantified via elasticities. These elasticities are shown to change when spatial dependency is considered among neighboring counties in terms of economic activity. A sensitivity analysis is conducted to identify the counties that return the highest increase in GDP – in both magnitude and percentage – from specific investments. For this analysis, three transportation investment variables are considered: bridges, investment in safety improvement projects, and traffic signals.

The results suggest that investments in bridges have the largest return on GDP considering only the county in which the investment is done, while the investment in other transportation-related projects has the largest return on GDP when considering impacts on neighbors. Considering where to make transportation investments from a spatial perspective reveals that while often investing in the larger counties, such as Philadelphia or Allegheny, will have the largest return on GDP, this is not always the case.

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APPENDIX A1

Table A1: Summary of the previous literature

Literature	**Investment**	**Performance indicators**	**Independent variables**	**Method**	**Study area**	**Geographic scale**
(Cohen and Paul, 2004)	Public & private infrastructure	• Overall private cost savings • Manufacturing production • Public infrastructure stock level	• Public capital shadow values • Private capital shadow values	• Cost function model • Spatial autoregressive (SAR) model • Instrumented variable technique	USA	State
(Gutiérrez et al., 2010)	Motorways	• Travel time • Economic gains	• Length of roadways • Total investment Population	• OD travel matrix • GIS mapping • Spillover matrix (Economic potential)	Spain	Region
(Agbelie, 2013)	Highway and railway	• Real gross domestic product per capita • Annual percentage changes in GDP	• Investment per kilometer of highway • highway infrastructure density • Railway density • employment rate • foreign direct investment per capita • percentage of industrial sector's contribution to GDP • percentage of service sector's contribution to GDP	• Translog production function	Countries in several continents	Country
(Chen and Li, 2021)	Multiple corridors	• Trade cost • GDP	• GDP • Tariff • Value of investment	• Global Trade Analysis Project (GTAP) model	BRI countries	Country

Literature	Investment	Performance indicators	Independent variables	Method	Study area	Geographic scale
			• Free trade area	• Computable general equilibrium (CGE) simulations		
(Mukwaya and Mold, 2018)	BRI – standard gauge railway	• Trade margin cost • Investment savings	• Import • Export • Industry output • GDP	• Global Trade Analysis Project (GTAP) • Computable general equilibrium (CGE) model	Multiple countries	Country
(Bell and McGuire, 1997)	Highway capital	• Gross State Product • Personal Income • Employment • Private capital stock	• Gross State Product • Personal Income • Employment • Private capital stock • Infrastructure spending • Census • Level of service of highway • VMT • Transit characteristics	• Industry-specific production function	USA	State
(Beguy et al., 2015)	Dam project	• GDP	• Consumption • Investment • Government spending • Export • Import • Labor • Capital	• New model	Niger	Country
(Bonakdarpour et al., 2021)	Highway, roadway, and public transit	• GDP • Employment • Production • Income • Capital stock	• GDP • Disposable income • Consumer spending • Tax receipts • Number of households	• IHS Markit's US Macroeconomic Model	USA	Sector and State

Literature	Investment	Performance indicators	Independent variables	Method	Study area	Geographic scale
		• Government revenue	• Foreign export • Inventory sales			
(Liu and Shi, 2018)	Bicycle accessibility measures	• Employment • Property value	• AADT • Bike facility • Bike lane • Protected bike lane	• Correlation analysis • Hedonic pricing regression analysis • Spatial equity analysis	Portland	Census block
(Wan and Zhang, 2017)	Road, telecommunication servers, and cable	• Reduction in labor and logistic cost of firms	• Length of infrastructure • Sales agglomeration • Share of sale • Share of asset • Capital intensity • Export • Tax profit • Share of foreign owned asset	• Cobb–Douglas production function • Solow's growth accounting framework	China	Firm
(Chen and Haynes, 2015)	Highway, public railway, and public transit	• Gross metropolitan product (GMP)	• Transportation investment • Employment • Highway stock • Rail stock • Transit stock • Population	• Cobb–Douglas production function • Spatial panel approach with fixed effects	US Northeast region	Region
(Donaldson, 2018)	Railroad project	• Trade cost reduction • Prices of six types of salt	• Prices, output, and trade flows of commodities • Total expenditure • Distance to source	• Graph theory algorithm • Equilibrium model based on Eaton and Kortum (2002)	Colonial India	District

