The Relationship between Infrastructure and Regional Economic Growth: Evidence from Mexico

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Abstract: The relationship between physical infrastructure and economic growth has been investigated by many, with the direction and magnitude of the result depending on the data and the empirical model applied. This paper adds to the literature by addressing spatial heterogeneity and possible endogeneity in a panel of 32 Mexican states for the period 2005-2018, thus many limitations of earlier studies are overcome. First results indicate a U-shaped relationship with positive spillovers; however, robustness checks do not confirm these findings. Most evidence points towards infrastructure not having any significant impact on regional economic growth in Mexico.

Keywords: Regional economic growth, infrastructure, spillovers, Mexico

JEL-Codes: H54, O18, R11, R42, R53

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1 Introduction

Ever since Aschauer (1989) found a positive relationship between the stock of infrastructure capital and TFP, researchers, international organizations and policy makers alike have advocated for the allocation of larger shares of public funds to infrastructure.[1] Maddison (2001) shows that transport infrastructure significantly contributed to the economic take-off in Western European countries. Agénor (2010) provides a theoretical foundation for infrastructure-led development and calls for governments to concentrate their investments on this area. Empirical studies reveal that infrastructure can promote welfare directly or indirectly (Donaldson, 2018), economic growth (Wang, Kim & Kim, 2021), poverty reduction (Andrés, Biller & Herrera Dappe, 2013) and gender equality (Agénor & Canuto, 2015); leading to the conclusion that developing countries suffer from an insufficient supply of infrastructure (Andres et al., 2014, for Asia; Calderón & Servén, 2003, for Latin America; and Estache, Wodon & Lomas, 2014, for Sub-Saharan Africa). Doumbia & Lauridsen (2019; for the World Bank) state the infrastructure investment gap to be the largest among the financing requirements to achieve the 2030 target for the global sustainable development goals (SDG).

Mexico's central audit institute (Auditoría Superior de la Federación; ASF; 2016) claims that infrastructure investments have contributed significantly to the nation's economic growth since 1960. Certainly influenced by these arguments, some of the key policy proposals of Mexico's current government are large transport infrastructure projects expected to increase welfare by mitigating regional income inequalities and stimulating growth (Gobierno de México, 2019).

However, the academic literature is not quite clear on whether these expectations are realistic. Flyvberg (2007) points out the significant budget overruns of large infrastructure investments and their common failure to recover the expected revenues. Some researchers find little to no effect of transport infrastructure on macroeconomic variables (Crescenzi & Rodríguez-Pose, 2012; Banerjee, Duflo & Quian, 2012; Deng et al., 2014; Zhang & Ji, 2018). However, it is commonly assumed that a country's income level determines the marginal effect of additional infrastructure, thus there is believed to be a threshold defining the significance and magnitude of the effect of infrastructure on economic growth (Hurlin, 2005; Crescenzi & Rodriguez-Pose, 2012). Precisely, Fuentes (2003) finds a significant positive correlation between physical infrastructure and economic output in Mexico only for the more developed regions.

This paper aims at investigating the effect of physical transportation infrastructure on regional economic growth in a beta conversion framework in Mexico for the period 2005-2018. This period is particularly interesting because infrastructure investment volume was doubled between 2009 and 2016 (Secretaría de Hacienda y Crédito Público, 2021). By using a panel of all 32 states, addressing spatial correlation, nonlinear effects and endogeneity, some of the limitations of earlier studies can be overcome. Considering the results of a meta-analysis of similar studies by Elburz, Nijkamp & Pels (2017), using a convergence growth-regression and a sub-national scope both increase the likelihood of observing a negative effect of infrastructure on growth; however, focusing on land transport, particularly roads, and measuring them in kilometres have been shown to be significantly correlated with positive outcomes. Hence, the expected sign of the result is ambiguous from both perspectives.

[1] Particularly, a similar analysis by the same author regarding Mexico finds public capital stock to have a larger, positive impact on per capita output and growth than private capital stock (Aschauer, 1998).

The panel structure of the data is analysed using a two-way fixed-effects (TWFE) model with clustered standard errors to account for heterogeneity between the states and autocorrelation across time. TWFE results indicate a U-shaped relationship between infrastructure and GDP per capita growth, as the linear term is assigned a negative, and the squared variable a positive coefficient. Split-sample analysis shows this effect to be increasing over time, and to be more significant for regions with lower average income levels. Following Arellano & Bover (1995), Blundell & Bond (1998) and Bond, Hoeffler & Temple (2001), Generalized Method of Moments (GMM) estimators are applied to address endogeneity. The Difference-GMM encounters similar results as the TWFE model, but is not consistent and the System-GMM estimators find the relevant variables to be non-significant, albeit lacking reliability. The Hansen test indicates this result might be caused by too many instruments. However, several approaches taken to reduce their number do not lead to different outcomes.

Empirical studies have observed that generally, the measurable impact of infrastructure on regional economic growth is lower than on the national scope, which has been attested to be caused by ignoring spatial spillovers between regions (Yu et al., 2013; Elburz, Nijkamp & Pels, 2017). Similarly, Rey & Montouri (1999) argue that spatial effects are key determinants of the regional convergence phenomenon, leading to omitted variable bias if they are not accounted for. Consequently, a Spatial Durbin Model (SDM) and a Spatial Lag Model (SLX) are implemented, though a LR-test shows that SLX is to be preferred. Here, the direct effects are similar to the TWFE model, while the spillovers have the opposite signs. A total of six different specifications for the spatial weight matrix are compared, finding that the simple physical binary contiguity option yields consistent results that are very similar to the estimations conducted with an inverse-distance weight matrix that considers links up to a distance of 400 kilometres, indicating that this is the space of influence for spatial spillovers of transport infrastructure in Mexico. However, robustness checks using alternative specifications to standardize the stock of infrastructure measure fail to confirm these findings. This warrants caution in the interpretation of the presented main results.

A meta-analysis conducted by Elburz, Nijkamp & Pels (2017) shows that of 43 studies investigating the relationship between infrastructure and regional economic outcomes, only about 5 percent include spatial spillovers (i.e., a spatial regression model).[2] Hence, this paper contributes to the current literature by providing new evidence of the spatial spillovers of infrastructure. To my knowledge, this is the first study on this topic accounting for spatial heterogeneity in Mexico.

The results indicate that transport infrastructure appears to have no significant impact on output growth during the considered period when using an endogenous growth model, with some indication of a significant negative effect depending on the way the infrastructure variable is standardized.

Chapter 2 revises the relevant literature regarding the impact of transportation infrastructure on economic growth. Chapter 3 explains the empirical approach and presents the identification strategies for both the direct and indirect effects. The dataset used in the empirical analysis is presented in chapter 4, along with an exploratory spatial data analysis to support the spatial specifications. Consequently, the main results are shown in chapter 5. Robustness checks can be found in chapter 6, while chapter 7 summarizes the main findings and concludes with a discussion on their implications and limitations.

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[2] Other methodologies: production function (47 percent), growth regression (22 percent), total factor productivity (5 percent).

2 Literature Review

There are several proposed mechanisms through which transportation infrastructure may affect economic growth: Traditionally, public infrastructure is assumed to increase private sector productivity (Aschauer, 1989; Barro, 1990). Endogenous growth theory proposes a reduction in trade costs and increased market integration, both of which push productivity (Hulten & Schwab, 2000; Agénor, 2010). Contributions from the New Economic Geography argue that factor mobility (labour, capital, technology) may be promoted by a higher degree of connectivity, leading to a more efficient location of firms and households (Krugman, 1991). Banerjee, Duflo & Quian (2012) argue that improved access to (higher quality) education and health may affect economic outcomes indirectly. Agénor & Moreno-Dodson (2006) propose that infrastructure improves labour productivity by reducing time spent commuting and increasing the speed at which certain tasks can be delivered.

Hansen's (1965) hypothesis claims that the effect of public capital investments depends on the characteristics of the target region. Agénor's (2010) theory of infrastructure-led development proposes that infrastructure investment promotes labour productivity and lowers consumer time preference, which is contrasted by otherwise unproductive government spending.

Several authors have addressed the question of the long-term impact of infrastructure on economic growth empirically. Those studies applying monetary measures for infrastructure stock or investment yield mixed results, ranging from non-significance (Holtz-Eakin & Schwartz, 1995; Crihfield & Panggabean, 1995) to positive (Easterly & Rebelo, 1993; Gupta et al., 2005; Zou et al., 2008) and negative (Devarajan, Swaroop & Zou, 1996). On the other hand, physical indicators of infrastructure stock often lead to findings indicating a significantly positive correlation with economic output or growth (Sanchez-Robles, 1998; Calderón & Servén, 2004, 2010).

Studies using cross-country panel data often find a significant effect of infrastructure stock on GDP or productivity (Canning & Pedroni, 1999; Calderón & Servén, 2003; Calderón, Moral-Benito & Servén, 2014). Demetriades & Mamuneas (2000) and Cohen & Paul (2004) show that infrastructure reduces costs and increases profits using augmented cost and profit functions. A meta-analysis of 33 studies investigating the relationship between transport infrastructure and productivity shows that roads have a larger (positive) effect than other transport modes and indices (Melo, Graham & Brage-Ardao, 2013).

Fisher (1997) and Shi, Guo & Sun (2017) note that studies seem to be sensitive to measurement approach, analytical technique, quality, institutions, non-linearities and regional heterogeneity. Gramlich (1994) and Estache & Fay (2009) point out econometric problems with many estimations, such as common trends, omitted variable bias, reverse causality, network effects, heterogeneity and poor data quality, that affect the reliability of reported results.

Elburz, Nijkamp & Pels (2017) conduct a meta-analysis regarding the relationship between transport infrastructure and economic development between 1995 and 2014. The authors identify type of infrastructure, research methodology, time span, type of infrastructure measure, and geographical scale as relevant factors in determining the result of a study, whereas output measure and focusing on a particular sector does not seem to affect the outcome. The authors construct 6 different specifications to analyse the findings of 43 studies. Selected results are presented in Table A1.

Calderón & Servén (2014) and Timilsina, Hochman & Song (2020) provide recent summaries of the existing literature regarding the effect of infrastructure development on economic variables. The researchers point out that many – especially earlier – studies on the topic of infrastructure and economic variables do so in the context of investigating the effects of public investment in general, which has some important limitations:

1) Infrastructure investment is not the only type of productive government spending in most countries (e.g. education, health, defence)
2) Infrastructure need not be built only by public entities
3) Often, the spending for new infrastructure and maintenance of the existing network cannot be differentiated; similarly, it is not possible to differentiate between quality and quantity

Thus, by using a variable for the stock of infrastructure instead of the flow, the focus lies on measuring the effect of access to infrastructure services (e.g. road transport) rather than productive government spending, which is more relevant to the analysis of public investments. Similarly, Bröcker & Rietveld (2009) and Calderón, Moral-Benito & Servén (2015) conclude that using the physical stock of infrastructure is the most sensible approach, especially in developing countries where corruption and government inefficiencies are, on average, more common issues (Zhang & Ji, 2018). Moreover, geographic differences can cause differences in construction costs (Rodrigue, 2020).

A potential issue are nonlinearities in the marginal effect (Fernald, 1999; Agénor & Moreno-Dodson, 2006). These network effects are another reason to use the stock of infrastructure as an indicator, since Romp & De Haan (2005) note that the marginal productivity of a new link depends on the capacity and composition of the existing links. One limitation related to measuring infrastructure in terms of its stock is that unproductive structures, so-called "white elephants" for example, are included in the measure (Oosterhaven & Knaap, 2003).

Nonetheless, the meta-analysis by Elburz, Nijkamp & Pels (2017) finds that out of 43 studies, only about 10 percent measure infrastructure in physical units (kilometres).[3] Calderón & Servén (2014) note that the literature investigating the relationship between physical infrastructure and economic growth is relatively recent (compared to studies on public investment), which might explain this observation.

Banerjee, Duflo & Quian (2012) point out that factor mobility may affect the measurable benefits of infrastructure. They use a model with immobile labour and a cost associated with capital mobility consistent with the empirical evidence, showing that capital is less mobile than goods and different regions are involved in the production of exports. Hence, the differences in income levels between better and worse connected places may be small and there might be no differences associated to the growth rate. Both of their assumptions are confirmed with empirical data on Chinese provinces.

Shi, Guo & Sun (2017) use a dynamic panel data approach with a vector error correction model (VECM) to investigate the relationship between infrastructure capital and China's regional economic growth. They show that particularly for the road network, an inverse U-shaped relationship between infrastructure and growth is identified in some time periods. They assign this result to the theory of the crowding-out effect of private capital: when public investment in infrastructure is over proportionally high, the correlation is negative in some time periods, indicating overinvestment.

[3] Meanwhile, 38 percent use an index (combining different types of transport infrastructure) and 51 percent apply monetary terms.

