Highway Conditions and Insufficient Maintenance in Germany: A Threat for Economic Growth? – Online Appendix

Gaus, D., & Link, H., DIW Berlin e.V., 2021

Appendix A: Map of the German County Layout

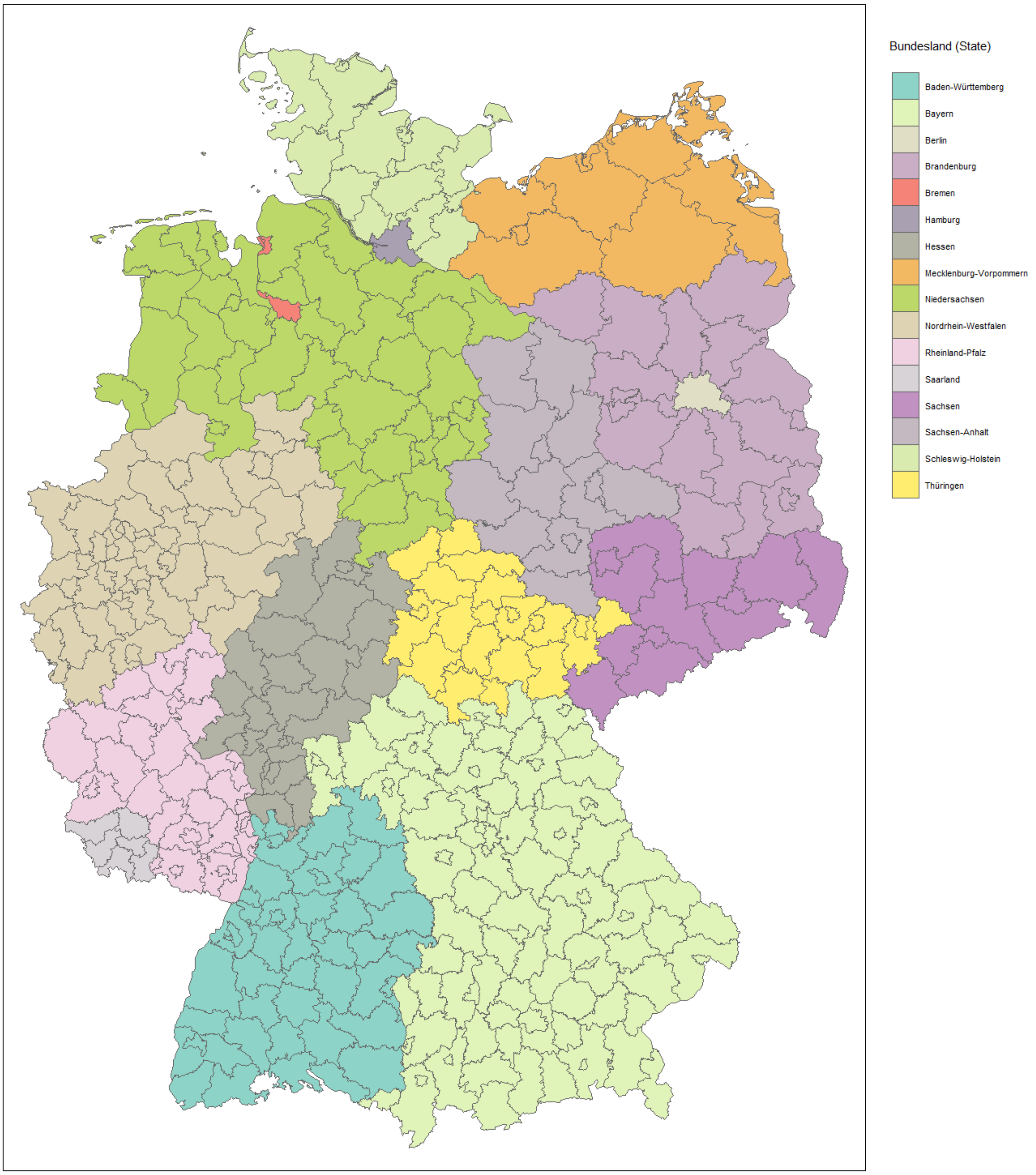

Figure 2 - Map of German Counties with Colors representing States

Appendix B: Calculation of County-Specific Capital Values

The German SNA provides data describing the total capital employed on national and state level. As we need county-specific information, we break these data down using industry and firm characteristics as follows. Besides the SNA data, we use information from the business register provided by the Federal Statistical Office. These data specify the number of registered firms differentiated by industry (17 categories, "WZ2008" system) and number of employees (4 categories) for all states and counties on an annual basis. We transform these data from absolute numbers of firms to relative shares, describing each state's and county's share in the total number of companies in Germany for each category. In addition, we include the share in the total German population (also provided by the Federal Statistical Office). As the SNA provides capital data on state level, we also calculate each state's share in the total capital employed in Germany and run the following pooled OLS regression:

$$\dot{y}_{it} = \sum_{z} \beta_z * \dot{z}_{it} + \sum_{s} \beta_s * \dot{s}_{it} + \beta_p * \dot{p}_{it} + \varepsilon_{it} \tag{13}$$

In this regression, the capital share $\dot{y}_{it}$ is explained through the shares in industry categories $\dot{z}_{it}$, size categories $\dot{s}_{it}$, and population $\dot{p}_{it}$. The results point out a very good fit ($R^2 = 0.99$) and show that the industry structure within a state allows to estimate the employed capital with high precision. As the explanatory variables are available on county level, this allows us to predict county-specific capital values from the estimated coefficients. While structural differences between states might exist, which could be modelled using fixed effects, it is unlikely that these characteristics are also present in the individual counties within states. We therefore use the pooled model under the assumption that no structural differences in the capital distribution exist between state level and county level instead of a fixed effects panel model. Obviously, this method cannot give perfectly accurate measures, but the very high accuracy in the estimated model underlines the validity of the approach.

