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A Study of German Counties

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Economic Effects of Transportation Infrastructure Quantity and Quality: A Study of German Counties

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Abstract

In this paper, we analyze the impact of transportation infrastructure quantity and quality on regional economic production. We exploit an extensive panel dataset on the German county level (N=401), expressing the capital value and condition of highways between 2007 and 2016, to estimate a spatially extended translog production function. The spatial specification uses SLX and SDEM models, with various linear and nonlinear variants estimated using FGLS and GMM estimators accounting for endogeneity. We find, in line with existing research, a positive impact of the quantity of transport infrastructure both locally and supra-regionally. We furthermore provide evidence for the claim that insufficient maintenance and low infrastructure conditions significantly slow economic growth through a negative correlation between GDP and the quality grade of highways. A more detailed analysis, distinguishing different types of highways and constructions, confirms these findings and underlines the importance of the Bundesstraßen network as compared to the Autobahn system. The estimated impact of the quality of bridges is rather ambiguous and requires further research to achieve a better understanding.

Keywords: Transport; Infrastructure; Public Capital; Economic Growth; Regional Development

JEL classification: O18; R12; R42

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1. Introduction

The role of public infrastructure within economies, the investment into these networks, and the quality of the provided systems are subjects of constant discussion in science and policy. The OECD claims that public infrastructure “supports growth, improves well-being and generates jobs” (OECD, 2017, p. 1), but also finds “a number of challenges” that policymakers face in the complex field of infrastructure investment (ibd.). The G20 defines one of these challenges as “a massive gap in financing for investment in new and existing infrastructure, which could generate a serious bottleneck to economic growth” (G20, 2019, p. 1) and stresses “the need to scale up infrastructure investment” (ibd.). The U.S. Congressional Research Service adds “the optimal level of infrastructure investment, the effectiveness of this investment, and the appropriate role of the federal government” as related issues (Mallett, 2018, p. 1). The existing literature on the topic makes clear that the discussion is not new: the question of sufficiency of public investment was raised from a policy-perspective already in Peterson (1990) and the general idea of public investment affecting economic development dates back to Smith (1776). On scientific grounds, economic theory suggests that public capital increases private investment and economic growth (Aschauer, 1990, p. 14). This assumption is widely discussed, with confirmation found across a wide range of empirical studies, as our literature review shows. Analyzing the impact of infrastructure quality, we contribute to a strand of this research that is, until now, understudied despite its high relevance for public welfare.

Transportation infrastructure is an important part of public capital and a major aspect of the political and scientific discussions. As it accounts for 6% of the total capital employed in the German economy (DIW, 2017, p. 41), the German Ministry of Transportation and Digital Infrastructure (BMVI) asserts that “wealth is created where infrastructure functions” (BMVI, 2017, p. 3). Similarly, the U.S. government mentions it as “a key ingredient of economic development in this country” (EOP, 2016, p. 251), fostering effects such as economies of scale, lower transportation and transaction costs, and access to larger markets (Carlsson, Otto, & Hall, 2013, p. 267). In addition, investment into transport infrastructure not only has an impact on the area the money flows into, but has supra-regional effects due to the network characteristics of the infrastructure and its importance for connecting regions. Despite its obvious importance, transport infrastructure investment is a primary subject of the underfunding phenomenon identified by the G20, with an increasing number of stakeholders stating their dissatisfaction with the current state of the network. The American Society of Civil Engineers (ASCE) gave the U.S. transport infrastructure a D+ grade in 2017, claiming it to be in a “mostly below standard” condition with “significant deterioration” (ASCE, 2017, p. 13). The U.S. Council on Foreign Affairs even defines a “threat to human safety of catastrophic failures like bridge collapses or dam breaches,” besides “billions of dollars in lost economic productivity” due to inadequate maintenance of transport infrastructure (McBride, 2018, para. 1). Grömling & Puls (2018, p. 94) find that 72% of 2600 surveyed companies in Germany find their undertakings negatively influenced by road infrastructure deficits, while an increasing number of businesses in the German Association of German Chambers of Industry and Commerce (DIHK) limits their investments due to logistical constraints (DIHK, 2017, p. 21). Similar reports are published by a large number of nations around the world. In 2010, the Global Risk Report named the failure of transport infrastructure as a globally present risk, finding in 2019 that the situation has not improved over the intervening years (WEF, 2019, pp. 82ff).

In any economy, limited financial resources must be balanced between transport network expansion and maintenance of the existing infrastructure to assure that both quantity and quality of the supplied systems meet the demand of businesses and individuals. Consequently, the G20 call for a "renewed emphasis on quality infrastructure investment" (G20, 2019, p. 1), making clear that a focus on road quantity and the construction of new roads is not an optimal allocation of resources. For the German case, claims for increased maintenance investment into transport infrastructure are made by, among others, Daehre (2012), Arndt et al. (2013), and Kunert & Link (2013). Kalaitzidakis & Kalyvitis (2005) analyze the relationship for the Canadian case and find an inefficient allocation, while Rioja (2013) develops a theoretical background and analyses case studies in multiple countries with similar conclusions.

While the economic impact of public investment generally, and transport infrastructure specifically, has seen great scientific attention, few publications focus on the specific effects of maintenance. Even more surprising, we can identify only one existing study that empirically addresses the topic using measured quality data, and thus real changes in quality, instead of monetary values. To provide a scientific foundation for this otherwise overlooked field and to support policy decisions on the topic, this paper empirically addresses the question "(How) Does fluctuating quality of transportation infrastructure, as a result of maintenance investment behavior, influence economic growth on a regional level in Germany?" Furthermore, it follows existing research on the economic impact of public capital and transport-related infrastructure endowment. We approach this question with three hypotheses, referring to the impact of quantity, quality, and a supra-regional impact respectively:

- H_1: The quantity of transport infrastructure, measured as gross asset value, is positively correlated with economic growth.
- H_2: The quality of transport infrastructure, measured as condition of roads and constructions, has a positive impact on economic growth, i.e. better quality increases growth.
- H_3: Both effects are present locally and supra-regionally, i.e. spillovers exist.

The paper is structured as follows: Section 2 presents a review of the existing literature in the field, from theory and methodology to empirical applications. Sections 3 and 4 explain our data and methodological approach, respectively. In addition, we use sub-section 4.2 to analyze the endogeneity problem inherent in many related studies. Our results are laid out and discussed in section 5, before drawing scientific and policy-related conclusions in section 6.

2. Literature Review

The idea that public capital affects economic developments dates back to the beginnings of economics as a science. The theoretical fundament of most modern research on this relationship is the neoclassical economic framework, within which the use of production functions relating inputs and output of aggregate economies or individual firms is based (cf. Cobb & Douglas, 1928). A contrary view developed in endogenous growth theory, claiming that economic growth is determined endogenously within economies instead of through externally identified factors (Romer, 1986, 1990a). We do not go into detail about the background of these theories, instead referring interested readers to any textbook about modern economic theory.

The modern debate about growth effects of public investment is based on the seminal work of Aschauer (1989, 1990), finding an increase in total factor productivity of 0.39% for a 1% increase in the ratio between public and private capital (Aschauer, 1989, p. 182). Compared to previous (cf. Eberts, 1986) and later research, the effect Aschauer estimates is extremely strong, suggesting implausibly high returns (Pereira & Andraz, 2013, p. 2). Overviews of the scientific discussion following Aschauer's publications are provided in, among others, Gramlich (1994), Romp & de Haan (2007), and Pereira & Andraz (2013), suggesting econometric issues including two-way causality, spurious correlations, and non-stationarity of the data (Gramlich, 1994, p. 1187; Romp & de Haan, 2007, p. 7). Despite being strongly criticized, the production function approach remains the most used methodology for the identification of productivity effects of public capital. Its relatively weak dependence on theoretical assumptions and the availability of data are arguments in favor of the method, as is the development of procedures accounting for the aforementioned problems. Econometrically, an important step is the use of generalized method of moments (GMM) estimators, driven by Arellano & Bond (1991) and Blundell & Bond (1998) and expanded into spatial models (see below), besides others, in Kelejian & Prucha (1999), Anselin (2011), and Lee & Yu (2014). A related approach to avoid endogeneity bias is the use of instrumental variables (IV) procedures, as suggested by M. N. Harris & Mátyás (2004) and Baltagi & Liu (2011). A comparison of different estimation methods is conducted in Kelejian & Robinson (1997). In application, the relevance of human capital as an input factor must be noted, introduced in Lucas (1988) and Romer (1990b). An empirical analysis of the German case is found in Brunow & Hirte (2009).

Employing these advances, a vast body of empirical evidence for the impact of public infrastructure investment exists. An extensive review is found in Pereira & Andraz (2013), including studies on the micro- and macroeconomic level in the U.S. and other parts of the world as well as providing an overview of the methodological debate. Furthermore, the meta-analyses of Melo, Graham, & Brage-Ardao (2013), Bom & Ligthart (2014), and Holmgren & Merkel (2017) analyze 563, 578, and 776 estimates, respectively, from a collection of publications. They calculate mean elasticities across all estimates in their respective samples of 0.06 (Melo et al., 2013), 0.11 (Bom & Ligthart, 2014), and 0.10 (Holmgren & Merkel, 2017), but find that these effects depend heavily on the specification of models. Aspects they find to influence the findings include the data structure and use of panel methods, the regional level of aggregation and use of spatial econometric techniques, the accounting for econometric issues such as endogeneity, and the measurement details of variables such as public capital. Furthermore, effects differ between countries, time, industries, and modes of transport, explaining the wide range of estimates found in individual studies. Recent analyses accounting for the identified shortfalls fall into a more narrow range of estimates while providing evidence for many parts of the world: Besides others, Barzin, D'Costa, & Graham (2018) identify the impact of Colombian roads, L. Liu & Zhang (2018) study the high speed rail construction in China, and Arbués, Baños, & Mayor (2015) in Spain as well as Börjesson, Isacsson, Andersson, & Anderstig (2019) in Sweden focus on European countries. All authors find positive effects on production output and employment, as do several studies for the German case: The reports by Bertenrath, Thöne, & Walther (2006) and Barabas et al. (2010) provide extensive background information as well as estimation results that are close to the findings of the mentioned meta-analyses. The publications by Allroggen, Scheffler, & Malina (2013) and Allroggen & Malina (2014) also find positive productivity and production efficiency effects of transport infrastructure.

While a large share of the existing studies measures economic effects through GDP growth, an alternative approach focuses on the labor market, identifying changes in employment or wage levels. Duranton & Turner (2012) find a significant growth of 1.5% in regional employment over 20 years due to a 10% increase in highway endowment for the U.S. highways, and a comparable example for Germany is provided by Möller & Zierer (2018). Both studies build on historical infrastructure maps as instruments in order to identify causal effects. Another approach to public capital, which is close to the one we take in this study, is used by Fritzsche (2019): Instead of monetary values measuring the quantity of public infrastructure endowment, she uses a quality variable identifying the condition of roads for a sample of German counties. With these data, she finds that previously taken approaches such as instrumenting infrastructure quality with accident information (Kalb, 2014) are less reliable and measured quality data are necessary for consistent findings. Rouse, Putterill, & Ryan (1997) use a comparable dataset for New Zealand, leading him to similar conclusions.