Contrary to this result, Ren, Dan & Wang (2018) identify a U-shaped relationship between road density on income in rural areas of Western China. On the other hand, Simon & Natarajan (2017) find no significance of nonlinear estimates regarding infrastructure on economic growth in India.

Regarding the research methodology (production function, total factor productivity, growth equation, spatial regression), Elburz, Nijkamp & Pels (2017) point out that most studies focus on a single approach, which makes it harder to compare results. A limitation of the production function approach is the direction of causality.

To address the potential problem of endogeneity regarding infrastructure, academics have proposed using instrumental variables for actual highway or railway networks. For example, historical roads (Donaldson & Hornbeck, 2016; Baum-Snow et al., 2015), planned networks (Baum-Snow, 2007; Duranton & Turner, 2011; Duranton, Morrow & Turner, 2014), proximity to the connection between historic metropolitan areas (Banerjee, Duflo & Quian, 2012; Iimi, Humphreys & Melibaeva, 2015) and algorithm-generated networks (Faber, 2014) have been suggested. This approach relies on the assumption that the chosen instrument fulfils the exclusion restriction, that is, there is no correlation with unobservable factors directly affecting economic development.

Fuentes (2003) conducts an analysis of the impact of physical infrastructure on regional GDP per capita levels in Mexico, clustering the states into intermediate development and delayed (see also Table A4). He finds that for 1998 cross-sectional data, a synthetic index of infrastructure stock (encompassing road, rail, airports and seaports) only has a significant (positive) effect on regions in the intermediate development cluster.

Hernández-García et al. (2020) regress Mexico's infrastructure investment (for all modes) on output between 1997-2018 and find a positive correlation at the national level and in five regional clusters.

Fingleton & López-Bazo (2006) and Rey & Montouri (1999) emphasize the importance of considering spatial effects in the analysis of regional economic development. In more recent years, the study of subnational and/or spillover effects of infrastructure has become more common. For example, Roy et al. (2014) find that physical infrastructure only has a significant (positive) impact on the more industrialized districts within the Indian state of Jharkhand.

The study by Crescenzi & Rodriguez-Pose (2012) examines the effect of road infrastructure on economic growth in NUTS2 regions of the European Union. Using panel data, accounting for spatial spillovers and applying Difference-GMM allows them to identify the lack of significance of the infrastructure variable. They find that its significance depends on the inclusion of an education variable. The researchers conclude that at the EU's high income level, transport infrastructure has not been a significant determinant of growth between 1990 and 2004.

Yu et al. (2013) investigate the indirect effects of transport infrastructure in Chinese provinces and classify these spillovers in two categories: either, they are derived from network expenditures promoted by neighbouring regions (Munnell, 1992), or arise from factor migration (Boarnet, 1998).

Summarizing, there is conflicting evidence regarding the impact of transport infrastructure on economic growth and development. Results are sensitive to the specifications used in terms of measurement, the geographical level of analysis as well as regarding econometric techniques. Spatial spillovers, despite their acceptance in mainstream economics, have not received sufficient attention.

3 Empirical Approach

3.1 Identification Strategy of the Direct Effects

Compared to cross-section models, panel data has the advantages of a greater availability of degrees of freedom and less multicollinearity, leading to more efficient estimators (Hsiao, 2007; Amidi, Majidi & Javaheri, 2020). Additionally, by considering both the intertemporal dynamics and individuality of the units of observation, panel data can control for the impact of unobservable, time-invariant characteristics of the units of observation (Hsiao, 2007). Finkel (1995) adds that panel data corrects for a certain degree of measurement error, which can be the source of bias. The two-way fixed-effects estimator is the preferred approach to establish a causal effect of infrastructure on economic outcome (Crescenzi & Rodriguez-Pose, 2012; Imai & Kim, 2019). Its validity relies on two key assumptions: past values of the independent variables do not directly affect the current outcome, and past outcomes do not affect the current values of independent variables (Imai & Kim, 2019).[4]

Reverse causality between the dependent variable and the infrastructure variable is a well-known source of endogeneity (Gramlich, 1994; Feng & Wu, 2018). The argumentation proposes that infrastructure promotes economic development, but that more is invested in regions with higher income, both due to stronger political influence of economically more successful states and because policy makers expect higher returns of additional transport services in economically dynamic locations. However, in the dataset applied here, there is a negative correlation between physical infrastructure and both, GDP per capita levels and growth (Table A3), which is contrary to the expected direction of the bias. A possible reason for this observation could be that in Mexico, investment in road infrastructure is decided by the states, thus considerations of effectiveness on the national level are less likely to affect them (CIEP, 2020). Nonetheless, the results have to be interpreted as the upper bound, since in case reverse causality was an issue, they might suffer from a positive bias.

Zergawu, Walle & Giménez-Gómez (2020) claim that using a system Generalized Methods of Moments (GMM) estimator based on Arellano & Bover (1995), Blundell & Bond (1998) and Bond, Hoeffler & Temple (2001) provides more reliable results, as standard models may still suffer from endogeneity between the lagged variable and region-specific fixed effects. The method relies on applying internal instruments in the form of suitable lags of the variables (Arellano & Bond, 1991). According to Nickell (1981) and Anderson & Hsiao (1982), the source of this endogeneity bias cannot be mitigated with demeaning or first differences. Kukenova & Monteiro (2009) conduct a Monte-Carto investigation on this matter and find that the System-GMM approach outperforms static and dynamic spatial Maximum Likelihood Estimation (MLE), dynamic Quasi Maximum Likelihood Estimation (QMLE), Least Squares Dummy Variables (LSDV) and Difference-GMM in terms of Root Mean Square Error (RMSE) and bias.

Nonetheless, Roodman (2007) points out that when the generated instrument count is higher than the number of observations, the results of System-GMM are less reliable. Further, Bivand, Millo & Piras (2021) claim that System-GMM is not suitable for spatial models, as the procedure assumes cross-sectionally uncorrelated errors. Additionally, Esposti (2007) argues that System-GMM is not superior to Difference-GMM in terms of statistical significance or theoretical consistency.

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[4] Lindgren, Pettersson-Lidbom & Tyrefors (2021) argue that using a traditional two-way fixed effects estimatior neglects heterogenous treatment effects and may bias the results when investigating the impact of infrastructure on economic outcomes. However, this discussion currently appears to be limited to Differences-in-Differences and event study approaches, thus it is not further considered in this study.

As proposed by Crescenzi & Rodriguez-Pose (2012) – based on similar arguments are presented here – the model is estimated with two-way fixed effects and Difference-GMM based on Blundell & Bond (2000) and Bond, Hoeffler & Temple (2001). This is implemented in STATA using xtabond2 (Roodman, 2009) . This paper will follow Bond, Hoeffler & Temple's (2001) advice on choosing between Difference-GMM and System-GMM: for the former to provide consistent results, the coefficients must lie between the estimations provided by Pooled OLS (upper bound) and the fixed effects estimation (lower bound). If this condition does not hold, System-GMM is to be preferred. To minimize the instrument count, a time-invariant impact of the endogenized variable is assumed.[5] In any case, in this analysis, as N (32) > T (14), non-stationarity is not a concern and will not affect the performance of the GMM-Diff approach (Binder, Hsiao & Pesaran, 2003; Baltagi, 2008; Wooldridge, 2010).

Equation (1) denotes the common growth specification based on the original models by Solow (1956) and Swan (1956) and the seminal papers by Barro et al. (1991) and Mankiw, Romer and Weil (1992). The hypothesis is that a region's economic growth ($\boldsymbol{\gamma_{i,t}}$) is inversely related to its initial per capita GDP ($\boldsymbol{y_{i,t-1}}$), while additional factors ($\boldsymbol{X_{i,t}}$) determine differences in the steady state across regions (Fingleton & Lopez-Bazo, 2006). Parameter $\boldsymbol{\beta}$ denotes the speed of convergence, hence the model is also known as beta convergence equation. If $\boldsymbol{\beta > 0}$, convergence is taking place, conditional on the significance of $\boldsymbol{\delta}$.

$$\boldsymbol{\gamma_{i,t} = c + \left(e^{-\beta T} - 1\right) lny_{i,t-1} + \delta X_{i,t} + \varepsilon_{i,t}} \tag{1}$$

The role of transport infrastructure in shaping regional economic growth in Mexico is investigated in a specification that includes a vector of control variables (***X'***), to account for relevant endogenous and external factors, as these condition the impact of any type of policy intervention (Ascani, Crescenzi & Iammarino, 2012). The linear and squared terms of the infrastructure variable ***Infra*** account for nonlinearities. Further, $\boldsymbol{\eta}$ covers time-invariant state-fixed-effects; $\boldsymbol{\lambda}$ controls for year-fixed effects that affect the entire country and $\boldsymbol{\varepsilon}$ denotes a well-behaved error term that is clustered at the state-level. Subscripts ***i*** and ***t*** refer to region and year, respectively. This is applied in equation (2).

$$\boldsymbol{lny_{i,t} = c + \alpha lny_{i,t-1} + \beta_1 Infra_{i,t} + \beta_2 Infra_{i,t}^2 + \delta_1 X_{\prime i,t} + \eta_i + \lambda_t + \varepsilon_{i,t}} \tag{2}$$

The growth rate is approximated by subtracting the lagged GDP per capita level from both sides of the equation, leading to the final specification (equation 3) (Crescenzi & Rodríguez-Pose, 2012):

$$\begin{aligned}\boldsymbol{\gamma_{i,t}} &= \boldsymbol{lny_{i,t} - lny_{i,t-1}} \\ &= \boldsymbol{c + (\alpha - 1) lny_{i,t-1} + \beta_1 Infra_{i,t} + \beta_2 Infra_{i,t}^2 + \delta_1 X'_{i,t} + \eta_i + \lambda_t + \varepsilon_{i,t}}\end{aligned} \tag{3}$$

Where $\boldsymbol{\alpha = e^{-\beta T}}$ and $\boldsymbol{(\alpha - 1) = \theta}$.

3.3 Identification Strategy of the Spatial Spillovers

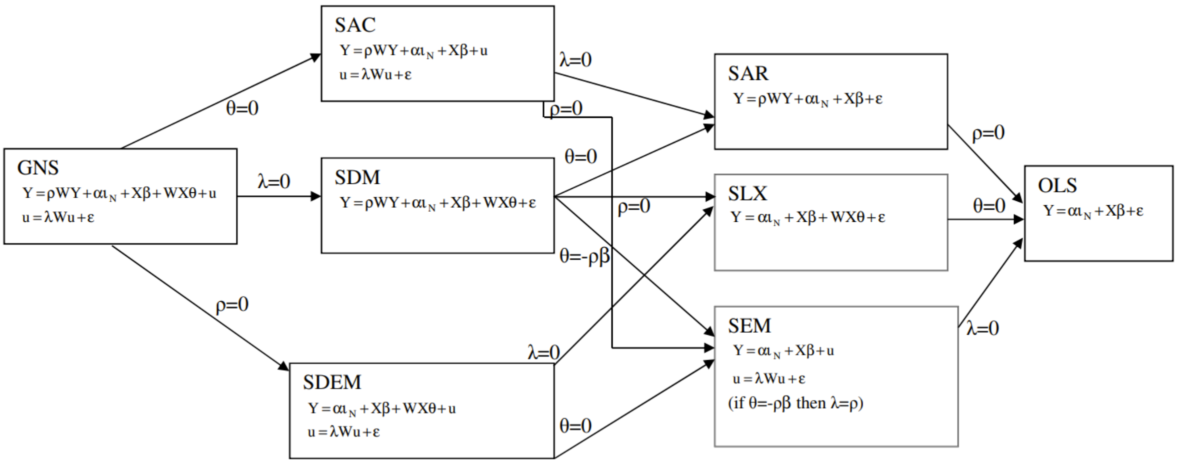
Several authors suggest addressing spatial heterogeneity in regional analysis (Amstrong, 1995; Rey & Montouri, 1999; López-Bazo et al., 1999, Bivand & Brundstad, 2006). Besides data-driven motives, there is a theoretical foundation for including spatial externalities in neoclassical growth models (Fingleton & Lopez-Bazo, 2006; Ertur & Koch, 2007) and dynamic models with a regional perspective (Patacchini & Zenou, 2007). Not accounting for the significant spatial lag of a variable leads to omitted variable bias, while ignoring spatially correlated errors causes inconsistent estimators (Anselin &

[5] Instead of the default procedure of creating a unique instrument for each year of the panel.

Arribas-Bel, 2013). Here, the regional analysis is limited to a single country, thus people, goods and services enjoy unlimited mobility between states and the interstate borders are unlikely to have any impact on mobility decisions of individuals and firms.