Literature	Investment	Performance indicators	Independent variables	Method	Study area	Geographic scale
			• Cost per unit distance of different modes			
(Snieska and Simkunaite, 2009)	Roadway	• GDP per capita	• Paved road length • Number of mobile phone line • population connected to wastewater collection	• Linear regression • Correlation analysis	Lithuania, Latvia and Estonia	Country
(Palei, 2015)	Various forms of infrastructure (including transportation)	• Global competitiveness	• Institutions • Infrastructure • macroeconomic environment, • health and primary education, • higher education and training, • goods market efficiency, • labor market efficiency, • financial market development, • technological readiness, • market size	• Regression analysis	N/A	Country
(Moomaw et al., 1995)	Three components including highways	• Public capital stock	• Private capital • Labor • Public capital stock	• Translog production function	USA	State

Literature	Investment	Performance indicators	Independent variables	Method	Study area	Geographic scale
(Khan et al., 2020)	Comprehensive: more than 30 components	• GDP growth	• Global infrastructure index • Transport infrastructure index • Energy infrastructure index • Internet, communication and technology infrastructure index • Net inflow of FDI (% of GDP) • Net inflow of FDI (% of GDP) • Inflation (annual %) • Higher secondary school enrolment	• Infrastructure index Donaubauer et al. (2016) • Cobb-Douglas production function • Pooled mean group (PMG)	South Asia	Country
(Ismail and Mahyideen, 2016)	Road density network, air transport, railways, and ports	• Export • GDP	• Distance • GDP of exporters and importers • Relative endowment • Population • Physical capital • Trade openness	• Augmented gravity model • Pooled mean group estimation (PMGE) • Autoregressive distributed lag (ARDL) model	Asia	Country
(Owusu-Manu et al., 2019)	Several sectors including transportation (railroad, highway)	• GDP	• Net electricity generation capacity • Mobile subscribers • Roadways • Electricity distribution losses	• Augmented Cobb-Douglas production function • Autoregressive distributed lag cointegration framework	Sub-Saharan Africa: Specifically, Ghana	Country

Literature	Investment	Performance indicators	Independent variables	Method	Study area	Geographic scale
			• Paved road • Inflation • Trade • Domestic credit to private sector • Population growth rate			
(Looney and Frederiksen, 1981)	Several sectors including surface road and earthed road	• GDP	• Population • Literacy • Income • Value of sales • Houses with electricity and water	• Production function • Cluster analysis • Two-stage least square	Mexico	State
(Yu et al., 2013)	Roads, railway, and waterway	• GDP	• Labor input • Private capital stock • Public capital stock • Transportation capital stock	• C-D production function • Spatial Durbin Model	China	Province
(Delgado and Álvarez, 2007)	High-capacity roads	• Private sector production	• Labor • Value of private capital • HCR capital	• Production-function framework • Stochastic frontier framework	Spain	Province
(Xie et al., 2016)	Paved road	• Environment	• population size • affluence • technical progress	• Spatial Durbin model	China	City
(Moreno and López-Bazo, 2003)	Stock of roads and highways, railway, harbors and maritime	• Return • Value added at factor cost and labor	• Price of labor • Private capital • Public capital • Labor productivity	• Production model • Inclusion of spillover variable	Spain	Province