Independent of the specific focus of the analyses, the literature provides overarching support for the hypothesis that public capital, both generally and transport-specifically, fosters economic growth. Despite this apparent congruence of production function-based studies, it is important to note that analyses finding no or even negative effects remain. The general concept is subject to criticism, as expressed in Felipe, Hasan, & McCombie (2008) and Felipe & McCombie (2012). An alternative approach within the branch of econometric methods is the use of cost functions, identifying effects on individual firms' cost structure instead of explaining aggregate output. This method is, for example, used in Berndt & Hansson (1992), and Bougheas, Demetriades, & Mamuneas (2000), both finding that public capital decreases private costs, thus enhancing productivity. Another option are vector autoregressive frameworks, for which Yu, de Jong, Storm, & Mi (2013) give an overview and an application in China.

A different methodology is applied in computable general equilibrium (CGE) models, which see increasing attention as more and better data become available. Project assessment strategies, especially for major infrastructure projects, implement CGE models in Brazil (Haddad, Perobelli, Domingues, & Aguiar, 2011) and Norway (Vold & Jean-Hansen, 2007), among others. A comprehensive presentation of the development and functioning of CGE models as well as their applications is found in Robson et al. (2018). An econometric approach relying on fewer assumptions than CGE models, but identifying a broader scope of relationships than just a production (or cost) function, is the simultaneous equations model (SEM). Each equation in these systems describes a relationship between variables, thus allowing to model two-way or indirect causalities and endogenously determined relations (Cornwell, Schmidt, & Wyhowski, 1992). While the methodologies for estimating several equations simultaneously are not new (cf. Baltagi, 1981), many of the econometric challenges inherent in growth-related applications have been solved more recently. This is especially true for dynamic models (Hsiao & Zhou, 2015) and for spatial methods (see below; X. Liu & Saraiva, 2019; Yang & Lee, 2019). An early empirical contribution in this field is Duffy-Deno & Eberts (1991), identifying a significant positive impact of total public investment on private income for U.S. cities. Kemmerling & Stephan (2002) use data on German cities to disentangle political investment behavior, as do Mizutani & Tanaka (2010) for the Japanese case.

While all these methods are based on macroeconomic or aggregated data, a growing body of empirical literature uses treatment effect identification strategies, which draw causal conclusions from different developments of comparable individuals, firms, or regions after a treatment. The treatment is commonly identified through increased accessibility due to transport infrastructure improvements such as the opening of new road or rail connections. A variety of methods is applied in this field: Gibbons & Machin (2005) use Difference-in-Differences models with unique treatment and control groups, Ahlfeldt & Feddersen (2015) identify discontinuities in their data, Yoshino & Abidhadjaev (2017) work with several treatment groups subject to different treatments, and Gibbons et al. (2019) estimate the effect of a continuous treatment intensity variable.

An aspect that becomes more and more important in the analysis of public capital effects, especially in the case of infrastructure networks, is the spatial component of such investments. In economic theory, this development is driven by New Economic Geography and an increasing impact of urban and regional science practices (Fujita, Krugman, & Venables, 1999). The methodological scope is widened through the use of spatial econometric methods, which are increasingly important (Elhorst, 2014). The intuitive idea behind this advance is that regional economic development is not determined exclusively within the region, but that other areas also have an impact. Factors like trade, mobility, and communication require analyzing interactive systems instead of independent units, while aspects like urbanization and agglomeration define how regions interact, influencing each other's economic development (Fingleton, 2001). In the context of public investment, the existence of such spillover effects is widely accepted, even though several cases of no or negative effects have been found (Arbués et al., 2015). Consequently, models and estimation procedures in the field of spatial econometrics are increasingly sophisticated: Among other examples, Elhorst (2001) introduces a time- and space-dynamic model, Kapoor, Kelejian, & Prucha (2007) account for spatially correlated error components, and Kelejian & Prucha (2004) apply spatial methods in an SEM framework. Even though the use of spatial econometric methods is the standard in newer research, discussions on the specification of models continue. Halleck Vega & Elhorst (2015), describing the wide range of models accounting for exogenous, endogenous, and autoregressive spatial components, advocate the use of the simple spatial lag of X (SLX) model as a starting point instead of the commonly used more complex models. Harris & Kravtsova (2009) point out the challenges in defining an appropriate spatial weighting matrix. Elhorst (2014, p. 17) provides a summary of available estimation techniques, including maximum likelihood (ML), IV, and GMM procedures and the importance of their respective assumptions. Empirically, a large body of literature provides evidence for the existence of spillovers: Besides the seminal work of Holtz-Eakin & Schwartz (1995), Pereira & Roca-Sagalés (2003) analyze the effects of total public capital in Spain, while Arbués et al. (2015) focus on transport infrastructure. Barabas et al. (2010) undertake a similar analysis for Germany, Chen & Haynes (2015) use data on the U.S. Northeast Megaregion, and Cosci & Mirra (2018) evaluate the effects of Italian highways.

Building on the existing body of literature, we follow the branch of production function approaches as the advances in this field allow for solving econometric and data-related challenges. We combine this approach, following the current standard in the field, with spatial econometric methods to account for spillovers. While the existing research focuses on the quantity of public capital and uses capital stock values to measure regional endowment, we identify a disregarded field of research in the quality of public capital. Some publications, such as Agénor (2005), study the allocation of public funds to construction and maintenance budgets, but we do not know of any study that identifies the economic effects of changes in the quality of infrastructure. This topic is finding increasing attention with deteriorating infrastructure especially in policy contexts. We therefore add to the literature by combining existing methods with a novel interpretation of public capital.

3. Data

We use yearly data at the German county (Landkreis) level from 2007 through 2016 combined from various sources. The German "Volkswirtschaftliche Gesamtrechnung der Länder" (VGRdL, 2018) supplies GDP and labor statistics for all 401 counties, as well as the total capital on state level differentiated by industries and asset types. We use these data to explain the states' share of the national total capital through their shares of firms differentiated by size and industry in a pooled-OLS panel regression and find a very good fit for this model. Consequently, we use the obtained estimates to approximate county-specific shares of state-level capital using the available county-level industry data of the VGRdL and calculate county-specific capital values. Furthermore, we obtain spatial information from the German Federal Agency for Cartography and Geodesy (BKG), retrieved via OpenDataLab (2016), and the population density from the database of the German Federal Institute for Research on Building, Urban Affairs and Spatial Development, INKAR (BBSR, 2018). To account for human capital effects, we include the share of workers with a university degree (cf. Brunow & Hirte, 2009, p. 806), obtained from the employment statistics of the federal employment agency (Arbeitsagentur, 2018). Finally, all financial values are deflated to 2010 prices using the CPI time series on state level from the German statistics office (Destatis, 2018). Table 1 shows the summary statistics of our variables.

The part of transportation infrastructure we pay attention to in this paper is the German Federal Highway System (*Bundesfernstraßen, BFS*), for which we obtained detailed data from the German Federal Highway Research Institute (BASt, 2017a). This supra-regional road system comprised 13,346km of *Autobahn* (BAB) and 38,597km of *Bundesstraße* (BS) in 2016; measuring individual lanes, we analyze 60,732km and 86,643km, respectively. In the context of the Condition Assessment and Evaluation (*Zustandserfassung und -Bewertung*, ZEB), the condition of the entire network is measured every four years, with data points being logged for lane sections no longer than 100m. We make use of this extensive dataset over three full periods from 2005 to 2016. To obtain the necessary county-level data, we aggregate in the following way: Firstly, we follow the methodology of BASt (2015) to calculate a grade between 1 (best) and 5 (worst) from the assessed damages, grooves, evenness, grip, and other measures for each section. Secondly, we assign geographic coordinates to the starting point of each section and construct the average grade for each county using all lane sections with a starting point in the county. As a small amount of sections is shorter than 100m (e.g., when connecting to another road), we use a weighted average with the weighting based on the section length. To enable a detailed analysis, we calculate three county-specific variables this way: C_A measuring the BAB quality, C_B describing the condition of the BS network, and C as an aggregate measure for both types of roads. While C_A and C_B are calculated using only the segments of the specific network, C follows the same methodology, but includes all sections of BAB and BS with no differentiation. As the assessment years differ between states within the four-year cycles, we allocate them to the respective third year (i.e., 2007, 2011, and 2015) and linearly interpolate in between.

Table 1
Summary Statistics and Sources of variables

	Description	Mean	Median	Var	Min	Max	Sources
Y	GDP (bn €, in prices of 2015)	7.07	4.37	*	0.87	141.24	VGRdL: R2B1
L	Employees' hours worked (Mill. h)	144.26	97.4	*	25.27	2623.23	VGRdL: R2B2
K	Total gross capital value (bn €, in prices of 2015)	39.92	30.73	*	1.65	743.28	VGRdL: R1B4
H	Share of employees with university degree (%)	0.11	0.10	0.003	0.03	0.36	Nat. Employment Statistics
G	Gross asset value of BFS system (Mill. €, in prices of 2015)	575.97	530.58	*	18.99	2581.98	Own calc., BASt, DIW, BKG
C	Condition of BFS system (grade)	2.92	2.90	0.09	2.02	3.98	Own calc., BASt
C_A	Condition of BAB (grade)	2.60	2.60	0.14	1.46	4.69	Own calc., BASt
C_B	Condition of BS (grade)	3.15	3.13	0.13	1.45	4.52	Own calc., BASt
C_C	Condition of bridges of BFS (grade)	2.34	2.34	0.07	1.20	3.19	Own calc., BASt
DU	Dummy: City Counties	0.27					INKAR
DE	Dummy: Former GDR	0.19					INKAR
PD	Population Density (cap/km^2)	520.72	198.00	*	35.6	4737.10	INKAR

Notes: * denotes Variance > 10^5

In addition, BASt supplied information describing the condition of constructions within this network (BASt, 2017b). These information contain the size, location, and condition grades on a yearly basis for all tunnels, bridges, retaining walls, noise barriers, and equipment (e.g., street signs) of the BAB and BS networks. As the number of tunnels is small and the impact of noise protection walls, retaining walls, and equipment on traffic behavior and economic growth is supposedly low, we focus on the quality of bridges. From the grades, which are available for each partial construction (e.g., a bridge consisting of separate structures for each direction counts as two partial constructions) and follow the pattern from 1 (best) to 5 (worst) used in the ZEB, we construct another variable using a procedure similar to the one described above. After identifying the location and assigning a county for all constructions, we calculate C_C as average grade of all bridges within each county, weighted by bridge area (i.e., length multiplied by width). To increase its informative value in counties with few bridges, this variable does not differentiate between the BAB and BS networks.