The main challenge in addressing spatial heterogeneity is selecting the adequate model and an appropriate spatial weight matrix. As shown in Figure 1, the general nesting spatial model (GNS) accounts for all kinds of potential spatial effects, from which all other specifications can be derived based on the significance of the relevant parameters. Researchers generally use theoretical reasons, statistical tests, or both, to determine the model of their choice. Theoretical assumptions drive the selection of the weight matrix. Both approaches have been criticized to lack scrutiny, thus a combination of the two is suggested (Corrado & Fingleton, 2012; Elhorst, 2017).

Figure 1: The relationships between different spatial dependence models for cross-section data



Note: GNS = general nesting spatial model, SAC = spatial autoregressive combined model, SDM = spatial Durbin model, SDEM = spatial Durbin error model, SAR = spatial autoregressive model (spatial lag model), SLX= spatial lag of X model, SEM = spatial error model, OLS = ordinary least squares model
Source: Halleck Vega & Elhorst, 2012

Particularly, the most popular models (SAR, SDM and SAC) all impose global spillover effects, that is, indirect effects affect all other regions, even if they are not connected via the spatial weight matrix (Halleck Vega & Elhorst, 2015). Additionally, the ratio between direct and indirect effects in the SAC and SAR models is the same for all variables (Elhorst, 2017). In the SEM specification, there are no spillovers at all, as only the errors are assumed to be correlated. The models that avoid these pitfalls are SDEM and SLX, as both limit the spatial effects to their local nature (only those regions connected via the spatial weight matrix influence each other) and indirect effects are not dependent upon direct effects (Gibbon & Overman, 2012; Halleck Vega & Elhorst, 2015; Elhorst, 2017).

In addition to the theoretical arguments laid out earlier, the Exploratory Spatial Data Analysis (ESDA) in section 4.2 will show that spillovers appear to affect the model, while spatial errors do not appear to be relevant. Consequently, both SDM and SLX will be computed using xsmle in STATA (Belotti, Hughes & Mortari, 2017). Additionally, a spatial model selection process as proposed by Elhorst (2010), combining bottom-up (Florax, Folmer & Rey., 2003) and top-down (LeSage & Pace, 2009) approaches, is followed. However, due to lack of theoretical and statistical evidence in favour of SAR, SEM, SAC or SDEM, these models are not investigated in detail.

The SDM model is specified by equation (4), adding spatial lags of all explanatory variables and the dependent variable:

$$\gamma_{i,t} = \varphi \sum_{j=1}^{n} W_{ij}\, \gamma_{i,t} + \theta_1 lny_{i,t-1} + \theta_2 \sum_{j=1}^{n} W_{ij}\, lny_{i,t-1} + \beta_1 Infra_{i,t} + \beta_2 Infra_{i,t}^2 + \beta_3 \sum_{j=1}^{n} W_{ij}\, Infra_{i,t} + \beta_4 \sum_{j=1}^{n} W_{ij}\, Infra_{i,t}^2 + \delta_1 X'_{i,t} + \delta_2 \sum_{j=1}^{n} W_{ij}\, X_{i,t} + \eta_i + \lambda_t + \varepsilon_{i,t} \quad (4)$$

While the SLX model lacks the spatial lag of the dependent variable, as equation (5) shows:

$$\gamma_{i,t} = \theta_1 lny_{i,t-1} + \theta_2 \sum_{j=1}^{n} W_{ij}\, lny_{i,t-1} + \beta_1 Infra_{i,t} + \beta_2 Infra_{i,t}^2 + \beta_3 \sum_{j=1}^{n} W_{ij}\, Infra_{i,t} + \beta_4 \sum_{j=1}^{n} W_{ij}\, Infra_{i,t}^2 + \delta_1 X_{i,t} + \delta_2 \sum_{j=1}^{n} W_{ij}\, X'_{i,t} + \eta_i + \lambda_t + \varepsilon_{i,t} \quad (5)$$

In both cases, $\sum_{j=1}^{n} W_{ij}$ denotes the multiplication of the specified variables with a spatial weight matrix. In line with Tobler's (1970) first law of geography – "everything is related to everything else, but near things are more related than distant things" and particularly, related studies (e.g. Crescenzi & Rodriguez-Pose, 2012), different weight matrices accounting for proximity are constructed, as displayed in Table 1.

Table 1: Spatial Weight Matrices

Name	C1	C2	ID1	ID2	ID3	ID4
Type	Contiguity	Contiguity	Inv.-Dist.	Inv.-Dist.	Inv.-Dist.	Inv.-Dist.
Limit	1st Border	2nd Border	300 km	400 km	555 km	None
Avg. Links	4.2	6.8	4.3	6.3	10.3	31
Max. Links	8	12	10	15	20	31

In the case of physical contiguity weight matrices (C1 and C2), the elements W_{ij} take the value of 1 whenever state j ($\forall\, j \neq i$) shares a border with state i. Additionally, in the case of C2, they would take the value of 0.5 if j is a second-degree neighbour to i.

Inverse-Distance weight matrices us the Euclidian distance between regions to determine the degree of impact one has on the other. ID4 denotes the unlimited case – all states' characteristics influence the outcome in all other states. The closest proximity of regions is 54 kilometres while the largest distance amounts to over 2,965 kilometres. The average distance between states is 555 kilometres. Consequently, ID3 was constructed to only account for regions that are within the average distance of each other, while ID1 and ID2 are more restrictive and have a similar number of links to C1 and C2, respectively. This allows for a comparison between the two different approaches, as naturally the number of links will increase the variance captured by each weight matrix.

One weakness of the inverse-distance weight matrices is that they will also consider states as neighbours when the shortest distance requires the crossing of water bodies, such as between Baja California Sur and Sinaloa (at 436 km, this is the case in ID3 and ID4). Further, it seems rather unlikely that spatial spillovers from one state affect the entire country (ID4). Also some of the other specifications (C2, ID2, ID3) lead to some states having a surprisingly high number of links. Nonetheless, all spatial weight matrices will be applied to investigate whether the assumptions hold (Table 10).

To account for states having different numbers of neighbours – many in the central highlands, less in the coastal periphery – all weight matrices are row-standardized.

4 Data

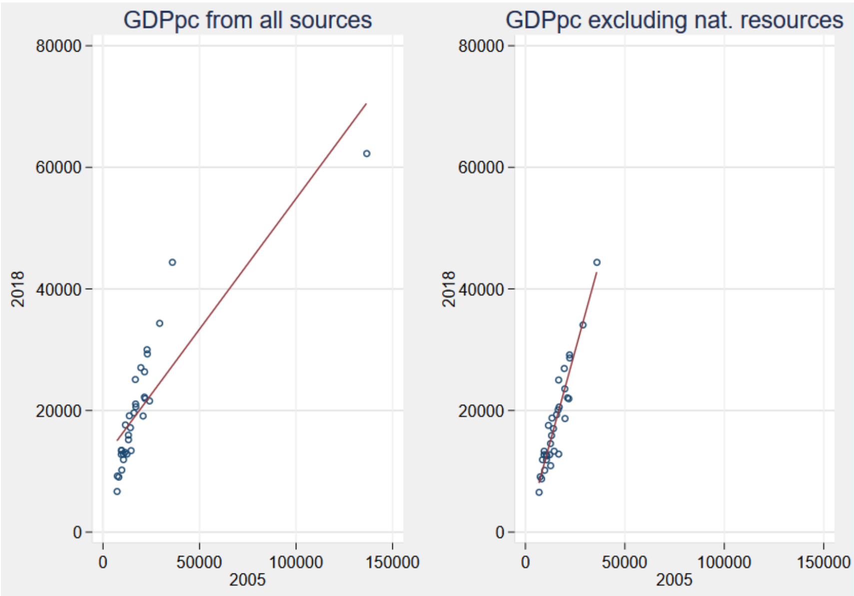
4.1 Dataset and Variables

The dataset is compiled using indicators from the OECD regional database and the statistical and geographical yearbook, by state, published by the Mexican National Institute of Statistics and Geography (INEGI, for its acronym in Spanish). The strongly balanced panel has a size of 14 years (2005-2018) and covers all 32 Mexican states. While neither the time nor the space dimension are large, both are very close to the average sample size of 15 years and 31 geographical regions observed by Elburz, Nijkamp & Pels (2017) in their meta-analysis of 43 studies on the same topic. Basic descriptive statistics of the variables can be found in Table A2.

4.1.1 Regional GDP per capita (in levels) and growth rate

The dependent variable, GDP per capita, is taken from the OECD regional database and measured in USD, with constant prices and PPP and base year 2015. This variable was then adjusted by excluding the share of GDP per capita that is obtained via the extraction of natural resources, as particularly income generated via petroleum distorts the observations in some states.[6] The adjustment factor was computed using GDP values and their sources published by INEGI. Figure 2 visualizes this process. For a better distributional quality, the variable is expressed in natural logarithms. The growth rate, as described in section 3.1, is approximated by the log difference of GDP per capita levels.

Figure 2: GDP per capita 2005-18



Source: Author's elaboration using STATA 17 with data from OECD and INEGI

4.1.2 Transport Infrastructure

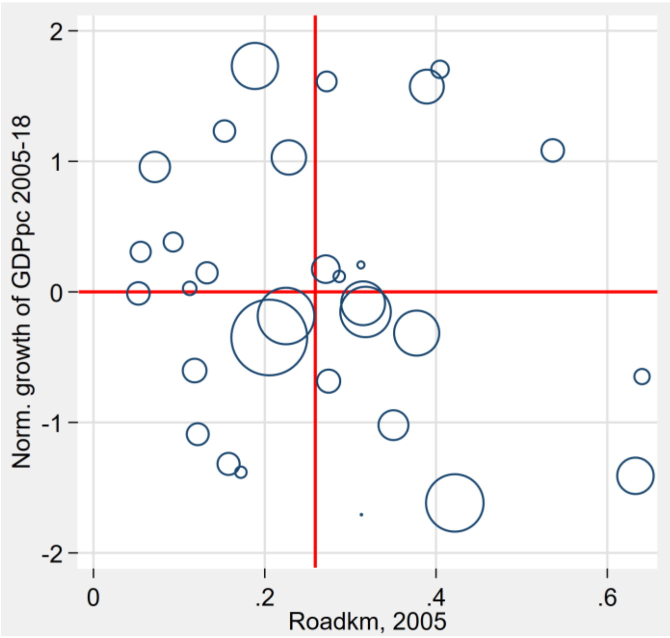
As discussed in chapter 2, measuring infrastructure as a stock variable expressed in kilometres has a number of advantages, such as reduced endogeneity issues and a stronger relationship with the amount and quality of actually available mobility services. Empirical studies have shown that roads are the most popular dimension of transport infrastructure (excluding synthetic indices) with stronger and more robust impacts on economic variables (Elburz, Nijkamp & Pels, 2017). The data on road kilometres was taken from INEGI. There is no consensus on how to best standardize the stock of

[6] Nonetheless, the results are not significantly affected by this adjustment.

infrastructure to account for differences in size (Crescenzi & Rodriguez-Pose, 2012). For the main results, the variable is standardized by total regional GDP to account for economic activity, which is assumed to be the main beneficiary of transport infrastructure. Standardization by area (square kilometres) and population is applied in robustness checks in section 6.

In Figure 3, the red lines indicate average values (horizontal: growth rate, vertical: infrastructure) and the circles position each state's initial infrastructure endowment (2005) while their size denotes the increase of Road kilometres between 2005 and 2018. It shows that there is no distinct pattern between initial infrastructure endowment (2005) and subsequent growth. However, the circles positioned in the lower right quadrant indicate that most of those states with an above-average initial infrastructure endowment experienced below-average growth, while those in the upper left quadrant show that many states with above-average growth had below-average infrastructure endowments.

Figure 3: Stock and growth of Infrastructure and GDP p.c. 2005-18



Source: Author's elaboration on OECD and INEGI data

4.1.3 Innovation

The effect of innovation, particularly research and development (R & D), on economic output is well established (Griliches, 1990; Nagaoka, Motohashi & Goto, 2010). Specifically, Torres-Preciado, Polanco-Gaytán & Tinoco-Zermeño (2014) confirm the positive effect – including spatial spillovers – of patent applications on regional economic growth in Mexico. Patent applications as reported by INEGI have been selected as the indicator for this dimension as they are a reliable measure of research output that is expected to generate economic returns. The standardization per capita ensures comparability between states. However, there are two major shortcomings to this choice: the actual economic impact of each patent displays a large variance and not all innovations are patented. The assignment of a patent to each region based on the residence of the first author has been shown to be quite robust (Carlino, Chatterjee & Hunt, 2007), though to my knowledge this has not been studied for the specific Mexican data I am using.[7]

[7] For a thorough discussion on the use of patents as indicators, see Griliches (1990) and Nagaoka, Motohashi & Goto (2010).