Literature	Investment	Performance indicators	Independent variables	Method	Study area	Geographic scale
	signaling, and airports					
(Cantos et al., 2005)	Roads, ports, airports, and railways	• Total factor productivity • Private production	• Employment • Private capital • Public capital in transportation • Infrastructure	• C-D production function • Total factor productivity approach	Spain	Region
(Yoshino and Abidhadjaev, 2018)	Kyushu high-speed rail line	• Tax revenue	• Number of taxpayers	• Difference-in-difference approach • Regression analysis	Japan	Region
(Cohen and Monaco, 2008)	Container ports; Highways	• Manufacturing cost • Employment	• Manufacturing output • Private capital input • Labor and material price • Stock of ports • Stock of highways	• Cost function model • First order spatial autocorrelation	USA	State
(Li et al., 2017)	New Silk Road Economic Belt (Railway; highway)	• GDP	• Density of road network • Total investment • Enrollment rate • Labor input • Years of education by labors • Volume of import export	• Spatial Lag model • Spatial Tobit model • Binary spatial weight matrix	China	Province
(Richaud et al., 1970)	Roadway	• Per capita income • Trade openness	• Road length per capita • GDP • Foreign direct investment (FDI)	• Growth equation Mankiw et al (1992) • Augmented Solow model	Africa	Country

Literature	**Investment**	**Performance indicators**	**Independent variables**	**Method**	**Study area**	**Geographic scale**
			• Domestic investment excluding FDI • Inflation • black market premium			
(Vlahinić Lenz et al., 2018)	Roadway and railway	• GDP	• Railway length • Total road network length	• Linear econometric model	Central and Eastern European States	Country

APPENDIX A2

Table A2. List of Improvements in MPMS system and categorization

Improvement Type	Total data points	Infrastructure	Safety	Operations	Multimodal	Other
Resurface	21296	x				
Restoration	8410	x				
Bridge Replacement	6938	x				
Miscellaneous	5142					x
Reflective Pavement Markers	4910		x			
Bridge Rehabilitation	4657	x				
Bridge Preservation Activities	4463	x				
Safety Improvement	4295		x			
Surface Treatment	3942	x				
Guiderail Improvement	2381		x			
Existing Signal Improvement	1803			x		
Reconstruct	1401	x				
Signing	1202			x		
Intersection Improvement	1074			x		
Widen	1052			x		
Corridor Safety Improvement	962		x			
Traffic System Management	821			x		
Surface Treatment Crack Sealing/ Joint Sealing	678	x				
Surface Treatment Micro-surfacing	593	x				
Interchange Improvement	423			x		
Bridge Improvement	422	x				
Lighting	418		x			

Bridge Deck Rehabilitation	385	x				
Pedestrian Facilities	359				x	
Variable Message Signs	359			x		
Bridge Deck Replacement	358	x				
Shoulder Improvement	347		x			
Bridge Painting	333	x				
Concrete Rehabilitation	330	x				
Add Lane	323			x		
Slides Correction	317					x
Transportation Enhancement	308			x		
New Roadway	285			x		
Divided Relocation	276		x			
Drainage Improvement	269					x
Median Barrier	221		x			
Relocation/Realignment	208					x
Bridge Washing	203					x
Pavement Preservation	188	x				
Bridge Removal	174					x
Widen/Resurfacing (no additional lanes)	161			x		
New Traffic Signal	134			x		
Add Turning Lane	131			x		
Tree Removal	131					x
RR High Type Crossing	112		x			
RR Warning Devices	108		x			
Replace/ Rehab	107	x				
New Interchange	66			x		
Park and Ride Lot	65				x	
Bicycle Facilities/ Services	60				x	
Video Cameras	54			x		
Noise Barriers	48					x

Dept. Force Culvert Replacement	47					x
New Bridge	45			x		
Rest Area Improvement	40					x
Wetland bank	35					x
Environmental Mitigation	33					x
Impact Attenuator	27		x			
Scenic Beautification	23					x
Research	16					x
Street Scapes	12					x
Clear Roadside	11					x
Transit System Improvement	10				x	
Jughandles	5			x		
Bike/ Ped Safety Education	4				x	
Daylighting	3					x
RR Gates	3		x			
Slope Failure	3					x
Transportation Study	3			x		
Truck Climbing Lane	3			x		
Intermodal Services	2				x	
Traffic Control Center	2			x		
Weigh Station	2					x
Crossbuck Signs	1		x			
Historic Preservation	1					x
Historic/ Scenic Highway	1					x
Intermodal Facility	1				x	