Highway capital data are calculated from the sophisticated transport infrastructure capital stock model of the BMVI/DIW publication "Transport in Figures" (*Verkehr in Zahlen*; DIW, 2017). This model differentiates total capital not only by transport modes, but further distinguishes between earthworks, superstructure and pavement, constructions, and equipment in road values for different types of roads. However, although highly detailed in this dimension, it does not offer a valuation for subnetworks below the national level. Thus, the provided values are broken down based on highway length, lane availability, constructions (bridges, tunnels, retaining walls, noise protection walls, traffic signs), and topography. For this purpose, we use different measures to determine county-specific shares of the various asset classes: For earthworks, these are shares in lane length and a topography classification, for superstructures we used the share in lane length, constructions are calculated based on their respective share in total size, and for equipment we use the share in road length. The data used for the network characteristics (length, lanes) are taken from the ZEB, identifying both the lane-specific area and the road length within counties. Furthermore, we combine the data from BASt (2017b) on constructions with the data in Korn et al. (2014, p. 7) to identify the respective shares of bridges, tunnels, and retaining walls. Topography data are taken from the Federal Service Centre for Geo-Information and Geodesy and implemented following the procedure of Korn et al. (2018, pp. 52ff) based on their finding of 61.8% of assets being in hilly regions (i.e., height variation above the median) and the remaining 38.2% in flat areas. Finally the county-level asset value is obtained by adding up the individual components.

With respect to the infrastructure variables, strong heterogeneity of the data can be exploited: The mean quantity increases significantly by 12% over time, with changes between -47% and +238% over the observed ten years (10th and 90th percentile are -2% and +31%, respectively). The quality points out an insignificant average improvement of 0.04 grades, significant improvement of 0.15 grades, and significant worsening of 0.02 grades for BAB, BS, and bridges respectively, while all three developments cover at least the range of one grade up and down, for BAB even two grades.

4. Methodology

This paper methodologically follows the strand of work started by Aschauer (1990) in estimating a production function with separated transport-related capital input. It expands this starting point into a spatial production function model with an analysis paying special attention to the impact of transport infrastructure quality and spillovers. We use a Translog specification of the function as described by Berndt & Christensen (1973), with GDP denoting output Y and capital K, labor L, and human capital H as production inputs. As a log-linear function, the Translog specification allows to account for non-linear relationships; furthermore it includes quadratic terms and interaction effects between the input variables and thus covers a wide range of functional forms (ibd.). The commonly used Cobb-Douglas function (Cobb & Douglas, 1928) is a specific case of the Translog model, with the coefficients of the quadratic and interaction terms being zero. The general form of the production function we use can be written as

$$\begin{aligned}\ln(Y) = \ln(A) + \beta_1 \ln(K) + \beta_2 \ln(L) + \beta_3 \ln(H) + \frac{1}{2}\beta_4 \ln(\mathrm{K})^2 + \frac{1}{2}\beta_5 \ln(L)^2 \\ + \frac{1}{2}\beta_6 \ln(H)^2 + \beta_7 \ln(K)\ln(L) + \beta_8 \ln(K)\ln(H) + \beta_9 \ln(L)\ln(H)\end{aligned} \tag{1}$$

The productivity factor A is determined by exogenous factors and allows for including further variables affecting productivity. Accounting for the panel structure of our data, including control variables R, and adding an idiosyncratic error term ε, we can rewrite equation (1) as

$$\begin{aligned}\ln(Y_{it}) = \ln(A_{it}) + \beta_1 \ln(K_{it}) + \beta_2 \ln(L_{it}) + \beta_3 \ln(H_{it}) + \frac{1}{2}\beta_4 \ln(\mathrm{K_{it}})^2 \\ + \frac{1}{2}\beta_5 \ln(L_{it})^2 + \frac{1}{2}\beta_6 \ln(H_{it})^2 + \beta_7 \ln(K_{it})\ln(L_{it}) \\ + \beta_8 \ln(K_{it})\ln(H_{it}) + \beta_9 \ln(L_{it})\ln(H_{it}) + \lambda R_{it} + \varepsilon_{it}\end{aligned} \tag{2}$$

We furthermore assume A to be a function of the quantity of highway capital G and its quality C. A multiplicative connection is established through $A = A(G, C) = (A_0 * G^{\gamma_1} * C^{\gamma_2})$ (cf. Aschauer, 1989). In logarithmic form as in equation (1), the expression turns into

$$\ln(A) \coloneqq \ln(A_0) + \gamma_1 \ln(G) + \gamma_2 \ln(C) \tag{3}$$

To account for a possible nonlinear influence, we estimate a second model that includes quadratic terms of *G* and *C*:

$$\ln(A) \coloneqq \ln(A_0) + \gamma_1 \ln(G) + \gamma_2 \ln(C) + \gamma_3 \ln(G)^2 + \gamma_4 \ln(C)^2 \quad (4)$$

Furthermore, we work with two specifications for highway quality. On the one hand, we estimate our model with the measure *C* as described in section 3, describing the aggregate quality of the pavement of BAB and BS. This setting is described above in equations (3) and (4). On the other hand, we analyze the individual effects of C_A, C_B, and C_C, describing the quality of BAB pavement, BS pavement, and highway constructions, respectively. The second specification has, for the linear and nonlinear form in *G* and *C*, respectively, the forms

$$\ln(A) \coloneqq \ln(A_0) + \gamma_1 \ln(G) + \gamma_2 \ln(C_A) + \gamma_3 \ln(C_B) + \gamma_4 \ln(C_C) \quad (5)$$

$$\begin{aligned} \ln(A) \coloneqq \ln(A_0) &+ \gamma_1 \ln(G) + \gamma_2 \ln(C_A) + \gamma_3 \ln(C_B) + \gamma_4 \ln(C_C) + \gamma_5 \ln(G)^2 \\ &+ \gamma_6 \ln(C_A)^2 + \gamma_7 \ln(C_B)^2 + \gamma_8 \ln(C_C)^2 \end{aligned} \quad (6)$$

The output elasticities, specified as first-order derivatives of $\ln(Y)$, provide the change in GDP resulting from a 1% change in the respective variable. While these elasticities are equal to the estimated values in the linear case, the nonlinear model requires them to be calculated manually and point-specifically. Following standard literature, we evaluate the respective derivatives at the variable mean to obtain average elasticities. Furthermore, we receive the distribution of the nonlinear variables using a bootstrap procedure adapted to the structure of our data. The starting point for this procedure is a cross-sectional block bootstrap as explained by Kapetanios (2008, p. 380), which means we resample county-specific blocks of the full period of 10 years into our bootstrap samples.

Control variables for social and/or sociodemographic characteristics are included to avoid a possible bias through omitted variables (cf. Barabas et al., 2010, p. 80ff). We used several sets of control variables, but find insignificant or weakly significant effects for most of them. To keep the focus on the variables of interest, and following the results of specification tests, we estimate our final model controlling for county fixed effects, population density *PD*, and (through dummy variables) status of an independent city *DU* (i.e., cities that constitute a county by themselves), counties in former Eastern Germany *DE*, and the crisis in 2007-09 *DS*.

As Kelejian & Robinson (1997, p. 116) mention, severe econometric issues are common in studies using production function approaches. In our case, specification tests following Pesaran (2004), Breusch (1978), Godfrey (1978), and Breusch & Pagan (1979) provide evidence for first-order autocorrelation (AR(1)), heteroscedasticity, and cross-sectional dependence in the error term. We address these problems in our estimation methodology, using a two-step feasible generalized least squares (FGLS) estimation procedure, as suggested by Prais & Winsten (1954), that corrects for AR(1). This also addresses cross-sectional dependence and heteroscedasticity by calculating panel-corrected robust standard errors (Beck & Katz, 1995). The software implementation of these methods is done in R, using the package panelAR.

4.1. Spatial Specification

In addition to the transport-related adjustment of the production function, we implement a spatial specification of the model. This is based on the assumption that network infrastructure like highways has an impact not only locally, but, due to its supra-regional importance, also influences economic developments on a larger scale. To account for such spillovers, we amend the model into a "Spatial Lag of X" (SLX) model with exogenous spillover effects. In this type of model, the dependent variable of one unit depends on the independent variables of other units (Elhorst, 2014). As a Moran's I test (Moran, 1950) on a yearly basis finds spatially autocorrelated error terms in some specifications and years (three out of ten years in maximum), we also estimate a Spatial Durbin Error Model (SDEM; Elhorst, 2014), but find that results are close to the SLX findings. In both cases, we restrict the exogenous spatial effects to *G* and *C* following Halleck Vega & Elhorst (2015), turning equation (3), (4), (5), and (6) into

$$\ln(A) \coloneqq \ln(A_0) + \gamma_1 \ln(G) + \gamma_2 \ln(C) + \gamma_1 \ln(WG) + \gamma_2 \ln(WC) \tag{7}$$

$$\begin{aligned} \ln(A) \coloneqq \ln(A_0) &+ \gamma_1 \ln(G) + \gamma_2 \ln(C) + \theta_1 \ln(WG) + \theta_2 \ln(WC) + \gamma_3 \ln(G)^2 \\ &+ \gamma_4 \ln(C)^2 + \theta_3 \ln(WG)^2 + \theta_4 \ln(WC)^2 \end{aligned} \tag{8}$$

$$\begin{aligned} \ln(A) \coloneqq \ln(A_0) &+ \gamma_1 \ln(G) + \theta_1 \ln(WG) \\ &+ \sum\nolimits_{r \in \{A,B,C\}} (\gamma_r \ln(C_r) + \theta_r \ln(WC_r)) \end{aligned} \tag{9}$$

$$\begin{aligned} \ln(A) \coloneqq \ln(A_0) &+ \gamma_1 \ln(G) + \theta_1 \ln(WG) + \gamma_3 \ln(G)^2 + \theta_3 \ln(WG)^2 \\ &+ \sum\nolimits_{r \in \{A,B,C\}} \left(\gamma_{r_1} \ln(C_r) + \theta_{r_1} \ln(WC_r) + \gamma_{r_2} \ln(C_r)^2 + \theta_{r_2} \ln(WC_r)^2\right) \end{aligned} \tag{10}$$

The spatial weighting matrix *W* defines the relative strength of impact between counties. Smith (n.d.) gives an overview on alternative specification for this matrix, as a wide range of options is used in the literature. Barabas et al. (2010) and Moreno & López-Bazo (2003) are examples for the commonly used specifications of distance decay functions and gravity models, respectively. The gravity model accounts for the relative importance of connections between agglomerations based on their respective size (Elhorst, 2018, p. 31):

$$w_{ij} = \frac{z_i^{\rho_1} * z_j^{\rho_2}}{d_{ij}^{\rho_3}} \tag{11}$$

While *d* is geometric distance, *z* can be any variable defining the size of a region. Based on the assumption that economic output proxies the relative importance of transport infrastructure (i.e., highway conditions in high GDP regions have a stronger effect on surrounding areas than those in low GDP areas), we choose the mean of GDP from 2008 to 2016 to determine the economic size of a region with $\rho_1 = \rho_2 = 1$. Following the standard literature, we row-normalize *W*. To analyze the robustness of our results with respect to the specification of *W*, we estimate the model for multiple values of ρ_3 in the gravity model as well as for different distance decay parameters in a simple inverse distance specification and show the results in the appendix. Our approach is supported by the findings that the results of the two specifications are close to each other and stable in the common range of decay parameters larger than 1. Considering it more meaningful, we choose the gravity model over the inverse distance matrix, but take the second one for robustness checks, each with a distance decay parameter of $\rho_3 = 2$.