4.1.4 Unemployment Rate

Okun's law, established in 1962, predicts a negative relationship between unemployment and economic output, in the short run (Okun, 1962; Prachowny, 1993). Empirical findings are mixed, nonetheless the hypothesis is generally assumed to hold for both, GDP and growth; also at the regional level (Kangasharju, Tavera & Nijkamp, 2012; Ball, Leigh & Loungani, 2013). As this relationship works in both directions, endogeneity is a serious concern (Huang et al., 2020). Additionally, unemployment captures inefficiencies in local labour markets and the potential stratification of inadequate skills (Gordon, 2001). The variable is obtained from the OECD regional database and refers to the share of unemployed persons aged 15-64 among the active labour force of a region.

4.1.5 Share of labour in primary sector

According to Caselli & Coleman (2001), employment in agriculture captures a certain degree of 'hidden unemployment' especially in rural areas. Further, the productivity in the primary sector is traditionally much lower than in other industries (Crescenzi & Rodriguez-Pose, 2012). The variable is sourced from INEGI and measured as the share of workers employed in agriculture, fishing, livestock, and hunting.

4.1.6 Organized Crime

Due to the strong presence of organized crime in Mexico, particularly related to drug trafficking, it is common practice to account for interregional differences in this regard (Bel & Holst, 2018). According to Brito, Corbacho and Osorio (2014), the homicide rate (per 100,000 inhabitants) is a good proxy for crime, as it suffers less from underreporting than other offenses (e.g. robbery). Nonetheless, the amount of underreporting can be assumed to be significant as about 80.000 people are considered 'missing', many of whom are assumed to be dead, since occasionally some are identified in both public and clandestine mass graves (Arista & Flores, 2021). While the presence of drug cartels alone does not vary much in the relevant time period, the impact of their activities largely depends on government interventions and wars with rival gangs, (Robles, Calderon & Magaloni, 2014). Further, Díaz Cayeros et al. (2012) find that in Mexico, the homicide rate is a suitable indicator for the intensity of extorsion by organized crime on the local population. The homicide rate increases due to turf wars between competing gangs and violence spurred by government crackdowns on organized crime (Robles, Calderon & Magaloni, 2014). In these situations, Mexican drug cartels display predatory behaviour towards the local population, while in monopolistic settings without government intervention they often support local firms and are less violent to attract investment and a stable economic environment. The homicide rate is measured as the logarithm of homicides per 100,000 inhabitants and sourced from INEGI, since Bel & Holst (2018) argue that they provide the most reliable data on this topic.

4.1.7 Human Capital

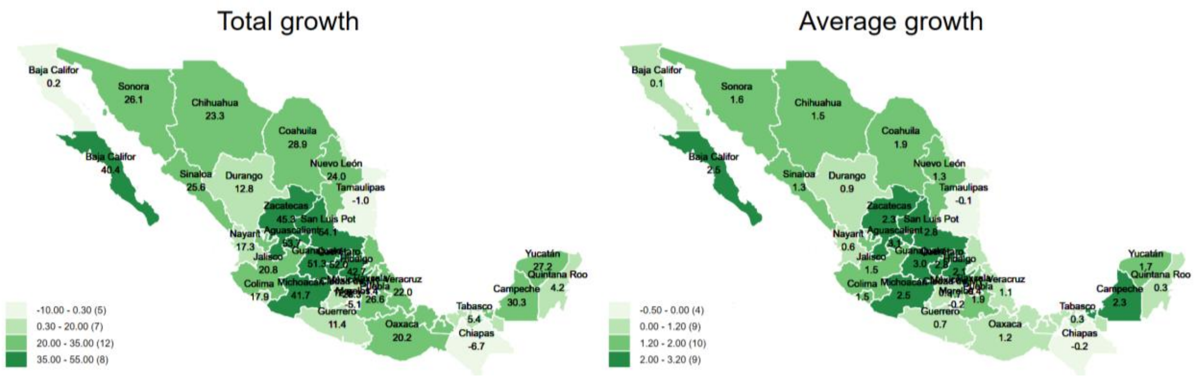
There is an ample body of literature regarding the significant positive impact of education on economic development going back to Becker (1964) and confirmed by Arellano & Fullerton (2005) for regional income in Mexico. Since Solow (1956), human capital is commonly included in neoclassical growth models. Malecki (1997) argues that educational attainment affects a region's reaction capabilities to change (such as increased connectivity, or new innovations). Here, the average years of schooling for persons 15 years and older (INEGI) serve as a proxy for this dimension, which is a common practice in research (Crescenzi & Rodriguez-Pose, 2012; Bel & Holst, 2018). Nonetheless, this variable naturally does not reflect quality, and may be downward biased for regions with an above-average share of people that obtain further education after the age of 15.

The correlation matrix of these variables is presented in Table A3. A relevant correlation exists between education and infrastructure, and education and share of labour force in the primary sector. For this reason, the exclusion of the education variable will be studied in section 5.

4.2 Exploratory Spatial Data Analysis

The motivation for an Exploratory Spatial Data Analysis (ESDA) is to diagnose spatial dependence in the data, which is crucial to choose the correct estimation strategy. Figure 4 displays the total and average GDP per capita growth between 2005 and 2018 per federal entity in Mexico, while Figure A1 reports maps for all individual years. The growth rates do not seem to be randomly distributed across the country. This indicates the possible presence of spatial autocorrelation.

Figure 4: GDP per capita, 2005-2018



Proper testing of spatial autocorrelation can be conducted with the global Moran's I (Anselin, 1995) and the G of Getis & Ord (1992). Both are global indices of spatial autocorrelation that express the overall degree of similarity between neighbouring regions (Pfeiffer et al., 2008). A contiguity weight matrix has been applied, which in the case of the Moran's I test was row-standardized while the Getis & Ord G requires a binary weight matrix. Table 2 presents these results.

Table 2: Spatial association tests

Year	Moran's I	E (I)	Getis&Ord G	E (G)
2005	0.107*	-0.032	-0.303	0.135
2006	-0.023	-0.032	0.169	0.135
2007	-0.183*	-0.032	0.015	0.135
2008	0.225***	-0.032	-0.851**	0.135
2009	0.076	-0.032	0.126*	0.135
2010	0.076	-0.032	0.171*	0.135
2011	0.116*	-0.032	0.282*	0.135
2012	0.024	-0.032	0.181**	0.135
2013	0.175**	-0.032	-0.548**	0.135
2014	0.146*	-0.032	0.252***	0.135
2015	0.331***	-0.032	1.089***	0.135
2016	0.356***	-0.032	0.778***	0.135
2017	0.072	-0.032	0.216	0.135
2018	0.217***	-0.032	-0.859***	0.135

*Significance level: *** p<0.01, ** p<0.05, * p<0.1*

Table 2 shows that the null hypothesis of the Moran's I (random distribution of GDP per capita growth across space) is rejected in 8 of 14 years. Since the Moran's I test statistic is larger than the expected value in 11 years, the result indicates a positive spatial autocorrelation: nearby regions tend to exhibit more similar growth rates. A possible reason for the lack of significance of the Moran's I test in some years is that it performs best in measuring spatial processes that are consistent across space, thus if there are different spatial dynamics at play, it may fail to detect their impact. Consequently, local spatial autocorrelation tests should be conducted. In the case of Geti & Ord's G, the test statistic rejects in 10 years the null hypothesis of no spatial clustering of GDP per capita growth.

The local Moran's I is a local index of spatial autocorrelation that measure, for each individual region, the degree of similarity to its neighbours (Pfeiffer et al., 2008). Figure 5 shows that for the average yearly growth rate, most regions do not present significant local spatial correlation. However, there is a significant hot spot located in the centre of the country, where several states display relatively high average growth rates and are surrounded by similar regions. Additionally, the map reveals two outliers: Baja California Sur has much higher average growth rates than Baja California, and Chiapas grew less, on average, than its neighbours. The individual maps for all 14 years are shown by Figure A2.

Figure 5: Cluster Map of average yearly growth rate of GDP per capita

Lagrange-Multiplier tests are presented in Table 3 to determine whether the null hypotheses – $\rho = 0$ for the spatial lag, and $\lambda = 0$ for the spatial error – are found to hold. These results were obtained using Pooled OLS, effectively failing to reject either null hypothesis.[8] Similarly, when the estimation is tested for each individual year, the spatial error null hypothesis and the spatial lag null hypothesis are never rejected by the Robust Lagrange Multipliers.

Table 3: LM Tests

	Test Statistic	p-value
Spatial error (H0: λ = 0)		
Lagrange multiplier	1.441	0.41
Robust Lagrange multiplier	1.182	0.41
Spatial lag (H0: ρ = 0)		
Lagrange multiplier	843	0.45
Robust Lagrange multiplier	497	0.44

[8] The results of the Pooled OLS model are presented in section 5.1.

5 Results

5.1 Results of the Direct Effect Model

First, both a random and a fixed effects model were estimated to conduct a Hausman test. The null hypothesis of no systematic differences in the coefficients is rejected with $p = 0.000$. Consequently, the random effects model would be inconsistent. The results of the two-way fixed effects estimations are presented in Table 4. Variables were added one-by-one to observe changes in parameters and test statistics. It is evident that adding the squared term of the infrastructure variable increases the fit of the model. All other additions have a negligible impact on any of the reported parameters.

Table 4: Results of Two-Way Fixed Effect Model

Depvar: Delta Y	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Control Variables	-	-	1	2	3	4	5
Constant	4.22***	5.32***	5.62***	5.65***	5.67***	5.78***	5.78***
L1.ln(GDPpc)	-0.41***	-0.50***	-0.53***	-0.53***	-0.53***	-0.54***	-0.54***
Roadkm (GDP)	-0.86**	-2.39***	-2.37***	-2.36***	-2.36***	-2.37***	-2.37***
Roadkm (GDP)^2		1.42***	1.35***	1.35***	1.35***	1.36***	1.36***
Patents p.c.			0.00**	0.00**	0.00**	0.00**	0.00***
Unemployment				0.00	0.00	0.00	0.00
Agriculture labour					0.00	0.00	0.00
ln(Homicides)						-0.01	-0.01
ln(Education)							0.00
Observations	448	448	448	448	448	448	448
Number of ID	32	32	32	32	32	32	32
Log-Likelihood	777	827	844	844	844	846	846
AIC	-1,525	-1,622	-1,655	-1,653	-1,651	-1,652	-1,650
BIC	-1,463	-1,556	-1,585	-1,579	-1,573	-1,570	-1,563
R-squared (overall)	0.03	0.02	0.02	0.02	0.02	0.02	0.02
R-squared (within)	0.45	0.56	0.59	0.59	0.59	0.59	0.59

*Significance level: *** p<0.01, ** p<0.05, * p<0.1*

All specifications include state and year fixed effects and apply clustered standard errors.

The coefficient of *Roadkm* is consistently negative, but positive for the squared term. Due to the variable being standardized by regional GDP, its values are below 1, which means that the combined effect is always dominated by the negative parameter. Regarding the control variables, all their coefficients are close to zero and only *Patents* is significant.

To investigate whether these insignificant, null effects are consistent over space and time, split-sample analysis are conducted. Table 5 reports the estimation of the original model in column (1). Column (2) and (3) show the estimations based on a split of the Mexican states according to income: Group 1 includes the lower income regions while Group 2 encompasses those with a higher average GDP per capita (see Table A4 for more details). This evaluation considers the possibility that the impact of infrastructure growth depends on regional income levels, as observed by Fuentes (2003). Columns (4) and (5) display the results obtained when splitting the sample period in two: the first period includes the seven years between 2005 and 2012, while the second denotes the years 2012-2018. This method sheds light on the question whether the relationship between infrastructure stock and economic growth has changed over time.

Table 5: Split Sample TWFE Results

Depvar: Delta Y	(1)	(2)	(3)	(4)	(5)
Split	-	Group 1	Group 2	Period 1	Period 2
Constant	5.78***	6.52***	7.22**	6.02***	9.75***
L1.ln(GDPpc)	-0.54***	-0.62***	-0.57***	-0.81***	-0.70***
Roadkm (GDP)	-2.37***	-2.24***	-2.67	-2.12***	-3.24***
Roadkm (GDP)^2	1.36***	1.37***	1.20	1.12**	1.95***
Patents p.c.	0.00***	0.00	0.00**	0.00	0.00**
Unemployment	0.00	0.00	0.00	-0.01*	0.01
Agriculture labour share	0.00	0.00	0.00	-0.00*	0.00
ln(Homicides)	-0.01	-0.03***	0.01	0.00	-0.01
ln(Education)	0.00	-0.06	-0.50	1.14	-1.03
Observations	448	224	224	224	224
Number of ID	32	16	16	32	32
Log-Likelihood	846	477	427	505	470
AIC	-1,650	-922	-824	-982	-911
BIC	-1,563	-867	-773	-934	-863
R-squared	0.59	0.63	0.70	0.75	0.71
R-squared (within)	0.59	0.63	0.70	0.75	0.71

Significance level: *** p<0.01, ** p<0.05, * p<0.1
All specifications include state and year fixed effects and apply clustered standard errors.