To obtain a distribution of the elasticities of the non-linear variables, we again refer to Kapetanios (2008). These variables include the input factors for all specifications as well as the infrastructure variables in the non-linear specifications (equations (8) and (10)). We combine this approach with the methodology applied by Loh (2008), which suggests using observation-specific marks. In this approach, the spatial variables are calculated from the original sample and treated as marks corresponding to their spatial unit instead of to the bootstrapped spatial reference system. Thus, we use the spatial values calculated in the original dataset and avoid recalculating them for each bootstrap sample based on the sample-specific weighting matrix. It must be noted that, as García-Soidán, Menezes, & Rubiños (2014) point out, the spatial auto-regressive parameter in the SDEM causes the assumption of independence to fail. In order to establish consistency of our bootstrap estimates, we adjust the spatial weight matrix *W* to each bootstrap sample by recalculating it for the randomly drawn set of counties.

4.2. Endogeneity Control Model

Severe endogeneity issues due to reverse causality are found in previous studies in the field, for example by Duffy-Deno & Eberts (1991) in a theoretical model and Kemmerling & Stephan (2008) in an empirical application. In our case, it also seems reasonable to assume that highway endowment does not just influence economic growth, but also depends on it: Political allocation processes might go either in the direction of investing more in flourishing regions, as there is high demand for infrastructure, or in the opposite direction of supporting left-behind areas to foster convergence. For the quality of infrastructure, the argument is that more economic output increases traffic and thus wear and tear of infrastructure. To get an impression about these connections, we set up and estimate a control model. We start by defining the public capital accumulation equation and identifying the investment *I* from *G* and capital outflow *D*:

$$G_{it} = G_{it-1} + I_{it} - D_{it} => I_{it} = G_{it} - G_{it-1} + D_{it} \tag{12}$$

Incorporating the assumed relationships between investment, existing capital stock, condition, and output similarly to Mizutani & Tanaka (2010), we identify the following investment and quality equations:

$$\ln(I_{it}) = \delta_1 \ln(G_{it-1}) + \delta_2 \ln(C_{it-1}) + \delta_3 \ln(Y_{it-1}) + \delta_4 \ln(WY_{jt-1}) + v_{it} \tag{13}$$

$$\ln(C_{it}) = \ln(C_{it-1}) + \eta_1 \ln(I_{it}) + \eta_2 (Y_{it}) + \eta_3 \ln(WY_{jt}) + u_{it} \tag{14}$$

In these equations, we expect the following relationships: δ_2 is positive, as worse conditions lead to higher investment, while δ_1, δ_3, and δ_4 are either negative implying convergence or positive implying divergence strategies with respect to highway endowment (δ_1), local GDP (δ_3), and regional GDP (δ_4). Similarly, we expect η_1 to be negative, as higher investment improves infrastructure quality, while η_2 and η_3 are expected to be positive, as more production output, leading to more traffic, decreases highway conditions. Inserting the first in the second equation and subtracting C_{it-1}, we can reformulate the model as

$$\begin{aligned} \Delta \ln(C_{it}) = {} & \varphi_1 \ln(G_{it-1}) + \varphi_2 \ln(C_{it-1}) + \varphi_3 \ln(Y_{it-1}) + \varphi_4 \ln(WY_{jt-1}) \\ & + \eta_2 \ln(Y_{it}) + \eta_3 \ln(WY_{jt}) + z_{it} \end{aligned} \tag{15}$$

$$\textit{with } \varphi_1 = \delta_1 \eta_1, \varphi_2 = \delta_2 \eta_1, \varphi_3 = \delta_3 \eta_1, \varphi_4 = \delta_4 \eta_1, \textit{ and } z_{it} = \eta_1 v_{it} + u_{it}$$

Mizutani & Tanaka (2010) and Kemmerling & Stephan (2008) develop similar models and estimate them using simultaneous equation modelling methodologies. We do not follow this approach due to data restrictions, especially with respect to investment.

As county-level information on actual investment are not available, we derive values from the capital stock model via equation (12). These data depend strongly on our calculation procedure for county-level capital values as described in the previous chapter and the assumption of a homogeneous outflow across counties and asset categories: We assume that a county's share of the national capital stock within a category (e.g., bridges) is equivalent to the county's share in the outflow of the category. This is reasonable for the capital stock model with a long-term averaged outflow function on the national level, but it can lead to serious distortions on the detailed level we estimate. This conclusion is also visible in the data: a mean outflow of 7.36 bn Euros per year and a median of 11.52 bn Euros denote between 1.3% and 1.4% of the capital stock (standard error: 18.29), which is reasonable, but in 9.7% of the observations the calculation returns a negative investment with a minimum of -96.68 bn Euros. This underlines the need for reliable, accounting-based investment data for further research, especially in combination with more exhaustive methodologies such as simultaneous equation models. As such data are not available, we estimate the control model set up above to get an impression of the causal directions in our model, but we acknowledge that the estimation results can only point in a general direction rather than provide reliable information about specific effects.

We estimate equations (13) and (15), while leaving out equation (14) due to the aforementioned unreliability of the investment data. For equation (13), we compare a standard fixed-effects panel estimator with individual- and time-fixed effects and the System-GMM estimator following Blundell & Bond (1998). Due to the lagged structure of this equation, we do not expect endogeneity caused by reverse causality, and thus expect both estimators to be consistent. The results are presented in Table 2.

The formulated expectations with respect to investment behavior are mostly confirmed: The left part of Table 2, showing the estimation of equation (13), highlights a public investment strategy clearly aiming for regional convergence. The coefficients of the public capital stock (δ_1), the local GDP (δ_3), and its spatially weighted counterpart (δ_4) are negative in both models, which means that regions well-endowed with infrastructure as well as economically strong areas receive less highway investment, while regions lagging behind are supported through

Table 2
Estimation of Equations (13) (left) and (15) (right): Road Quality and Investment Model

Symbol	Variable	FE-Panel	System-GMM	Symbol	Variable	System-GMM
δ_1	$\ln(G_{it-1})$	-9.897***	-1.832	φ_1	$\ln(G_{it-1})$	-0.011***
		(0.689)	(1.185)			(0.004)
δ_2	$\ln(C_{it-1})$	2.791***	-4.209	φ_2	$\ln(C_{it-1})$	-0.046***
		(1.035)	(3.225)			(0.015)
δ_3	$\ln(Y_{it-1})$	-3.332***	-1.487	φ_3	$\ln(Y_{it-1})$	0.026
		(1.242)	(1.285)			(0.022)
δ_4	$\ln(WY_{jt-1})$	-8.838***	-3.147**	φ_4	$\ln(WY_{jt-1})$	-0.019
		(2.878)	(1.560)			(0.022)
				η_2	$\ln(Y_{it})$	0.047*
						(0.026)
				η_3	$\ln(WY_{jt})$	-0.049*
						(0.026)

Notes: *, **, & *** relate to significance on the 90, 95, and 99%-levels, respectively higher investment. However, it must be noted that the local effects are not found to be signifcant using the GMM estimator and that, even though the sign is consistently negative, the estimated values differ severely between the two estimation procedures. Furthermore, the effect of highway quality (δ_2) is estimated significantly positive with 2.79 using the panel estimator, thus confirming the expectation, but the GMM coefficient for this variable is insignificantly negative with a rather high value of -4.21. These data show that the assumption of two-way causality between the public capital stock and GDP is indeed reasonable, and that adequate measures against a potential bias should be taken in the estimation procedure. As we cannot guarantee the reliability of the investment data and as the results between the two estimators differ, however, no conclusions concerning the size of such dependencies can be drawn.

The estimation of equation (15), which is given in the right part of Table 2, provides insights into the development and the determinants of highway quality. Due to the composite nature of the equation and its error term $z_{it} = \eta_1 v_{it} + u_{it}$ as well as due to the expected two-way causal relationships, the assumption of exogeneity does not hold in equation (15). As the panel estimator might be biased in this situation, we use only the System-GMM procedure. Starting with the contemporaneous effect of local and regional production, we find η_2 and η_3 to be significant on the 90% level, providing some evidence that GDP indeed affects highway quality. While the local effect (η_2) is positive, meaning that higher GDP in a county corresponds to worse roads in the same county, the negative spatial effect (η_3) states that a GDP increase in surrounding regions involves better highway quality. With φ_3 and φ_4, the same effects are found for the local and spatial GDP lagged by one year, even though these coefficients are not significant at a 90% level and the model interprets them as indirect effects through the investment equation. This provides evidence that the assumption of two-way causality between GDP and road quality is reasonable and must be taken into account. Furthermore, the GMM estimation returns strongly significant negative coefficients for the lagged public capital and the lagged highway quality. Due to the equation structure and their multiplicative construction, we cannot interpret these coefficients without further assumptions. Taking the findings from equation (13) into account, we do not find support for our assumption of η_1 being negative, but the results cannot provide evidence for the opposite case either, leaving the effect of investment on road quality unclear.

This model cannot provide precise descriptions of the interdependence between GDP, highway quality, and investment due to the uncertain reliability of the data, but the results show that the assumption of two-way causality is reasonable. A Wu-Hausman test (Greene, 2012, pp. 234ff) provides evidence for inconsistency of the OLS estimation of specifications (7), (9), and (10) at a 99% confidence level, supporting the use of an estimator accounting for endogeneity. The standard approach to avoid such problems is the use of instrumental variables (IVs). As strong instruments for panel data sets are hard to find, even more so for several variables, we exploit the spatial characteristics of our model. Instead of additional exogenous instruments, we use spatial, temporal, and spatiotemporal lags of the respective variables as instruments. As Lee & Yu (2014) and Kelejian & Robinson (1997) point out, the simultaneity problem can be addressed in this setting using a general method of moments (GMM) IV estimator. The consistency of such an estimator using spatial lags of dependent variables as instruments is proven by Kelejian & Robinson (1993, p. 302). We use the R package SPLM to implement the procedure and estimate a model that accounts for the endogeneity. F-tests for weak instruments confirm that all our instruments are meaningful for all specifications in (7) to (10) with p<0.0001, so the results are less prone to simultaneity bias.

5. Results

We estimate the production function specified in the previous chapter using several methodologies and specifications to check the robustness of our findings. These alternatives include the FGLS and the GMM estimation, each used to calculate a linear and a non-linear version of the models with an aggregate quality measure and with specific variables for BAB, BS, and bridge quality. Following the previously specified forms, we estimate equation (2) using specifications (7), (8), (9), and (10). The results of the specifications with an aggregated quality variable (equations (7) and (8)) are shown in Table 3, the estimation outcomes with disaggregated quality data ((9) and (10)) are shown in Table 4. In both cases, the tables show elasticities, i.e. the derivation of $\ln(Y)$ with respect to the variable under consideration. For variables with a non-linear effect, the elasticity is calculated manually as the derivation at the sample mean of the variable and the standard errors are bootstrapped, as explained in the methodology section. Detailed full estimation results are presented in Table 5 and Table 6 in the appendix. Several aspects stick out from the data in these tables, including similar outcomes for linear and non-linear specifications, support for our hypotheses especially in the model with a single condition measure, and differences between the FGLS and GMM estimation.

5.1. Model with Aggregated Road Quality

Starting with the model including an aggregate quality measure, we observe support for all our hypotheses in all specifications. Table 3 shows these results for the FGLS and GMM estimation of the linear (7) and non-linear (8) forms.