Table 5 shows that the infrastructure variables are highly significant (with a negative total impact) only among the lower-income states. While the significance is similar across time, the size of the coefficients is higher in the more recent time period (2012-18), thus the magnitude of the negative impact has increased over time. Regarding the control variables, *R&D* is only significant (with a very small coefficient) in higher-income regions and in more recent years, which is to be expected since patent applications are more common in these dimensions. Interestingly, homicides only have a significant (small, negative) impact on growth in the lagging regions. *Unemployment* and *sector composition* were slightly significant between 2005 and 2011. The *education* variable presents no significance.

Table 6 reports the results of the GMM approach to control for endogeneity bias. Bond, Hoeffler & Temple (2001) propose using the Pooled OLS estimations as providing the upper bound, and the TWFE results as the lower bound to establish whether the Difference-GMM estimation is consistent. As reported in column 3, the significant coefficients do not fall within those limits. Thus, the Diff-GMM estimations are not consistent and System-GMM should be preferred. The System-GMM has been estimated in two ways: endogenizing only the lag of GDP per capita (column 4), or by endogenizing the infrastructure variables as well (column 5). The control variables are assumed to be exogenous.

Table 6 shows that most variables are not significant in the GMM specifications, including the time lag of GDP per capita value. *Roadkm* is negative and statistically significant in the Diff-GMM estimation. While not significant, the System-GMM approach that endogenizes *Roadkm* is the only model where it appears with a negative coefficient, while the squared term has a positive coefficient. It is also the only specification that finds *education* to have a significant effect, which is positive. The Sargan test for overidentifying restrictions rejects the null hypothesis that instruments are not weak in the second Sys-GMM specification. However, this test is not robust to heteroskedasticity, so that its outcome in this context is not relevant. Hansen's J statistic on the other hand is weakened by many instruments, but robust otherwise. Its null hypothesis is not rejected.

However, Roodman (2009) suggests that a p-value above 0.25 for the Hansen test indicates it might be weakened by too many instruments. Further, there seems to be no second-order autocorrelation, but the System-GMM models reject the null hypothesis of no first-order autocorrelation, which is the desired context to specify relevant instruments via lags. All GMM-models have a larger number of instruments (33-99) than units of observations (32), which is associated with inconsistent results (Roodman, 2007).

Table 6: Results of GMM

Depvar: Delta Y	(1)	(2)	(3)	(4)	(5)
Model	Pooled OLS	TWFE	Diff-GMM	Sys-GMM	Sys-GMM
Constant	0.21	5.78***		0.32	0.50
L1.ln(GDPpc)	-0.02	-0.54***	-0.64***	-0.06	-0.09
Roadkm (GDP)	-0.01	-2.37***	-3.23***	-0.05	-0.07
Roadkm (GDP)^2	-0.03	1.36***	1.61*	0.02	-0.05
Patents p.c.	0.00*	0.00***	0.00	0.00	0.00
Unemployment	0.00	0.00	0.00	0.00	0.00
Agriculture labour share	0.00	0.00	0.00	0.00	0.00
ln(Homicides)	0.00	-0.01	0.01	-0.01	0.00
ln(Education)	0.02	0.00	0.37	0.14	0.19
Observations	448	448	416	448	448
Number of ID		32	32	32	32
# of instruments			33	53	99
AR(1) p-value			0.32	0.02	0.03
AR(2) p-value			0.38	0.29	0.30
Sargan Test (p-value)			0.00	0.00	0.00
Hansen Test (p-value)			0.23	1.00	1.00

*Significance level: *** p<0.01, ** p<0.05, * p<0.1*

Specifications (2)-(5) include state and year fixed effects; all apply clustered standard errors.

As these results indicate signs of overfitting (Roodman, 2009), additional analyses are conducted. Table 7 reports the results for a specification that excludes all control variables except for *patents*.

Table 7: Results of GMM for restricted model

Depvar: Delta Y	(1)	(2)	(3)	(4)	(5)
Model	Pooled OLS	TWFE	Diff-GMM	Sys-GMM	Sys-GMM
Constant	0.22	5.62***		1.42	1.09
L1.ln(GDPpc)	-0.02	-0.53***	-0.62***	-0.14	-0.11
Roadkm (GDP)	-0.01	-2.37***	-3.21***	-0.16	-0.21
Roadkm (GDP)^2	-0.02	1.35***	1.55**	0.04	0.03
Patents p.c.	0.00*	0.00**	0.00	0.00	0.00
Observations	448	448	416	448	448
Number of ID		32	32	32	32
# of instruments			29	45	91
AR(1) p-value			0.26	0.03	0.03
AR(2) p-value			0.40	0.28	0.29
Sargan Test (p-value)			0.01	0.00	0.00
Hansen Test (p-value)			0.19	0.83	1.00

Significance level: *** p<0.01, ** p<0.05, * p<0.1

Specifications (2)-(5) include state and year fixed effects; all apply clustered standard errors.

The results are the same as with the unrestricted model: the Diff-GMM estimated coefficients are not consistent, and the System-GMM are not reliable due to a high instrument count. However, a simple F-test on the Pooled OLS model shows that the restricted model is not valid, and the excluded variables should be accounted for.

Another approach regards the split of the sample in two time periods, to minimize the number of instruments through a reduction of the time dimension. Table 8 shows the results, which are the same as with the original and the other restricted model.

Table 8: Results of GMM for Split Model

Depvar: Delta Y	(1)	(2)	(3)	(4)	(5)	(6)
Model	Diff-GMM	Sys-GMM	Sys-GMM	Diff-GMM	Sys-GMM	Sys-GMM
Split Period	Period 1	Period 1	Period 1	Period 2	Period 2	Period 2
Constant		-0.42**	-0.23		0.59	0.38
L1.ln(GDPpc)	-1.20***	0.06**	0.02	-1.13***	-0.05	-0.06
Roadkm (GDP)	-3.43***	-0.02	-0.18	-3.82***	-0.04	-0.34
Roadkm (GDP)^2	1.84***	-0.01	0.09	2.22**	0.00	0.28
Patents p.c.	0.00	0.00	0.00	0.00	0.00	0.00
Unemployment	-0.01	0.00	0.00	0.00	0.00	0.00
Agriculture labour	0.00	0.00**	0.00	0.00	0.00	0.00
ln(Homicides)	0.00	0.00	0.00	-0.01	0.00	-0.01
ln(Education)	1.76	-0.08	0.01	-1.83*	-0.03	0.16
Observations	192	224	224	192	224	224
Number of ID	32	32	32	32	32	32
# of instruments	19	32	50	19	32	50
Sargan Test (p-value)	0.68	0.00	0.00	0.86	0.00	0.00
Hansen Test (p-value)	0.38	0.18	0.99	0.78	0.45	0.98
AR(1) (p-value)	0.44	0.00	0.00	0.47	0.08	0.11
AR(2) (p-value)	0.75	0.02	0.02	0.63	0.17	0.20

Significance level: *** p<0.01, ** p<0.05, * p<0.1
All specifications include state and year fixed effects and apply clustered standard errors.

Ultimately, the low number of units of observations are the major cause of weakness in both, the Difference-GMM and the System-GMM approach to mitigate endogeneity by transformations and internal instruments. Further, Bellemare, Masaki & Pepinsky (2017) question the suitability of lags as instruments on both a theoretical and empirical basis. None of the exceptions, under which they conclude time lags would be valid, unbiased instruments, apply to this dataset. Indeed, the direct effect of the lagged infrastructure variable on contemporaneous growth is positive and highly significant, which is not consistent with the impact the contemporaneous infrastructure variable displays.

5.2 Results of the Spatial Spillover Specifications

As there is both theoretical and data-driven evidence for spatial heterogeneity in the model, the above reported results may be biased by the omission of spatially lagged variables. Table 9 displays the estimations of the Pooled OLS, the TWFE panel model, the Spatial Durbin Model (SDM) and the Spatial Lag Model (SLX). The latter two are repeated each without the *education* variable. Here, a binary, row-standardized contiguity weight matrix (C1) was applied to estimate the spatial spillovers.

Table 9: Results of Spatial Spillover Specifications

Depvar: Delta Y	(1)	(2)	(3)	(4)	(5)
Model	TWFE	SDM	SLX	SDM	SLX
Spatial Weight Matrix	-	C1	C1	C1	C1
Constant	5.78***				
L1.ln(GDPpc)	-0.54***	-0.64***	-0.63***	-0.64***	-0.62***
Roadkm (GDP)	-2.37***	-2.86***	-2.56***	-2.87***	-2.54***
Roadkm (GDP)^2	1.36***	1.74***	1.45***	1.75***	1.42***
Patents p.c.	0.00***	0.00***	0.00***	0.00***	0.00***
Unemployment	0.00	0.00	0.00	0.00	0.00
Agriculture labour	0.00	0.00	0.00	0.00	0.00
ln(Homicides)	-0.01	-0.01	0.00	-0.01	0.00
ln(Education)	0.00	-0.09	0.16		
W*Growth Rate		-0.03		-0.03	
W*L1.ln(GDPpc)		0.36***	0.31***	0.36***	0.32***
W*Roadkm (GDP)		1.28**	1.39**	1.30**	1.37**
W*Roadkm (GDP)^2		-1.20**	-1.33**	-1.23**	-1.29**
W*Patents p.c.		0.00*	0.00	0.00*	0.00
W*Unemployment		0.00	-0.01	0.00	-0.01
W*Agriculture labour		0.01*	0.01*	0.01*	0.01*
W*ln(Homicides)		0.03**	0.03**	0.03**	0.03**
W*ln(Education)		0.12	-0.16		
Observations	448	416	448	416	448
Number of ID	32	32	32	32	32
Log-Likelihood	846	855	898	855	898
AIC	-1,650	-1,671	-1,760	-1,675	-1,763
BIC	-1,563	-1,595	-1,686	-1,607	-1,698
R-squared	0.59	0.02	0.02	0.02	0.02
R2 (within)	0.59	0.41	0.45	0.43	0.44

*Significance Level: *** p<0.01, ** p<0.05, * p<0.1*
All specifications include state and year fixed effects and apply clustered standard errors.

The results indicate that the direct effects estimated by both spatial models are similar in sign, significance, and magnitude to the coefficients of the two-way fixed-effects panel model. The lagged *GDP per capita* variable, the infrastructure variables and *Patents* are highly statistically significant at the 1% significance level. The other control variables are not. In all cases, *Roadkm* has a negative and relatively large coefficient, while its squared term has a positive sign and is smaller in size. Dropping the *education* variable leads to minimal adjustments in the coefficients of the other variables, while significance is not affected. Compared to the TWFE model, SDM and SLX assign a larger coefficient to *education*, albeit it remains non-significant.

Regarding the spatial spillovers, there are significant spatial lags for the lagged *GDP per capita* variable, the infrastructure variables, *agricultural labour* and *homicides*. Dropping the *education* variable results in similarly small changes as with the direct effects. The parameters have similar signs and magnitudes in both models, although the SDM presents slightly larger coefficients for the infrastructure variables.

Other spatial models such as SEM, SAR, SAC and GNS are not reported, as the ESDA indicates neither is appropriate, and the adequate statistical tests to compare these models to SDM and SLX also reject their suitability.

Furthermore, SDM and SXL are the preferred models for this case as argued in section 3.3. However, the results indicate that the spatial lag of the dependent variable (SDM) is not significant. Comparing Akaike's Information Criterion (AIC) and the Bayesian Information Criterion (BIC) shows that SLX performs better than SDM. A LR-test confirms that the SLX model is to be preferred.

In Table 10, the SLX model (including the education variable) is estimated with different specifications of the spatial weight matrix. C1 and C2 are binary contiguity weight matrices, with C1 accounting for direct neighbours and C2 also considering second degree neighbours. Inverse Distance matrices ID1-ID3 use different distance limits, while ID4 has none and considers all states to influence each other, though the impact is greater the closer they are. 555km (radius of ID3) is the average distance between states, while ID1 (cut-off: 300 km) and ID2 (cut-off: 400 km) were specified so as to resemble C1 and C2 in terms of links. Table 1 presents the characteristics of the different weight matrices applied. All matrices were row-standardized to control for different amounts of neighbour states.