As the FGLS estimates exhibit increasing returns to scale, we also develop a restricted version of equation (1) imposing constant returns to scale through $\beta_L + \beta_K = 1$. The detailed derivation of this restriction is contained in the appendix: due to the non-linearity of the Translog function, the restriction is imposed on the elasticities, and thus affects all input-related coefficients. The elasticities estimated for the restricted model using the non-linear specification (7) are shown in the third column of Table 3. We attribute the increasing returns to scale in the unrestricted model to omitted control variables even though we do not find significant effects of these variables when we account for them in our model: Evans & Karras (1994) find a significant impact of the unemployment rate, while Barabas et al. (2010) include the age structure. Through the restriction of our model, β_L decreases in all specifications to values around 0.8. While the loss in model fit is negligible and the infrastructure-related estimates as well as the returns to capital and human capital input stay unaffected by the restriction, we see significant changes in the control variables. We thus conclude that indeed our findings are driven by labor-related omitted variables.

The estimated effects of the input variables in the GMM, the restricted FGLS, and the unrestricted FGLS besides β_L are in the common range for production function results (cf. Melo et al., 2013): the labor elasticity is found to be 0.78-0.82, the elasticity we find for capital input

Table 3
Estimated Elasticities at Sample Means for Production Function with aggregated Road Quality
(Full Estimation Results in Table 5 in the Appendix)

		FGLS			GMM	
Symbol	Variable	Linear (7)	Nonlinear (8)	Restricted	Linear (7)	Nonlinear (8)
α_0	Intercept	16.68***	17.32***	16.14***		
		(2.15)	(2.47)	(2.14)		
β_L	ln(L)	0.99***	0.99***	0.78***	0.82***	0.82***
		(0.05)	*(0.05)*	*(0.00)*	*(0.08)*	*(0.08)*
β_K	ln(K)	0.23***	0.23***	0.22***	0.24***	0.24***
		(0.02)	*(0.02)*	*(0.00)*	*(0.03)*	*(0.03)*
β_H	ln(H)	0.37***	0.37***	0.39***	0.27***	0.27***
		(0.02)	*(0.02)*	*(0.00)*	*(0.04)*	*(0.04)*
γ_G	ln(G)	0.01	0.03	0.01	0.07***	0.10**
		(0.02)	*(0.02)*	(0.02)	(0.02)	*(0.03)*
γ_C	ln(C)	-0.04*	-0.04	-0.04**	-0.06***	-0.06
		(0.02)	*(0.03)*	(0.02)	(0.02)	*(0.04)*
θ_G	ln(WG)	0.26***	0.25***	0.26***	0.26***	0.27***
		(0.05)	*(0.06)*	(0.05)	(0.04)	*(0.06)*
θ_C	ln(WC)	-0.14	-0.13**	-0.12	-0.08*	-0.07
		(0.11)	*(0.07)*	(0.11)	(0.05)	*(0.08)*
λ_U	DU	0.68**	0.68**	0.39		
		(0.34)	(0.34)	(0.29)		
λ_E	DE	-0.45	-0.42	-0.85**		
		(0.45)	(0.45)	(0.38)		
λ_S	DS	-0.03**	-0.03**	-0.04**	-0.06***	-0.06***
		(0.02)	(0.02)	(0.02)	(0.00)	(0.00)
λ_{PD}	ln(PD)	-0.59***	-0.58***	-0.47**	-0.35***	-0.33
		(0.20)	(0.20)	(0.19)	(0.06)	(0.06)
ρ	Spatial AR				0.39	0.39
R^2	R-squared	0.9984	0.9984	0.9893		

Notes: Standard Errors in Brackets; Bootstrapped Standard Errors in *Italics*;
*, **, & *** relate to significance on the 90, 95, and 99%-Level, respectively

(β_K) ranges from 0.22 and 0.24, and human capital effects are between 0.27 and 0.37. These results and their stability across different specifications support our production function approach. In all our estimations we find higher GDP in urban counties and lower output in the former East German states as well as during the crisis, which is expected, whereas a significant negative impact of population density throughout all specifications is surprising. For the GMM results, no impact of the county-specific, time-constant variables can be estimated, as we also use county fixed effects (these can be obtained from the authors upon request).

With respect to the transportation-related variables, the estimation results in Table 3 provide evidence for all our hypotheses. Firstly, we find a positive impact of the quantity of highways, connecting better endowment in a county with a higher local output. This effect is positively significant between 0.07 and 0.10 in the GMM models accounting for potential endogeneity, thus in line with existing research, and insignificant between 0.01 and 0.03 in the FGLS case. We attribute the lower values in the FGLS estimation to reverse causality issues and expect the GMM results to be more reliable, as this estimator tackles the endogeneity issue.

Concerning spatial effects, we find strong spillover impacts between 0.25 and 0.27, meaning a 1% increase in the highway capital stock in all counties but one causes an increase in GDP of 0.25% in the unchanged county. This is a relatively high effect compared to existing literature, which we attribute to our specification of W without a cut-off distance and with a moderate decay parameter. Our comparison over a range of decay parameters, displayed in the appendix, shows that a stronger decay decreases the effect of the spatial variables and increases the impact of the local variables. Thus, a stronger spatial decay shifts the estimated impact from spatial to local variables, effectively lowering the spillovers.

Furthermore, Table 3 notes the impact of infrastructure quality on local and supra-regional economic development, supporting our second hypothesis. The local effect of a change in highway quality is estimated to be -0.04 in the FGLS and -0.06 in the GMM model, with significance at levels between 90% and 99% in the linear specifications and insignificance in the nonlinear model due to slightly higher standard errors. As lower grades refer to better condition, these results highlight that worse highway quality is correlated with a decrease in local economic output and that the effect is, depending on the specification, almost as strong as (GMM) or even stronger than (FGLS) the impact of the capital stock quantity.

On a supra-regional level, we find spatial spillovers in all specifications, ranging from -0.07 to -0.14. Compared to the impact of highway quantity, the quality has a lower spatial effect, but it is still found to be significant at the 90% or even 95% level in several specifications.

These findings provide clear support for our hypotheses and point out the importance of infrastructure quality on regional GDP, both through their values and through their stability across specifications and estimation procedures. Finally, Table 3 shows that the non-linear expansion of the transport infrastructure terms does not add to the explanatory power of the model. The detailed estimates in Table 5 in the appendix support this, as the only significant non-linear coefficient is the estimate for $\ln(G)^2$ in the GMM estimation.

5.2. Model with Disaggregated Road Quality

The estimation results of specifications (9) and (10), exploiting the details of our dataset through separate measures for the quality of BAB, BS, and bridges, are presented in Table 4. With respect to the variables of our general production function as specified in equation (2), a considerable share of the values is identical to the numbers in the simpler model presented in Table 3, with no severe differences found. Some shifts in the control variables are observable, while the returns on all three input variables stay constant. As increasing returns to scale in the FGLS estimation remain, we add a restricted version of specification (9) with $\beta_L + \beta_K = 1$ again, which is presented in the third column of Table 4. The conclusions from this estimation are the same as in the simpler model, so we refer to the discussion above. In general, we find the production function to be highly robust throughout the various specifications we estimate, which supports the methodology. Again, the non-linear expansion leads to little improvement of the model fit, even though Table 6 in the appendix points out that several quadratic terms have a significant impact.

The effects of the highway quantity estimated in the models with disaggregated quality measures also remain very close to the values of the respective base models (i.e., with only one quality variable as presented in Table 3), even though a decrease from 0.26 to 0.22 is observed for the spatial effect in the FGLS estimations. Thus, the more detailed models provide further evidence for the positive effects of public capital, as formulated in our first hypothesis and in line with existing research. Additionally, the results point out the importance of spatial spillovers, as supra-regional effects of the capital stock are found to be significant at a 99% confidence level in all specifications presented in Table 4 with values between 0.21 and 0.26.

Table 4
Estimated Elasticities at Sample Means for Production Function with disaggregated Road Quality (Full Estimation Results in Table 6 in the Appendix)

		FGLS			GMM	
Estimator	Variable	Linear (9)	Nonlinear (10)	Restricted	Linear (9)	Nonlinear (10)
α_0	Intercept	15.76***	15.58***	15.21***		
		(1.90)	(2.11)	(1.89)		
β_L	ln(L)	1.01***	1.01***	0.80***	0.85***	0.85***
		(0.05)	*(0.05)*	*(0.00)*	*(0.08)*	*(0.08)*
β_K	ln(K)	0.22***	0.22***	0.20***	0.23***	0.22***
		(0.02)	*(0.02)*	*(0.00)*	*(0.03)*	*(0.03)*
β_H	ln(H)	0.36***	0.36***	0.39***	0.27***	0.27***
		(0.02)	*(0.02)*	*(0.00)*	*(0.04)*	*(0.04)*
γ_G	ln(G)	0.02	0.03	0.01	0.06***	0.10**
		(0.02)	*(0.02)*	(0.02)	(0.02)	*(0.03)*
γ_{C_A}	ln(C_A)	0.01	0.01	0.01	0.01	0.01
		(0.01)	*(0.02)*	(0.01)	(0.01)	*(0.02)*
γ_{C_B}	ln(C_B)	-0.02	-0.01	-0.03	-0.06***	-0.05
		(0.02)	*(0.03)*	(0.02)	(0.02)	*(0.03)*
γ_{C_C}	ln(C_C)	0.03	0.03	0.03	0.00	0.02
		(0.02)	*(0.03)*	(0.02)	(0.02)	*(0.06)*
θ_L	ln(WG)	0.22***	0.21***	0.22***	0.25***	0.26***
		(0.04)	*(0.05)*	(0.05)	(0.03)	*(0.06)*
θ_{C_A}	ln(WC_A)	0.08	0.08	0.08	0.10***	0.10
		(0.06)	*(0.06)*	(0.06)	(0.03)	*(0.07)*
θ_{C_B}	ln(WC_B)	-0.27***	-0.27***	-0.26***	-0.18***	-0.17**
		(0.05)	*(0.07)*	(0.05)	(0.04)	*(0.08)*
θ_C	ln(WC_C)	0.31**	0.31***	0.30**	0.39***	0.36***
		(0.13)	*(0.08)*	(0.14)	(0.07)	*(0.11)*
λ_U	DU	0.78**	0.78**	0.47*		
		(0.32)	(0.32)	(0.28)		
λ_E	DE	-0.52	-0.50	-0.93**		
		(0.44)	(0.44)	(0.37)		
λ_S	DS	-0.04**	-0.04**	-0.04**	-0.06***	-0.06***
		(0.01)	(0.14)	(0.02)	(0.00)	(0.00)
λ_{PD}	ln(PD)	-0.63***	-0.62***	-0.50***	-0.37***	-0.34***
		(0.19)	(0.19)	(0.19)	(0.06)	(0.06)
ρ	Spatial AR				0.37	0.38
R^2	R-squared	0.9984	0.9984	0.9895		

Notes: Standard Errors in Brackets; Bootstrapped Standard Errors in *Italics*;
*, **, & *** relate to significance on the 90, 95, and 99%-Level, respectively

As Table 4 also shows, the estimated effects of all six quality variables, which are the local and the spatial values of the BAB, BS, and bridge quality, respectively, are highly consistent throughout all specifications. In addition, the sign of the spatial impact corresponds to the sign of the local effect in all three quality variables.

For the quality of the BAB, a local effect of 0.01 is found in all specifications, and a spatial impact of 0.08 for all FGLS- and 0.10 for the GMM-estimations is identified. On the local level, the effect is insignificant at meaningful confidence levels with standard errors larger than the estimated values, and only the linear GMM-estimation procedure finds a significant effect of the spatial variable. All other specifications support insignificance of the spatial effect of BAB quality. Thus, we conclude that the quality of the BAB network is of minor importance for regional economic developments, which is understandable given its role: As a road network connecting main agglomerations, a large part of the German economy, especially small and local businesses, does not depend on or might not even have reasonable access to this system. We therefore expect the much denser BS network, linking rural areas, villages, cities, and metropolises throughout the country with each other, to have a more meaningful effect, and indeed this is confirmed by our results.

Within counties, a BS quality decrease of 1% corresponds to a GDP slowdown of 0.01% to 0.03% according to the FGLS estimator and 0.05% to 0.06% in the more consistent GMM estimation, even though significance at common levels is found only in the GMM values of the linear model. This provides some support for our second hypothesis and the results of our base model (Table 3). Besides this local effect, the BS network is of strong importance across county borders, as the estimated spatial quality effect shows: In four of our five specifications, significance at the 99% confidence level is found (95% in the fifth estimation) for values of -0.26 to -0.27 in the FGLS- and -0.17 to -0.18 in the GMM-estimated models. These values not only support our quality-related hypothesis, but they also point out the contribution of our GMM-estimation procedure to the correction of an endogeneity bias of the FGLS-estimates. We conclude that as the BS system is of major importance for businesses operating locally and on a more regional basis, it has the potential to considerably influence economic growth.

The third quality variable, describing the condition of bridges, has an unclear effect on GDP. We estimate insignificant effects between 0.00 and 0.03 for the local impact, but we obtain estimates of 0.30-0.31 (FGLS) and 0.36-0.39 (GMM) for the spillovers, significant at at least the 95% confidence level. While the local values allow for the conclusion that bridge quality has very little effect on economic developments, if any, the spatial results strongly reject our quality-related hypothesis for the case of highway constructions. A possible explanation might be that the data on the quality of bridges are differently measured and structured than the surface condition data from the ZEB, or that the hypothesis is just not supported by the empirical data. The result suggests that the surface quality of highways affects businesses through other channels than the condition of bridges, but further research is necessary to identify the underlying phenomena.

Before drawing conclusions and discussing our results from a policy-oriented perspective, we want to outline the robustness of our estimation results across the different specifications. For all variables in all models, we see that the differences between the linear and the nonlinear case are extremely small. While the linear model has the advantage of directly observable standard errors (and thus significance levels), we expect the nonlinear case to be slightly more precise. We see, however, that the non-linear effects are hardly significant, and that the linear and non-linear models fit the data equally well. We conclude that the non-linear terms increase the complexity of the model while adding little to its explanatory power.

5.3. Robustness Checks

To confirm our findings, we also estimate a Cobb-Douglas version of the model (Cobb & Douglas, 1928), i.e. we change equation (1) into

$$\ln(Y) = \ln(A) + \beta_1 \ln(K) + \beta_2 \ln(L) + \beta_3 \ln(H) \qquad (16)$$

Furthermore, we estimate specifications with interaction effects between highway capital and quality, between inputs and the transport-related variables, and including both kinds of effects. In all cases, changes compared to the results presented here are negligible. As mentioned in the

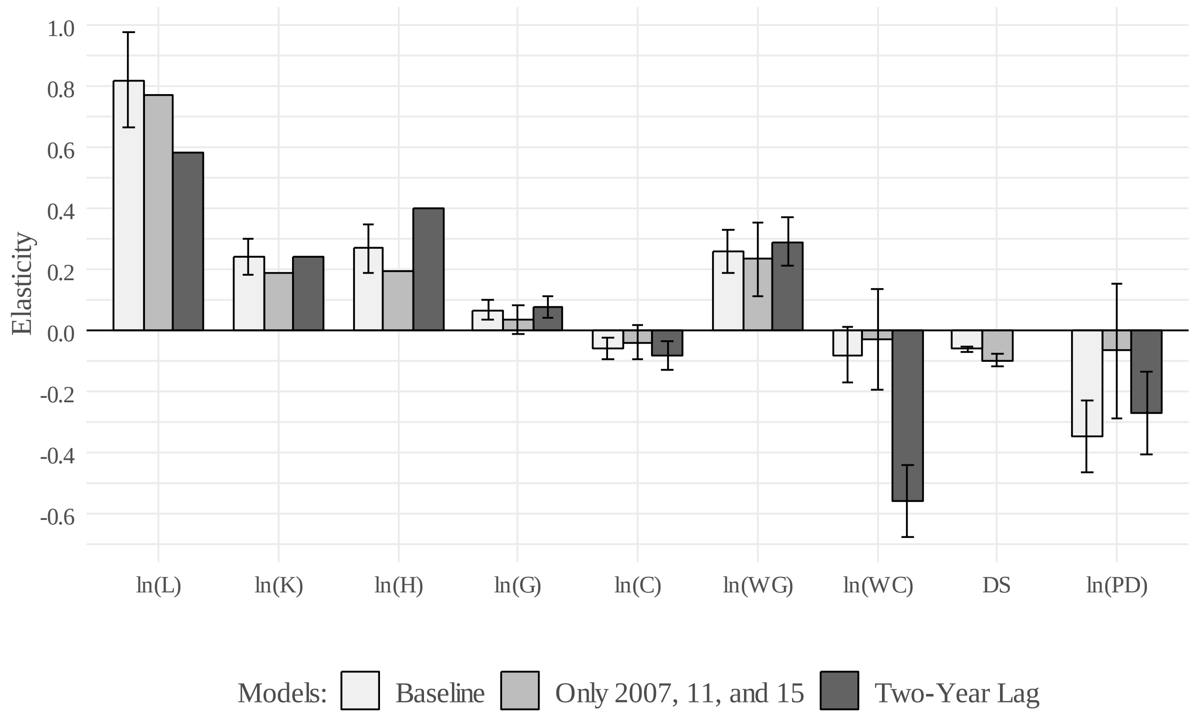

Figure 1 –Robustness Check Models: Elasticities for GMM of Specification (7) with 95% CIs

previous chapter, we also use different specifications of the spatial weighting matrix *W* and the spatial model specification, using both SLX and SDEM estimators. In Tables 3 and 4, we present the SLX case for the FGLS and a SDEM for the GMM estimator, following respective tests as explained in the methodology section. In all cases, we find very similar results to those presented here, which points out the robustness of our model.

Another aspect we pay attention to in the robustness checks is the slow development over time of many of our variables. While we account for autocorrelation in the estimation, we compare the obtained results with two robustness check models: In the first one, we restrict our sample to three specific years, and in the second we introduce lags. Following the structure of the ZEB, we reduce the sample to include only data for the years 2007, 2011, and 2015. These are the years we attribute the three ZEB measurement cycles to, which means that any changes in the ZEB between these years are linearly interpolated. In the second robustness check, we replace the traffic variables with their own lags for up to three years. Figure 1 compares the estimated elasticities for the GMM estimation of specification (7) using the complete dataset, the reduced dataset for only 2007, 2011, and 2015, and the infrastructure variables lagged by two years. It shows that the differences in the results are, on an overall scale, small and that the direction of all coefficients stays constant throughout the estimations. Neither the deletion of 70% of the information in the reduced dataset nor the inclusion of lags leads to strong changes in the results.

The coefficient of the spatially weighted quality variable in the lagged model differs significantly from the other two specifications, suggesting an unreasonably strong effect that is also found in the FGLS-estimated control model. However, as the impact remains negative, we see this as driven by data characteristics specific to the first two years. Further comparisons with a model leaving out the first two years provide results similar to the base model and do not replicate the strong impact of the spatial quality variable. Overall, the figures point out that our methodology is robust with respect to the signs and, with few exceptions, size of the estimated coefficients and that the same conclusions can be drawn throughout all robustness checks.

We furthermore estimate our model using several subsamples restricting years, states, or both, again finding that the estimation results change little. The signs and the general size of the coefficients stays constant throughout the specifications, providing further support for the robustness of our findings. The results of all robustness checks are available upon request from the authors.

6. Conclusion

In this paper, we provide evidence for the importance of endowment with, and quality of, transportation infrastructure for economic growth within both the region of investment and its surrounding area. The results of our estimations suggest that counties endowed with, and surrounded by, more highways tend to be significantly more productive than less connected regions. Especially the condition of the BS system has a similar, yet not as strong effect: better roads improve the economic prospects of regions. We conclude that public investment into transport infrastructure, if adjusted to demand and maintained in good shape, can foster growth. On the other hand, insufficient and neglected infrastructure can limit positive developments.

Overall, the results strongly support our hypotheses. All specifications fulfil the expectation with respect to the impact of highway capital, finding support for the hypothesis that investment spurs economic growth. This is in line with findings of existing research for various settings. A supra-regional impact of the public capital stock is found in the literature, for which we provide further evidence.

Concerning the quality effects of infrastructure, our analysis opens a new strand of research. The data we use, based on the ZEB and adjusted for this application, has not been used in economic contexts before. Public discussions about the state of roads in Germany need scientific research and our analyses show that quality has an effect on regional development. Looking at an aggregate measure of highway surface quality, we find worsening infrastructure to correlate with economic slowdowns, with a 1% decrease in conditions corresponding to a 0.04% to 0.06% decrease in local GDP. This effect is as strong as the impact of highway capital, making clear that a one-sided discussion about quantity leaves out a crucial element of the overall picture. Making full use of the detailed dataset, we differentiate between BAB, BS, and bridge conditions and draw more detailed conclusions: the effect we observe for the condition of the total highway network is driven by the BS system. The analysis shows that the BS network in Germany has the potential to become a bottleneck for regional economic growth, if maintained insufficiently, but also that high road quality can be a decisive factor in favor of regions. This makes intuitive sense, as the BS network connects locations directly on local, regional, and national levels and is essential for businesses on a daily basis, whereas the BAB network is used mostly for longer-distance transport. Finding the expected effect for the BS network, but not for the BAB, we conclude with respect to the second hypothesis that the quality of transport infrastructure can have an impact on economic developments, but it varies between different types of networks. The conclusion holds on both a local level and for the spatially weighted variables, with strong spillovers of the total quality and the BS quality found in the estimation of the single- and multiple-quality measure specifications, respectively. Furthermore, we find that higher quality of bridges correlates with lower production output especially in the spatial variable, which needs further research to be understood and explained.

Another conclusion we draw is that the findings depend on the specific definition of the infrastructure under consideration. It is therefore crucial to keep aspects like data availability on different levels of aggregation and detailedness of the estimated models in mind and check the robustness of results. Accounting for endogeneity through a GMM estimator in comparison to an FGLS procedure, we see some indications for a weak bias in the FGLS results due to reverse causality. In addition to a GMM estimation, several methodologies can be used to address this issue: examples are given by, among others, Mizutani & Tanaka (2010), using simultaneous equations to incorporate the autoregressive and endogenous nature of the data into the estimation, and Carlsson et al. (2013), using a feedback loop. Due to data availability and reliability reasons, we leave this for future research.