Table 10: Parametrization of the Spatial Weight Matrix (SDM & SLX)

epvar: growth rate	(1)	(2)	(3)	(4)	(5)	(6)
Model	SLX	SLX	SLX	SLX	SLX	SLX
Spat. Weight Matrix	C1	C2	ID1	ID2	ID3	ID4
Constant						
L1.ln(GDPpc)	-0.63***	-0.64***	-0.62***	-0.61***	-0.63***	-0.59***
Roadkm (GDP)	-2.56***	-2.54***	-2.62***	-2.67***	-2.62***	-2.40***
Roadkm (GDP)^2	1.45***	1.39***	1.49***	1.55***	1.56***	1.35***
Patents p.c.	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Unemployment	0.00	0.00	0.00	0.00	0.00	0.00
Agriculture labour	0.00	0.00	0.00	0.00	0.00	0.00
ln(Homicides)	0.00	0.00	0.00	0.00	-0.01	0.00
ln(Education)	0.16	-0.30	-0.11	0.05	0.53	0.51
W*Growth Rate						
W*L1.ln(GDPpc)	0.31***	0.32**	0.43***	0.48***	0.41***	0.71***
W*Roadkm (GDP)	1.39**	0.81	1.43**	1.87***	2.33***	4.72**
W*Roadkm (GDP)^2	-1.33**	-1.57	-0.92**	-1.27**	-1.79***	-4.54*
W*Patents p.c.	0.00	0.00	0.00**	0.00*	0.00	0.00*
W*Unemployment	-0.01	0.01	0.01*	0.01	-0.01	-0.02
W*Agriculture labour	0.01*	0.02***	0.01**	0.01***	0.01***	0.03**
W*ln(Homicides)	0.03**	0.06**	0.02**	0.03**	0.00	0.04
W*ln(Education)	-0.16	0.26	0.08	-0.10	-1.23*	-3.42
Observations	448	448	448	448	448	448
Number of ID	32	32	32	32	32	32
Log-Likelihood	898	905	903	901	901	884
AIC	-1,760	-1,774	-1,771	-1,767	-1,765	-1,732
BIC	-1,686	-1,700	-1,697	-1,693	-1,692	-1,658
R-squared	0.02	0.01	0.00	0.00	0.01	0.00
R2 (within)	0.45	0.45	0.36	0.29	0.17	0.02

Significance Level: *** p<0.01, ** p<0.05, * p<0.1
State and year fixed effects and clustered standard errors.

Table 10 reports the main effects and the spillovers. Direct, indirect and total marginal effects can be found in Table A5. The direct effects are very similar across the different weight matrices, with the notable exception of the education variable, which changes both sign and magnitude, however, remains insignificant in all models. The coefficient of *Roadkm* is significant at the 1% level, and on average about -2.57. The squared term of *Roadkm* is similarly significant, but positive, and on average, takes the value of 1.47.

Regarding the spatial spillovers, the lagged GDP per capita levels are found to have significant, positive spillovers. The coefficients of the infrastructure variables are significant in all models except the one applying the second-degree neighbour contiguity weight matrix (column 2). The coefficient of the linear *Roadkm* variable is positive, varying in values between 1.39 and 4.72, while spillovers associated with the squared term are estimated to be negative, ranging from -4.54 to -0.92. Evidently, the magnitude increases with the number of links considered by the spatial weight matrix.

Regarding the marginal effects (Table A5), only the direct ones are highly statistically significant. The indirect effects's significance and magnitude varies according to the spatial weight matrix used. The total marginal effect of the linear infrastructure variable is negative and significant (except for ID3 and ID4), while the squared term has no significant total marginal impact (except for ID1), which is evidently the result of the indirect effect's lack of significance compared to the direct effects. This indicates that despite some evidence of positive spatial spillovers, additional infrastructure is more likely to have a total negative impact on regional economic growth.

Considering the weight matrices, there is no reason to assume that all states affect each other to some degree, considering the distances of up to 2,965 kilometres. This makes ID4 an unlikely alternative from a theoretical perspective. Additionally, column (6) presents a considerably higher magnitude of spillovers than the other specifications and the worst results for AIC/BIC and Log Likelihood, compared to the other specifications. The unique results presented by spatial weight matrices C2 (first and second order neighbours; no significant infrastructure spillovers) and ID3 (cut-off at 555 kilometres; large, significant, negative spillovers of education) also warrant caution. Spillover of the squared Roadkm variable using ID1 is markedly lower (0.92) than in all other specifications (ranging from -4.54 to -1.27), and it is the only model encountering significant total marginal effects of the squared infrastructure term.

In related literature, C1 is the most commonly chosen specification for a spatial weight matrix in this context (Yu et al., 2013). Due to the very similar results using ID2, columns (1) and (4) present the preferred specifications of this section. These results point towards a U-shaped relationship between infrastructure stock (standardized by regional GDP) and economic growth, as well as spatial spillovers of infrastructure in both, neighbouring regions with direct borders (column 1) and regions located within 400 kilometres (column 4). The spillovers are positive for the linear and negative for the squared term, with a smaller magnitude than for the direct effects. This means that if a state is surrounded by neighbours with a sufficiently higher stock of infrastructure, the total effect experienced by that region from infrastructure on growth may be positive.

Possibly, different characteristics of roads affect their impact on economic growth. Gonzalez-Navarro & Quintana Domeque (2016) show that paving streets has a positive effect on household income in a small Mexican town. Between 21 and 82 percent of roads are paved throughout Mexico's regions, and 100 percent in the capital. In this analysis, only paved roads are considered by the infrastructure variable Table 11 presents the main results. The marginal effects are shown in Table A6.

Table 11: Paved Roads Adjustment

Depvar: Delta Y	(1)	(2)	(3)	(4)
Road km	Total	Paved	Total	Paved
Model	SLX	SLX	SLX	SLX
Spatial Weight Matrix	C1	C1	ID2	ID2
Main Effects				
L1.ln(GDPpc)	-0.63***	-0.52***	-0.61***	-0.51***
Roadkm (GDP)	-2.56***	0.01	-2.67***	-0.01
Roadkm (GDP)^2	1.45***	-3.69*	1.55***	-3.78*
Patents p.c.	0.00***	0.00***	0.00***	0.00***
Unemployment	0.00	0.00	0.00	0.00
Agriculture labour share	0.00	0.00	0.00	0.00
ln(Homicides)	0.00	0.00	0.00	0.01
ln(Education)	0.16	0.83**	0.05	1.02***
Spatial Spillovers				
W*L1.ln(GDPpc)	0.31***	0.18**	0.48***	0.23***
W*Roadkm (GDP)	1.39**	-1.29	1.87***	-0.06
W*Roadkm (GDP)^2	-1.33**	2.63	-1.27**	0.06
W*Patents p.c.	0.00	0.00	0.00*	0.00*
W*Unemployment	-0.01	0.00	0.01	0.01
W*Agriculture labour	0.01*	0.00	0.01***	0.00
W*ln(Homicides)	0.03**	-0.01	0.03**	0.02*
W*ln(Education)	-0.16	-0.20	-0.10	-0.78***
Observations	448	448	448	448
Number of ID	32	32	32	32
Log-Likelihood	898	844	901	844
AIC	-1,760	-1,652	-1,767	-1,652
BIC	-1,686	-1,578	-1,693	-1,578
R-squared	0.02	0.03	0.00	0.03
R2 (within)	0.45	0.37	0.29	0.27

Significance Level: *** p<0.01, ** p<0.05, * p<0.1
State and year fixed effects and clustered standard errors.

Excluding non-paved roads from the estimation leads to mostly insignificant estimators that do not present spillovers. Compared to the original model considering all road types (columns 1 and 3), the goodness of fit is slightly worse. The direct infrastructure term is positive, but not significant in either specification, and close to zero. The squared term is large, negative, and significant at the 10 percent level in both. Spillovers are not significant in either model, but of a relatively large magnitude in the case of the contiguity weight matrix C1 and close to zero with the inverse-distance weight matrix ID2. These results may indicate that among paved roads, the share of sections having a positive or non-significant impact is larger than among all roads, where the negative effect is more significant.

6 Robustness Tests

This section will investigate the robustness of the main results obtained in section 5. As the support for the spatial specifications is strong, the preferred model is the SLX specification including all control variables. The binary contiguity weight matrix C1, accounting only for direct borders, and the inverse distance weight matrix ID2 that considers neighbours up to a distance of 400 kilometres, are applied.

For this purpose, the infrastructure variable is adjusted by changing its standardization either to population (per capita) or area (square kilometres) instead of regional GDP. Table 12 reports the main results, while Table A6 presents the marginal effects. Columns (1) and (4) display the results obtained in section 5. Out of the four new specifications, three find the squared infrastructure term to be not significant, while one shows a significant impact of the direct terms (column 5). The same applies to the spillovers: only the population-standardized model applying the inverse-distance weight matrix ID2 encounter significant spillovers at the 10 percent level, but of a low magnitude.

Table 12: Testing Standardization Methods

Depvar: Delta Y	(1)	(2)	(3)	(4)	(5)	(6)
Standardization	GDP	Pop	Area	GDP	Pop	Area
Spatial Weight Matrix	C1	C1	C1	ID2	ID2	ID2
Main Effects						
L1.ln(GDPpc)	-0.63***	-0.31***	-0.32***	-0.61***	-0.32***	0.18**
Roadkm	-2.56***	-0.05	0.37	-2.67***	-0.05*	0.66
Roadkm^2	1.45***	0.00	-0.53	1.55***	0.00**	-0.11
Patents p.c.	0.00***	0.00**	0.00**	0.00***	0.00***	0.00
Unemployment	0.00	0.00	-0.00*	0.00	-0.01**	0.00
Agriculture labour share	0.00	0.00	0.00	0.00	0.00	0.01
ln(Homicides)	0.00	-0.01	0.00	0.00	0.00	0.01
ln(Education)	0.16	0.29	0.19	0.05	0.44*	-0.66***
Spatial Spillovers						
W*L1.ln(GDPpc)	0.31***	0.10	0.14*	0.48***	0.16**	-0.33***
W*Roadkm	1.39**	-0.01	-0.26	1.87***	0.22*	0.11
W*Roadkm^2	-1.33**	0.00	0.23	-1.27**	-0.02	-0.26
W*Patents p.c.	0.00	0.00	0.00	0.00*	0.00*	0.00***
W*Unemployment	-0.01	-0.01**	-0.01**	0.01	0.00	-0.01**
W*Agriculture labour	0.01*	0.01	0.01	0.01***	0.01	0.00
W*ln(Homicides)	0.03**	-0.01	0.00	0.03**	0.01	0.00
W*ln(Education)	-0.16	-0.85	-0.53	-0.10	-0.58**	0.25
Observations	448	448	448	448	448	448
Number of ID	32	32	32	32	32	32
Log-Likelihood	898	738	739	901	744	740
AIC	-1,760	-1,440	-1,441	-1,767	-1,452	-1,444
BIC	-1,686	-1,367	-1,367	-1,693	-1,378	-1,370
R-squared	0.02	0.00	0.00	0.00	0.00	0.00
R2 (within)	0.45	0.01	0.04	0.29	0.19	0.15

Significance Level: *** p<0.01, ** p<0.05, * p<0.1
All specifications include state and year fixed effects and apply clustered standard errors.

While there is currently no preferred method to standardize infrastructure variables, each approach captures a different dimension. The suitable approach is related to the channel through which infrastructure is expected to affect the economy. For instance, the standardization by population is mostly relevant to measure the infrastructure capacity per person for commuting and accessing healthcare and education. However, the strongest evidence exists for infrastructure increasing private sector productivity by reducing trade costs and increasing market integration (Aschauer, 1989; Barro, 1990, Hulten & Schwab, 2000; Agénor, 2010). Arguably, the available infrastructure capacity for each unit of economic activity (GDP) is the best measure to account for these effects.

7 Discussion and Conclusion

This study focused on investigating the relationship between transport infrastructure and economic growth, using modern econometric techniques to overcome some of the limitations of earlier studies, contributing, to my knowledge, a first analysis of this topic on the level of Mexico's federal entities using a spatial model. A major challenge of this type of analysis is simultaneity between the dependent and the explanatory variable. Hence, transport infrastructure stock was chosen as the key explanatory variable, as this decreases endogeneity issues, and evaluated in kilometres, which has been shown to have a more significant impact than other measures (Calderón, Moral-Benito & Servén, 2015; Elburz, Nijkamp & Pels, 2017). Nonlinearities due to network effects are measured by the squared term of the infrastructure variable (Agénor & Moreno-Dodson, 2006). A vector of control variables accounts for relevant endogenous and external factors (Ascani, Crescenzi & Iammarino, 2012; Crescenzi & Rodriguez-Pose, 2012).

The two-way fixed effects model exhibits a significant, U-shaped relationship of infrastructure and economic growth on the regional level in Mexico for the period 2005-2018. A split-sample analysis using TWFE shows that the significant impact of infrastructure on economic growth is limited to those Mexican regions with lower income. Additionally, the magnitude of the coefficients has increased over time. There could be several reasons for these observations. For example, higher income regions may have reached the growth-maximizing infrastructure stock earlier, while lagging regions are still benefitting from additional investments. Also, economic growth above a certain threshold may not depend on transport infrastructure as much as for lower levels of development. Difference- and System-GMM were applied to further control endogeneity by using internal instruments. While the first displays similar results as the TWFE estimation, it lacks consistency. The latter suffers from too many weak instruments due to the moderate number of regions, rendering the results unreliable. Reducing the instrument count by either dropping the control variables, or splitting the dataset in two time periods does not mitigate these issues.

A spatial specification of the endogenous growth model was set up to account for spillovers between regions. Due to both, theoretical and data-driven motives, SDM and SLX specifications were chosen along six different spatial weight matrices. Results indicate that the SLX model in combination with a spatial weight matrix considering either spillovers of direct neighbours only, or of all states located within 400 kilometres, is the preferred specification. As in the TWFE, both infrastructure variables present a highly significant direct effect, with the linear term having a negative and the squared term a positive coefficient. The spillovers are also significant, but have the opposite signs. Repeating the analysis considering only paved road sections, only the squared term of the variable is significant, and there are no significant spillovers; indicating that different characteristics of roads matter in terms of their impact on regional economic growth.

Testing the robustness of the results by applying alternative specifications for the infrastructure variable (standardization by area and population instead of GDP) find a significant direct impact only in half of the tested specifications, while spatial spillovers were not detected. This means that the main results are highly sensitive to the way infrastructure endowment is measured. The correlation matrix (Table A3) shows that each standardization method causes significant differences in the variable, explaining the variation in results. Nonetheless, the chosen standardization by GDP to obtain the main results was motivated to account the density of economic activity in a state, which is better in capturing the potential channel through which transport infrastructure increases private sector productivity, as proposed by many scholars such as Aschauer (1989), Barro (1990), Hulten & Schwab (2000) and Agénor (2010). Thus, the results may also indicate that in Mexico, infrastructure stock has a significant negative impact on productivity, while the other proposed channels (as presented in section 2) are not relevant.

In any case, there are some important limitations to this study that have to be taken into account when considering its findings. While the scope of the data is around the average in observed by Elburz, Nijkamp & Pels (2017) in similar studies, the relatively small number of units of observations (32) makes the results of Difference-GMM and System-GMM methods inconsistent and unreliable. On the other hand, for measuring a long-term impact, a larger time scale would be required. Further, it would be interesting to include a reliable estimate of internal migration, as there are relevant theoretical arguments for factor mobility being a possible channel through which infrastructure affects economic growth (Banerjee, Duflo & Quian, 2012).[9] Moreover, all roads have been considered regardless of their quality (e.g. number of lanes, condition, toll fee) and function (local or inter-regional network). It is to be expected that local streets create less spillovers to other states, thus the mixed approach may present a downward bias in the estimation of indirect effects. Possibly, different characteristics of roads also affect their relationship with economic growth, which may explain the lack of significance in many specifications. Last but not least, the infrastructure of neighbouring countries (USA and Guatemala) has not been taken into account by default: it is not Mexican, nor under their influence. However, the actual mobility options for the border states are better than these models assume. But due to limitations to the movement of people and goods between countries, they can also not be compared to national infrastructure that is equally accessible for all Mexicans.

These findings are broadly in line with similar investigations in terms of data and methodology. For instance, even though their Difference-GMM approach provides consistent estimates, Crescenzi & Rodriguez-Pose (2012) find no significant impact of infrastructure (or their spillovers) on growth for EU regions (with neither standardization method). Banerjee, Duflo & Quian (2012) report similar results, while using a different specification. Regarding the effect of certain aspects of the analysis on the outcome as investigated by Elburz, Nijkamp & Pels (2017; see also Table A1), using a growth regression, a sub-national scope and having a more recent publication date may have contributed to encountering a negative relationship. On the other hand, measuring infrastructure in kilometres and focusing on land transport and roads may have lead to a more positive outcome than if another measure had been chosen. Relying on fixed effects, using contiguity and distance-based spatial weight matrices in a panel data setting may have increased the likelihood of not encountering significant estimators.

Further research into the case of Mexico is required to determine whether these results can be confirmed using alternative macroeconomic modelling techniques such as VAR and VEC models, threshold regressions or instrumental variables. Also, applying a production function approach to measure the short-term impact of infrastructure on output rather than its growth rate may yield valuable insights. From a policy-perspective, it is also necessary to study the impact of other types of transport infrastructure, such as airports, train lines and seaports. Finally, more investigation is required to determine how to adequately choose a suitable standardization method for infrastructure variables.

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[9] I have computed estimations for internal migration based on population, deaths and births (Puhani, 2001). However, the values were vastly different from the three years of data available at INEGI. This could be due to international migration, particularly to the US, affecting a significant number of movements. In any case, including the estimated variable did not alter the results.

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Appendix

Table A1: Selected Results of Meta-Analysis by Elburz, Nijkamp & Pels (2017)

Approach	Implication	Significance
Production Function	Positive	In 0 of 6 specifications
TFP	Positive	In 2 of 6 specifications
Growth regression	Negative	In 2 of 6 specifications
Spatial regression	Mostly negative	In 0 of 6 specifications
Fixed Effects	Mostly negative	In 0 of 6 specifications
Random Effects	Positive	In 1 of 6 specifications
OLS	Positive	In 3 of 6 specifications
GMM	Negative	In 0 of 6 specifications
Length of infrastructure (km)	Positive	In 6 of 6 specifications
GDP (as dependent)	Positive	In 0 of 6 specifications
Non EU/US country[10]	Negative	In 0 of 6 specifications
Roads	Positive	In 3 of 3 specifications
Land transport	Positive	In 3 of 3 specifications
Sub-national scope[11]	Mostly negative	In 17 of 18 specifications
Distance weight matrix	Negative	In 1 of 6 specifications
Contiguity weight matrix	Positive	In 0 of 6 specifications
Economic weight matrix	Negative	In 4 of 6 specifications
Panel Data	Positive	In 0 of 6 specifications
Cross-Section	Positive	In 3 of 6 specifications
Publication year[12]	Negative	In 2 of 6 specifications

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[10] Specifically, China, India or Turkey; which are middle income countries like Mexico (World Bank, 2021).
[11] Interstate, interprovincial and interregional
[12] Indicating a more recent publication is more likely to present smaller or more negative estimates than earlier results.

Table A2: Descriptive Statistics

Variable		Mean	Std. dev.	Min	Max	Observations	
Growth rate	overall	0.012	0.058	-0.442	0.414	N =	448
	between		0.010	-0.006	0.030	n =	32
	within		0.057	-0.429	0.427	T =	14
L1.ln(GDP)	overall	9.606	0.394	8.802	10.685	N =	448
	between		0.390	8.842	10.564	n =	32
	within		0.086	9.108	9.897	T =	14
Roadkm (GDP)*	overall	0.310	0.210	0.000	0.946	N =	448
	between		0.209	0.000	0.758	n =	32
	within		0.038	0.171	0.500	T =	14
Patents p.c.	overall	13.886	18.951	0.000	105.805	N =	448
	between		13.345	1.173	58.230	n =	32
	within		13.647	-24.184	68.121	T =	14
Unemployment	overall	4.116	1.544	0.900	8.600	N =	448
	between		1.119	1.657	6.057	n =	32
	within		1.082	1.208	7.473	T =	14
Agriculture labour share	overall	14.672	9.174	0.147	40.690	N =	448
	between		9.199	0.452	38.906	n =	32
	within		1.414	9.238	21.381	T =	14
ln(Homicides)	overall	2.553	0.850	0.531	5.205	N =	448
	between		0.682	0.850	3.984	n =	32
	within		0.521	1.297	4.707	T =	14
ln(Education)	overall	2.164	0.110	1.803	2.414	N =	448
	between		0.099	1.921	2.367	n =	32
	within		0.051	2.047	2.273	T =	14
Roadkm (GDP)* Paved	overall	0.123	0.076	0.000	0.409	N =	448
	between		0.075	0.000	0.340	n =	32
	within		0.019	0.042	0.268	T =	14
Roadkm (Area)	overall	0.279	0.169	0.052	0.752	N =	448
	between		0.169	0.054	0.687	n =	32
	within		0.028	0.148	0.415	T =	14
Roadkm (Pop)	overall	4.203	2.351	0.010	9.668	N =	448
	between		2.367	0.015	9.057	n =	32
	within		0.295	2.501	5.942	T =	14

Source: Author's elaboration based on data from INEGI & OECD

**The lowest values are found in the capital district of Mexico City due to its small size (low stock of infrastructure) and high GDP levels. Excluding the federal district from the analysis does not alter the results.*

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Table A3: Correlation Matrix

	Growth Rate	Lagged Log of GDPpc	Roadkm (GDP)	Patents p.c.	Unem-ployment	Agricultural labour	Log of Homicides	Log of Education	Paved Roadkm (GDP)	Roadkm (area)	Roadkm (pop)
Growth Rate	1.00										
Lagged Log of GDPpc	-0.02	1.00									
Roadkm (GDP)	-0.08	-0.62	1.00								
Patents p.c.	0.12	0.53	-0.46	1.00							
Unemployment	-0.02	0.35	-0.36	0.23	1.00						
Agricultural labour	-0.02	-0.82	0.74	-0.45	-0.49	1.00					
Log of Homicides	0.02	0.08	-0.12	0.21	0.23	-0.04	1.00				
Log of Education	0.02	0.80	-0.58	0.52	0.51	-0.82	0.26	1.00			
Paved Roadkm (GDP)	-0.11	-0.54	0.86	-0.40	-0.29	0.63	-0.13	-0.44	1.00		
Roadkm (area)	-0.02	-0.49	-0.13	-0.06	0.01	0.12	0.20	-0.14	-0.10	1.00	
Roadkm (pop)	-0.01	-0.19	0.80	-0.39	-0.23	0.36	-0.11	-0.18	0.72	-0.37	1.00

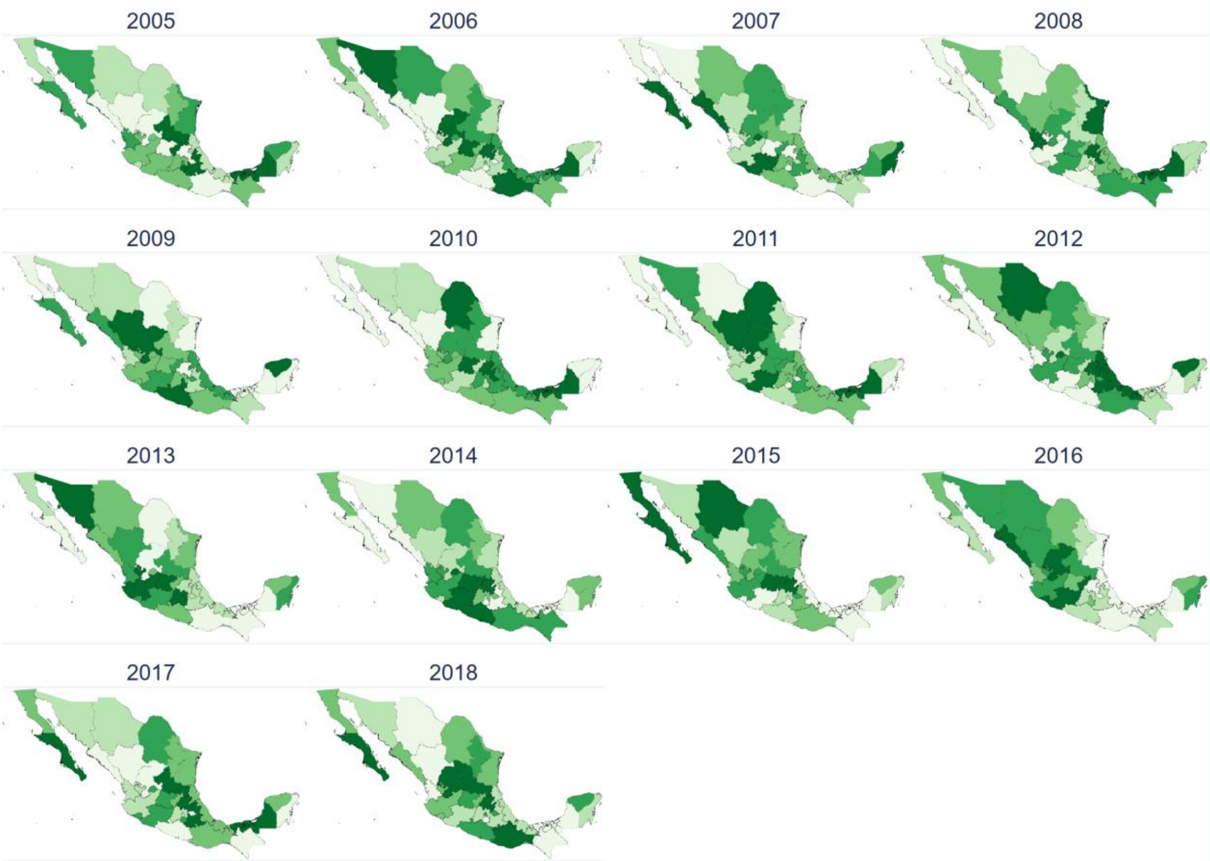
Source: Author's elaboration based on data from INEGI & OECD

[Back to section 3.1 (Identification Strategy).]