In order to avoid insufficient highway infrastructure limiting positive economic development in Germany, two important lessons can be learned from our findings: On the one hand, expanding the network can foster positive developments, especially in and around fast-growing regions, with highway access being an important tool to address regional divergence. On the other hand, it is necessary to adjust the maintenance funding of transport infrastructure in Germany to rising levels of traffic before accessibility becomes a limiting factor. Increasing productivity leads to more and heavier traffic. Thus, greater investment is important to slow the decrease in bridge conditions, stabilize highway quality, and support further economic growth.

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Appendix

Appendix A: Derivation of Restricted Version of Equation (1)

Recall Equation (1):

$$\begin{aligned}\ln(Y) = \ln(A) + \beta_1 \ln(K) + \beta_2 \ln(L) + \beta_3 \ln(H) + \frac{1}{2}\beta_4 \ln(\mathrm{K})^2 + \frac{1}{2}\beta_5 \ln(L)^2 \\ + \frac{1}{2}\beta_6 \ln(H)^2 + \beta_7 \ln(K)\ln(L) + \beta_8 \ln(K)\ln(H) + \beta_9 \ln(L)\ln(H)\end{aligned} \tag{1}$$

The restriction $\beta_K + \beta_L = 1$ in full specification is expressed as follows:

$$\frac{\partial \ln(Y)}{\partial \ln(K)} + \frac{\partial \ln(Y)}{\partial \ln(L)} = 1 \tag{17}$$

The first-order derivatives of Equation (1) w.r.t. $\ln(K)$ and $\ln(L)$ are:

$$\frac{\partial \ln(Y)}{\partial \ln(K)} = \beta_1 + \beta_4 \ln(K) + \beta_7 \ln(L) + \beta_8 \ln(H) \tag{18}$$

$$\frac{\partial \ln(Y)}{\partial \ln(L)} = \beta_2 + \beta_5 \ln(L) + \beta_7 \ln(K) + \beta_9 \ln(H) \tag{19}$$

We denote the sample mean of $\ln(X)$ as $\overline{\ln(X)}$ and evaluate the derivatives at the sample mean. Imposing the restriction from Equation (17) and rearranging, we reformulate as follows:

$$\beta_1 + \beta_2 + (\beta_4 + \beta_7) * \overline{\ln(K)} + (\beta_5 + \beta_7) * \overline{\ln(L)} + (\beta_8 + \beta_9) * \overline{\ln(H)} = 1 \tag{20}$$

Further rearranging terms, we derive the following expression:

$$\beta_2 = 1 - \beta_1 - (\beta_4 + \beta_7) * \overline{\ln(K)} - (\beta_5 + \beta_7) * \overline{\ln(L)} - (\beta_8 + \beta_9) * \overline{\ln(H)} \tag{21}$$

Replacing β_2 in Equation (1) with this expression and rearranging to isolate the estimation coefficients, we finally obtain the restricted model specification to be estimated:

$$\begin{aligned}\ln(Y) - \ln(L) = \ln(A) + \beta_1(\ln(K) - \ln(L)) + \beta_3 \ln(H) \\ + \beta_4\left(\frac{1}{2}\ln(\mathrm{K})^2 - \overline{\ln(K)}\ln(L)\right) + \beta_5\left(\frac{1}{2}\ln(L)^2 - \overline{\ln(L)}\ln(L)\right) \\ + \frac{1}{2}\beta_6 \ln(H)^2 + \beta_7\big(\ln(K)\ln(L) - \overline{\ln(K)}\ln(L) - \overline{\ln(L)}\ln(L)\big) \\ + \beta_8\big(\ln(K)\ln(H) - \overline{\ln(H)}\ln(L)\big) + \beta_9\big(\ln(L)\ln(H) - \overline{\ln(H)}\ln(L)\big)\end{aligned} \tag{22}$$

Appendix B: Spatial Decay Analysis

The following graphs provide the estimated elasticities based on the specification given in Equation (7), i.e. with an aggregate measure for road quality and in the linear specification, using the FGLS estimation procedure. The solid lines refer to the spatial weighting matrix based on the gravity model given in Equation (11); the dotted lines show the values of an inverse distance weighting scheme. More details are given in section 4.1.

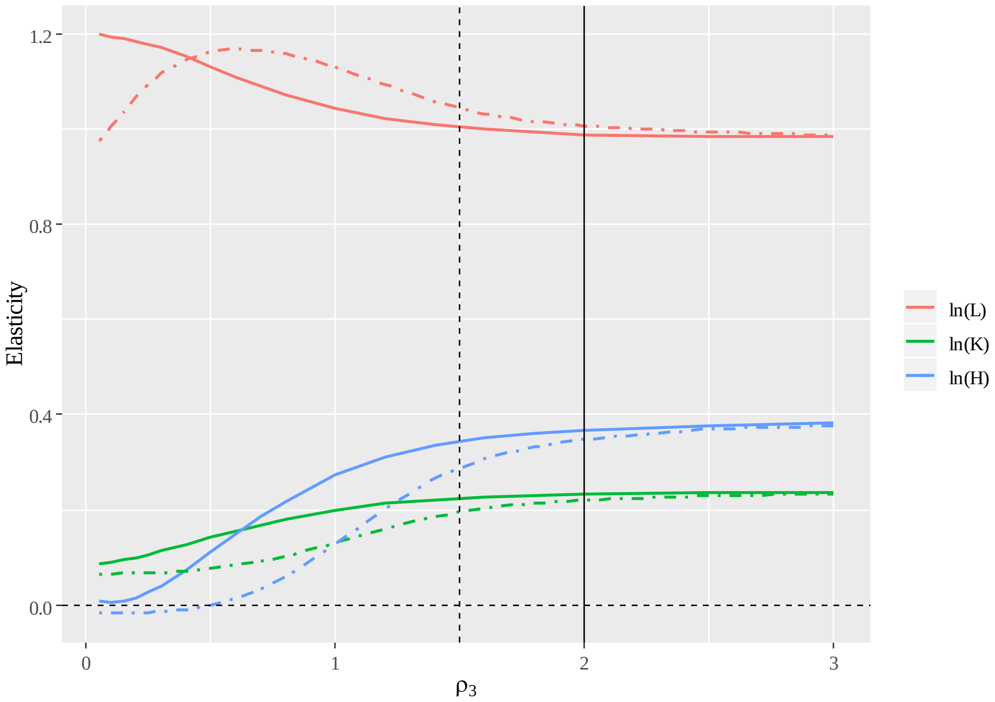

Figure 2 – Spatial Decay Analysis: Production Inputs (Solid: Gravity Model; Dashed: Inverse Distance)

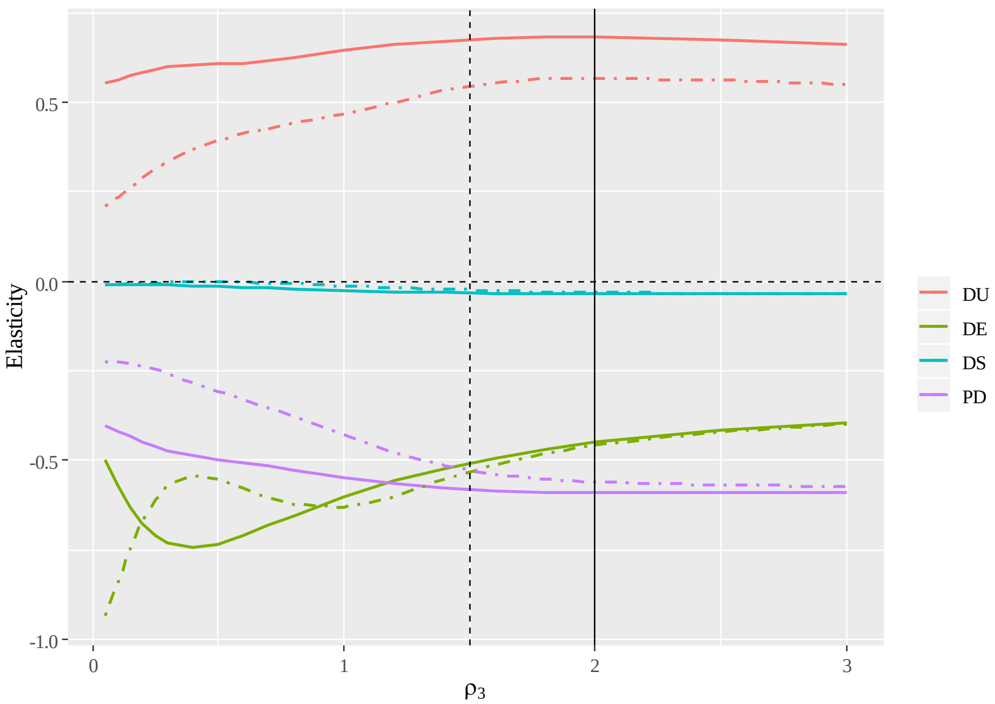

Figure 3 – Spatial Decay Analysis: Control Variables (Solid: Gravity Model; Dashed: Inverse Distance)

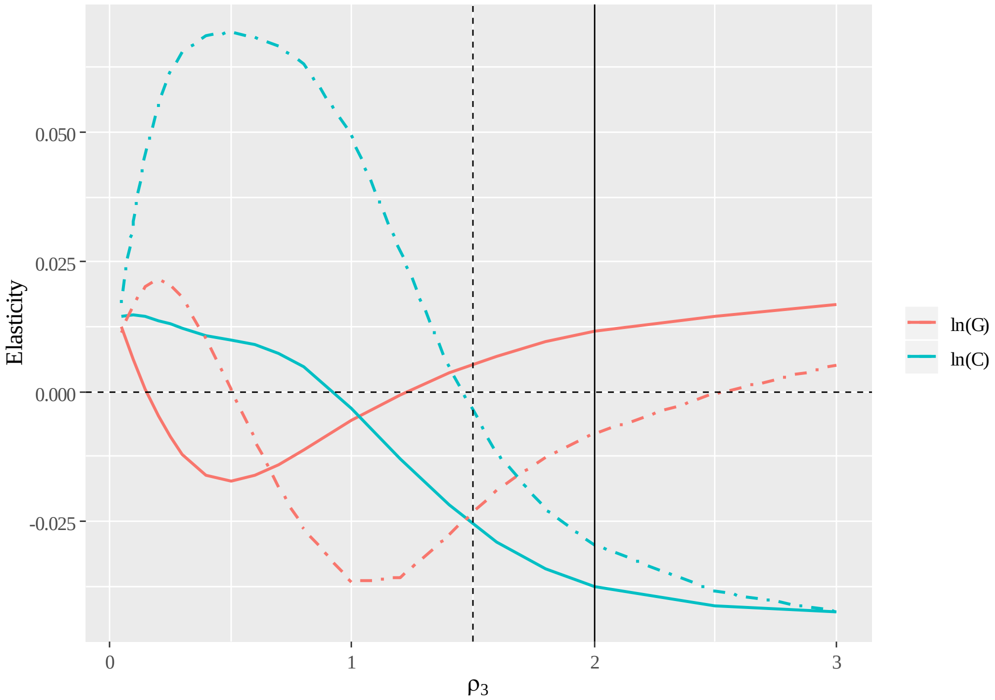

Figure 4 – Spatial Decay Analysis: Local Infrastructure Variables
(Solid: Gravity Model; Dashed: Inverse Distance)