[Back to section 4.2 (ESDA).]

[Back to section 7 (Conclusion).]

Figure A1: Regional Growth Rates 2005-2018



Source: Author's elaboration using STATA 17, SPMAP by Pisati (2018) and Data from INEGI & OECD

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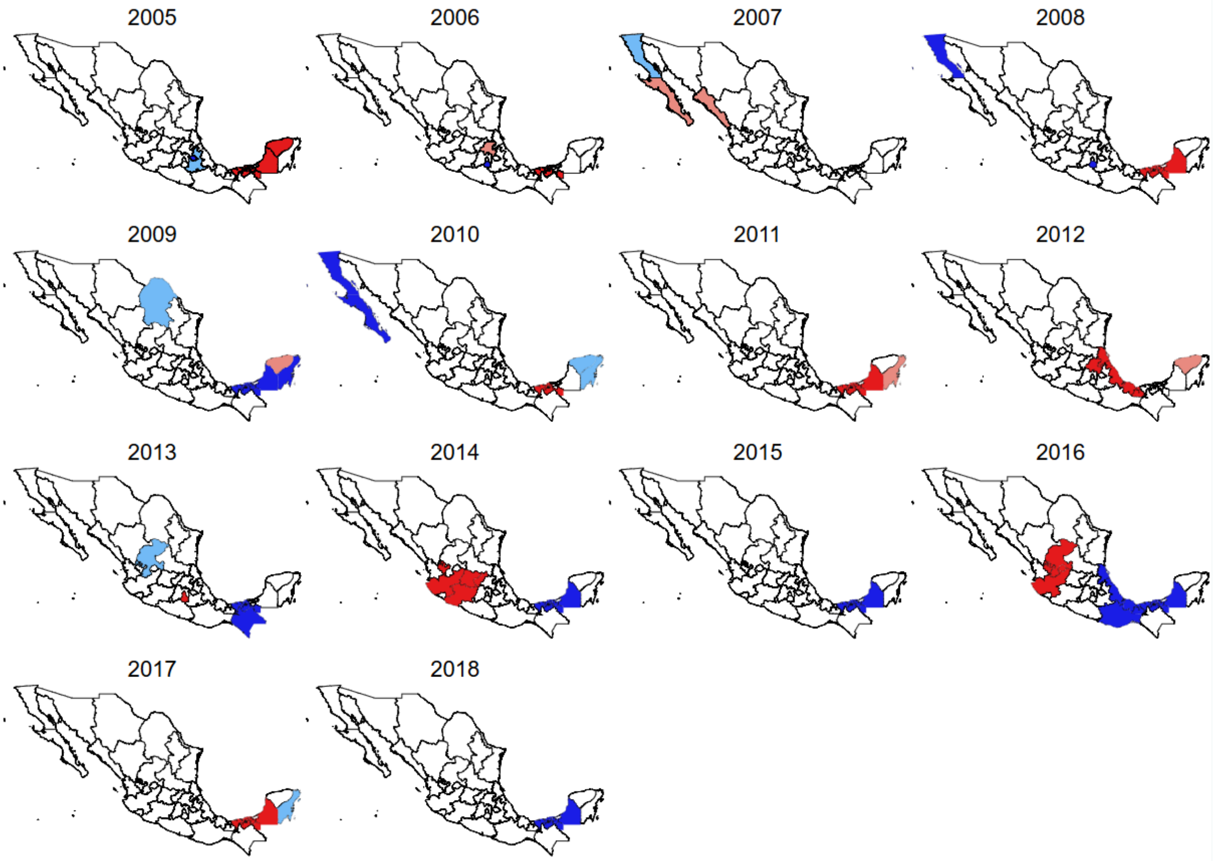
Figure A2: Local Moran's I Cluster Maps



Source: Author's elaboration using STATA 17, sg162 by Pisati (2001) and Data from INEGI & OECD Spatial Weight Matrix C1 was applied.

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Table A4: Split Group Classification

Group 1		Group 2	
State	**Fuentes (2003)**	**State**	**Fuentes (2003)**
Chiapas	Lagging	Aguascalientes	Intermediate
Durango	Lagging	Baja California	Intermediate
Guanajuato	Lagging	Baja California Sur	Intermediate
Guerrero	Intermediate	Campeche	Lagging
Hidalgo	Lagging	Chihuahua	Intermediate
México	Intermediate	Ciudad de México	Intermediate
Michoacán	Lagging	Coahuila	Intermediate
Morelos	Lagging	Colima	Lagging
Nayarit	Lagging	Jalisco	Intermediate
Oaxaca	Lagging	Nuevo León	Intermediate
Puebla	Lagging	Querétaro	Lagging
Tabasco	Lagging	Quintana Roo	Lagging
Tlaxcala	Lagging	San Luis Potosí	Intermediate
Veracruz	Lagging	Sinaloa	Intermediate
Yucatán	Lagging	Sonora	Intermediate
Zacatecas	Lagging	Tamaulipas	Intermediate

Source: Author's elaboration using data by INEGI, OECD and Fuentes (2003)

The classification for this analysis was obtained by calculating the average GDP per capita values for each state for the period of analysis, 2005-2018. The 16 regions with the lower income (on average, 11.217 USD) were assigned to Group 1, while Group 2 is composed of the 16 states with a higher per capita income (on average, 21.390 USD). Additionally, the classification by Fuentes (2003) is displayed. It was computed using seven different indicators of development for the year 1998.

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Table A5: Marginal Effects of Spatial Models

	(1)	(2)	(3)	(4)	(5)	(6)
Model	SLX	SLX	SLX	SLX	SLX	SLX
Spat. Weight Matrix	C1	C2	ID1	ID2	ID3	ID4
DIRECT						
L1.ln(GDPpc)	-0.61***	-0.63***	-0.59***	-0.59***	-0.61***	-0.58***
Roadkm (GDP)	-2.49***	-2.53***	-2.56***	-2.57***	-2.51***	-2.29***
Roadkm (GDP)^2	1.38***	1.37***	1.46***	1.49***	1.48***	1.27***
Patents p.c.	0.00***	0.00***	0.00***	0.00***	0.00***	0.00***
Unemployment	0.00	0.00	0.00	0.00	0.00	0.00
Agriculture labour	0.00	0.00	0.00	0.00	0.00	0.00
ln(Homicides)	0.00	0.00	0.00	0.00	-0.01	0.00
ln(Education)	0.18	-0.27	-0.07	0.06	0.48	0.46
INDIRECT						
L1.ln(GDPpc)	0.14	0.18	0.24***	0.31***	0.27***	0.78***
Roadkm (GDP)	0.76	0.19	0.47	1.11*	2.05**	5.96
Roadkm (GDP)^2	-1.19*	-1.39	-0.43	-0.92	-1.86**	-6.25
Patents p.c.	0.00**	0.00	0.00***	0.00**	0.00	0.01*
Unemployment	-0.01	0.01	0.01	0.01	-0.01	-0.03
Agriculture labour	0.01*	0.03**	0.01**	0.01**	0.02**	0.05**
ln(Homicides)	0.04**	0.07**	0.03*	0.04**	-0.01	0.06
ln(Education)	-0.22	0.11	0.06	-0.11	-1.55*	-4.80
TOTAL						
L1.ln(GDPpc)	-0.47***	-0.45**	-0.36***	-0.27**	-0.35***	0.20
Roadkm (GDP)	-1.74**	-2.34*	-2.09***	-1.46*	-0.46	3.67
Roadkm (GDP)^2	0.19	-0.02	1.03*	0.57	-0.39	-4.98
Patents p.c.	0.00***	0.00	0.00***	0.00***	0.00**	0.01**
Unemployment	-0.01	0.01	0.01	0.01	-0.01	-0.03
Agriculture labour	0.01	0.03**	0.01*	0.01**	0.02**	0.05**
ln(Homicides)	0.04*	0.07*	0.03	0.04*	-0.01	0.06
ln(Education)	-0.04	-0.16	-0.02	-0.04	-1.07	-4.34

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Table A6: Marginal Effects of Paved Roads Adjustment

	(1)	(4)	(3)	(4)
Road km	Total	Paved	Total	Paved
Model	SLX	SLX	SLX	SLX
Spatial Weight Matrix	C1	C1	ID2	ID2
SR DIRECT				
L1.ln(GDPpc)	-0.61***	-0.51***	-0.31***	-0.50***
Roadkm (GDP)	-2.49***	-0.13	-0.04*	-0.06
Roadkm (GDP)^2	1.38***	-3.43	0.00*	-3.68*
Patents p.c.	0.00***	0.00***	0.00***	0.00***
Unemployment	0.00	0.00	-0.01**	0.00
Agriculture labour share	0.00	0.00	0.00	0.00
ln(Homicides)	0.00	0.00	0.00	0.01
ln(Education)	0.18	0.83***	0.42*	0.99***
SR INDIRECT				
L1.ln(GDPpc)	0.14	0.05	0.11	0.13*
Roadkm (GDP)	0.76	-1.64	0.23	-0.07
Roadkm (GDP)^2	-1.19*	1.99	-0.02	-0.84
Patents p.c.	0.00**	0.00	0.00*	0.00**
Unemployment	-0.01	-0.01	0.00	0.01
Agriculture labour share	0.01*	0.00	0.01	0.00
ln(Homicides)	0.04**	-0.01	0.01	0.03*
ln(Education)	-0.22	0.02	-0.52*	-0.58*
SR TOTAL				
L1.ln(GDPpc)	-0.47***	-0.46***	-0.21**	-0.37***
Roadkm (GDP)	-1.74**	-1.77	0.19	-0.13
Roadkm (GDP)^2	0.19	-1.44	-0.01	-4.51*
Patents p.c.	0.00***	0.00*	0.00***	0.00***
Unemployment	-0.01	-0.01	0.00	0.01
Agriculture labour share	0.01	0.00	0.01	0.00
ln(Homicides)	0.04*	0.00	0.01	0.03*
ln(Education)	-0.04	0.86	-0.09	0.40

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Table A7: Marginal Effects of Standardization Methods Testing

	(1)	(2)	(3)	(5)	(6)	(7)
Standardization	GDP	Pop	Area	GDP	Pop	Area
Model	SLX	SLX	SLX	SLX	SLX	SLX
Spatial Weight Matrix	C1	C1	C1	ID2	ID2	ID2
SR DIRECT						
L1.ln(GDPpc)	-0.61***	-0.30***	-0.32***	-0.31***	-0.31***	0.11*
Roadkm (GDP)	-2.49***	-0.05	0.33	-0.04*	-0.04*	0.75
Roadkm (GDP)^2	1.38***	0.00	-0.49	0.00*	0.00*	-0.19
Patents p.c.	0.00***	0.00***	0.00***	0.00***	0.00***	0.00*
Unemployment	0.00	-0.00*	-0.01**	-0.01**	-0.01**	0.00
Agriculture labour share	0.00	0.00	0.00	0.00	0.00	0.01
ln(Homicides)	0.00	-0.01	0.00	0.00	0.00	0.01
ln(Education)	0.18	0.22	0.15	0.42*	0.42*	-0.65***
SR INDIRECT						
L1.ln(GDPpc)	0.14	0.02	0.07	0.11	0.11	-0.21***
Roadkm (GDP)	0.76	-0.03	-0.23	0.23	0.23	0.86
Roadkm (GDP)^2	-1.19*	0.00	0.13	-0.02	-0.02	-0.45
Patents p.c.	0.00**	0.00	0.00	0.00*	0.00*	0.00**
Unemployment	-0.01	-0.02**	-0.02**	0.00	0.00	0.00
Agriculture labour share	0.01*	0.01	0.01	0.01	0.01	0.00
ln(Homicides)	0.04**	-0.01	-0.01	0.01	0.01	0.00
ln(Education)	-0.22	-1.02	-0.60	-0.52*	-0.52*	-0.40
SR TOTAL						
L1.ln(GDPpc)	-0.47***	-0.28***	-0.24***	-0.21**	-0.21**	-0.51***
Roadkm (GDP)	-1.74**	-0.08	0.10	0.19	0.19	-0.01
Roadkm (GDP)^2	0.19	0.01	-0.36	-0.01	-0.01	-3.78*
Patents p.c.	0.00***	0.00*	0.00**	0.00***	0.00***	0.00***
Unemployment	-0.01	-0.02***	-0.02***	0.00	0.00	0.00
Agriculture labour share	0.01	0.01	0.01	0.01	0.01	0.00
ln(Homicides)	0.04*	-0.02	-0.01	0.01	0.01	0.01
ln(Education)	-0.04	-0.80	-0.45	-0.09	-0.09	1.02***

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