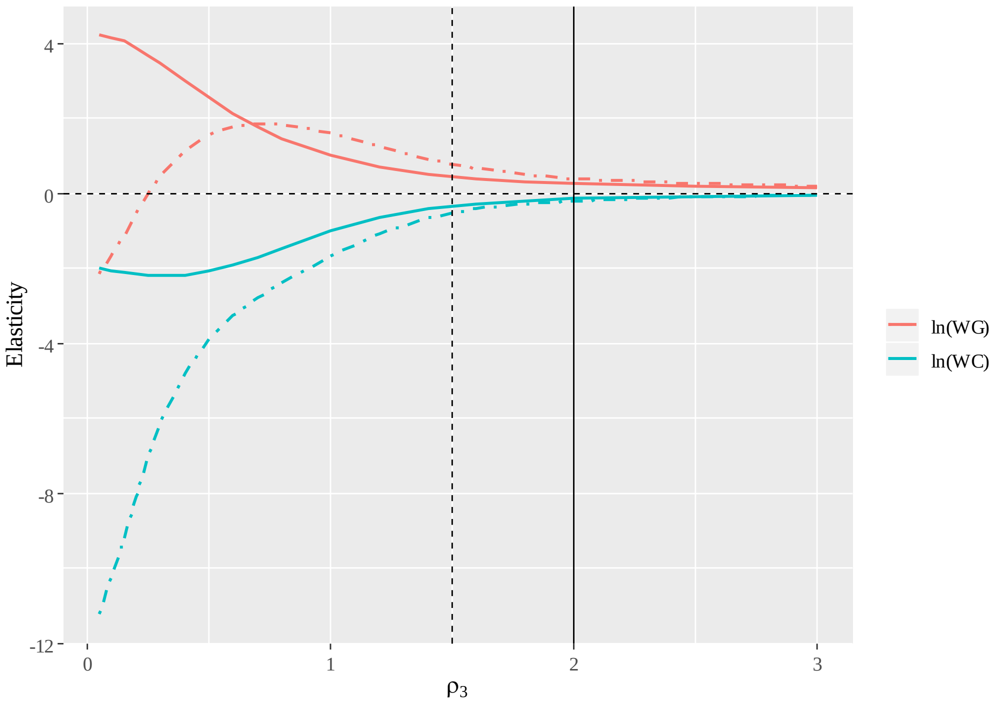

Figure 5 – Spatial Decay Analysis: Spatial Infrastructure Variables
(Solid: Gravity Model; Dashed: Inverse Distance)

Appendix C: Full Estimation Results

Table 5
Estimation of Production Function with aggregate Road Quality

		FGLS			GMM	
Symbol	Variable	Linear (7)	Nonlinear (8)	Restricted	Linear (7)	Nonlinear (8)
α_0	$\ln(A_0)$	16.68***	17.32***	16.14***		
		(2.15)	(2.47)	(2.14)		
β_{L_1}	$\ln(L)$	-0.80**	-0.82**	-0.74	0.44	0.42
		(0.33)	(0.33)		(0.31)	(0.31)
β_{K_1}	$\ln(K)$	-1.12***	-1.10***	-1.01***	-1.26***	-1.20***
		(0.15)	(0.15)	(0.17)	(0.11)	(0.11)
β_{H_1}	$\ln(H)$	1.84***	1.89***	1.67***	1.78***	1.85***
		(0.23)	(0.23)	(0.24)	(0.15)	(0.15)
β_{LL}	$\ln(L)\ln(L)$	0.18***	0.19***	0.17***	0.07**	0.07**
		(0.04)	(0.04)	(0.04)	(0.03)	(0.03)
β_{KK}	$\ln(K)\ln(K)$	0.07***	0.07***	0.06***	0.07***	0.07***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
β_{HH}	$\ln(H)\ln(H)$	0.10***	0.11***	0.10***	0.07***	0.07***
		(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
β_{LK}	$\ln(L)\ln(K)$	-0.02	-0.02	-0.03	-0.05**	-0.05**
		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
β_{LH}	$\ln(L)\ln(H)$	-0.13***	-0.14***	-0.12***	-0.09***	-0.09***
		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
β_{KH}	$\ln(K)\ln(H)$	-0.03*	-0.04**	-0.02	-0.08***	-0.08***
		(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
γ_1	$\ln(G)$	0.01	-0.17***	0.01	0.07***	-0.31***
		(0.02)	(0.06)	(0.02)	(0.02)	(0.11)
γ_2	$\ln(C)$	-0.04*	-0.17	-0.04**	-0.06***	-0.10
		(0.02)	(0.30)	(0.02)	(0.02)	(0.22)
γ_3	$\ln(G)^2$		0.02			0.03***
			(0.01)			(0.01)
γ_4	$\ln(C)^2$		0.06			0.02
			(0.14)			(0.11)
θ_1	$\ln(WG)$	0.26***	0.10	0.26***	0.25***	0.26
		(0.05)	(0.51)	(0.05)	(0.04)	(0.44)
θ_2	$\ln(WC)$	-0.14	0.61	-0.12	-0.08*	0.84
		(0.11)	(1.17)	(0.11)	(0.05)	(0.94)
θ_3	$\ln(WG)^2$		0.01			0.00
			(0.04)			(0.03)
θ_4	$\ln(WC)^2$		-0.35			-0.42
			(0.53)			(0.44)
λ_U	DU	0.68**	0.68**	0.39		
		(0.34)	(0.34)	(0.29)		
λ_E	DE	-0.45	-0.42	-0.85**		
		(0.45)	(0.45)	(0.38)		
λ_S	DS	-0.03**	-0.03**	-0.04**	-0.06***	-0.06***
		(0.02)	(0.02)	(0.02)	(0.00)	(0.00)
λ_{PD}	$\ln(PD)$	-0.59***	-0.58***	-0.47**	-0.35***	-0.33
		(0.20)	(0.20)	(0.19)	(0.06)	(0.06)
ρ	Spatial AR				0.39	0.39

Notes: Standard Errors in Brackets;
*, **, & *** relate to significance on the 90, 95, and 99%-Level, respectively

Table 6
Estimation of Production Function with disaggregated Road Quality

		FGLS			GMM	
Estimator	Variable	Linear (9)	Nonlinear (10)	Restricted	Linear (9)	Nonlinear (10)
α_0	Intercept	15.76***	15.58***	15.21***		
		(1.90)	(2.11)	(1.89)		
β_{L_1}	$\ln(L)$	-0.51*	-0.55*	-0.44	0.51*	0.57*
		(0.30)	(0.31)		(0.30)	(0.30)
β_{K_1}	$\ln(K)$	-1.04***	-1.02***	-0.92***	-1.18***	-1.10***
		(0.14)	(0.14)	(0.16)	(0.11)	(0.11)
β_{H_1}	$\ln(H)$	1.78***	1.83***	1.60***	1.71***	1.77***
		(0.22)	(0.22)	(0.23)	(0.14)	(0.15)
β_{LL}	$\ln(L)\ln(L)$	0.15***	0.15***	0.13***	0.06*	0.06**
		(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
β_{KK}	$\ln(K)\ln(K)$	0.06***	0.06***	0.06***	0.07***	0.06***
		(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
β_{HH}	$\ln(H)\ln(H)$	0.10***	0.11***	0.10***	0.06***	0.07***
		(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
β_{LK}	$\ln(L)\ln(K)$	-0.01	-0.01	-0.02	-0.04*	-0.04**
		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
β_{LH}	$\ln(L)\ln(H)$	-0.11***	-0.11***	-0.09***	-0.08***	-0.07***
		(0.03)	(0.03)	(0.03)	(0.02)	(0.02)
β_{KH}	$\ln(K)\ln(H)$	-0.04**	-0.04**	-0.03**	-0.08***	-0.08***
		(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
γ_1	$\ln(G)$	0.02	-0.17***	0.01	0.06***	-0.31***
		(0.02)	(0.06)	(0.02)	(0.02)	(0.11)
γ_{A_1}	$\ln(C_A)$	0.01	0.14	0.01	0.01	0.25***
		(0.01)	(0.11)	(0.01)	(0.01)	(0.08)
γ_{B_1}	$\ln(C_B)$	-0.02	-0.30**	-0.03	-0.06***	-0.27**
		(0.02)	(0.12)	(0.02)	(0.02)	(0.13)
γ_{C_1}	$\ln(C_C)$	0.03	-0.01	0.03	0.00	-0.50***
		(0.02)	(0.15)	(0.02)	(0.02)	(0.17)
γ_3	$\ln(G)^2$		0.02***			0.03***
			(0.01)			(0.01)
γ_{A_2}	$\ln(C_A)^2$		-0.07			-0.13***
			(0.06)			(0.04)
γ_{B_2}	$\ln(C_B)^2$		0.13**			0.10*
			(0.06)			(0.06)
γ_{C_2}	$\ln(C_C)^2$		0.02			0.31***
			(0.09)			(0.10)
θ_1	$\ln(WG)$	0.22***	0.55	0.22***	0.25***	0.60
		(0.04)	(0.49)	(0.05)	(0.03)	(0.43)
θ_{A_1}	$\ln(WC_A)$	0.08	-0.01	0.08	0.10***	0.02
		(0.06)	(0.22)	(0.06)	(0.03)	(0.28)
θ_{B_1}	$\ln(WC_B)$	-0.27***	-0.29	-0.26***	-0.18***	0.89
		(0.05)	(0.84)	(0.05)	(0.04)	(0.64)
θ_{C_1}	$\ln(WC_C)$	0.31**	-0.11	0.30**	0.39***	-0.64
		(0.13)	(0.76)	(0.14)	(0.07)	(0.71)
θ_3	$\ln(WG)^2$		-0.03			-0.03
			(0.04)			(0.03)
θ_{A_2}	$\ln(WC_A)^2$		0.05			0.04
			(0.14)			(0.15)
θ_{B_2}	$\ln(WC_B)^2$		0.01			-0.46*
			(0.35)			(0.28)
θ_{C_2}	$\ln(WC_C)^2$		0.24			0.57
			(0.47)			(0.41)

Table 6 (continued)
Estimation of Production Function with disaggregated Road Quality

		FGLS			GMM	
Estimator	Variable	Linear (9)	Nonlinear (10)	Restricted	Linear (9)	Nonlinear (10)
λ_U	DU	0.78**	0.78**	0.47*		
		(0.32)	(0.32)	(0.28)		
λ_E	DE	-0.52	-0.50	-0.93**		
		(0.44)	(0.44)	(0.37)		
λ_S	DS	-0.04**	-0.04**	-0.04**	-0.06***	-0.06***
		(0.01)	(0.14)	(0.02)	(0.00)	(0.00)
λ_{PD}	ln(PD)	-0.63***	-0.62***	-0.50***	-0.37***	-0.34***
		(0.19)	(0.19)	(0.19)	(0.06)	(0.06)
ρ	Spatial AR				0.37	0.38

Notes: Standard Errors in Brackets;
*, **, & *** relate to significance on the 90, 95, and 99%-Level, respectively