Appendix C: 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:

$$\frac{\partial \ln(Y)}{\partial \ln(K)} + \frac{\partial \ln(Y)}{\partial \ln(L)} = 1 \tag{14}$$

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

$$\frac{\partial \ln(Y)}{\partial \ln(K)} = \beta_1 + \beta_4 \ln(K) + \beta_7 \ln(L) + \beta_8 \ln(H) \tag{15}$$

$$\frac{\partial \ln(Y)}{\partial \ln(L)} = \beta_2 + \beta_5 \ln(L) + \beta_7 \ln(K) + \beta_9 \ln(H) \tag{16}$$

We denote the sample mean of $\ln(X)$ as $\overline{\ln(X)}$ and evaluate the derivatives at the sample mean. Imposing Equation (14) and rearranging, we can reformulate as follows:

$$\beta_1 + \beta_2 + (\beta_4 + \beta_7) * \overline{\ln(K)} + (\beta_5 + \beta_7) * \overline{\ln(L)} + (\beta_8 + \beta_9) * \overline{\ln(H)} = 1 \tag{17}$$

$$\beta_2 = 1 - \beta_1 - (\beta_4 + \beta_7) * \overline{\ln(K)} - (\beta_5 + \beta_7) * \overline{\ln(L)} - (\beta_8 + \beta_9) * \overline{\ln(H)} \tag{18}$$

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:

$$\begin{aligned}\ln(Y) - \ln(L) = \ln(A) + \beta_1(\ln(K) - \ln(L)) + \beta_3 \ln(H) \\ + \beta_4 \left(\frac{1}{2}\ln(\mathrm{K})^2 - \overline{\ln(K)}\ln(L)\right) + \beta_5 \left(\frac{1}{2}\ln(L)^2 - \overline{\ln(L)}\ln(L)\right) \\ + \frac{1}{2}\beta_6 \ln(H)^2 + \beta_7\big(\ln(K)\ln(L) - \overline{\ln(K)}\ln(L) - \overline{\ln(L)}\ln(L)\big) \\ + \beta_8\big(\ln(K)\ln(H) - \overline{\ln(H)}\ln(L)\big) + \beta_9\big(\ln(L)\ln(H) - \overline{\ln(H)}\ln(L)\big)\end{aligned} \tag{19}$$

Appendix D: Full Estimation Results

		FGLS			GMM	
Symbol	Variable	Linear (6)	Nonlinear (7)	Restricted	Linear (6)	Nonlinear (7)
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	0.54*	0.51*
		(0.33)	(0.33)		(0.31)	(0.31)
β_{K_1}	$\ln(K)$	-1.12***	-1.10***	-1.01***	-1.25***	-1.19***
		(0.15)	(0.15)	(0.17)	(0.11)	(0.11)
β_{H_1}	$\ln(H)$	1.84***	1.89***	1.67***	1.73***	1.79***
		(0.23)	(0.23)	(0.24)	(0.15)	(0.15)
β_{LL}	$\ln(L)\ln(L)$	0.18***	0.19***	0.17***	0.06**	0.06**
		(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***	0.06***	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	-0.07***	-0.08***
		(0.02)	(0.02)	(0.02)	(0.01)	(0.01)
γ_1	$\ln(G)$	0.01	-0.17***	0.01	0.07***	-0.27**
		(0.02)	(0.06)	(0.02)	(0.02)	(0.11)
γ_2	$\ln(C)$	-0.04*	-0.17	-0.04**	-0.07***	-0.11
		(0.02)	(0.30)	(0.02)	(0.02)	(0.23)
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***	0.28***	0.45
		(0.05)	(0.51)	(0.05)	(0.04)	(0.44)
θ_2	$\ln(WC)$	-0.14	0.61	-0.12	-0.20***	0.70
		(0.11)	(1.17)	(0.11)	(0.05)	(1.14)
θ_3	$\ln(WG)^2$		0.01			-0.01
			(0.04)			(0.03)
θ_4	$\ln(WC)^2$		-0.35			-0.41
			(0.53)			(0.53)
β_L	$\frac{\partial \ln(Y)}{\partial \ln(L)}$	0.99***	0.99***	0.78***	0.82***	0.82***
		(0.05)	*(0.05)*	*(0.00)*	*(0.08)*	*(0.08)*
β_K	$\frac{\partial \ln(Y)}{\partial \ln(K)}$	0.23***	0.23***	0.22***	0.24***	0.23***
		(0.02)	*(0.02)*	*(0.00)*	*(0.03)*	*(0.03)*
β_H	$\frac{\partial \ln(Y)}{\partial \ln(H)}$	0.37***	0.37***	0.39***	0.26***	0.26***
		(0.02)	*(0.02)*	*(0.00)*	*(0.04)*	*(0.04)*
γ_G	$\frac{\partial \ln(Y)}{\partial \ln(G)}$	0.01	0.03	0.01	0.07***	0.09**
		(0.02)	*(0.02)*	(0.02)	(0.02)	*(0.03)*

Table 4: Estimation of Production Function with aggregated Road Quality

		FGLS			GMM	
Symbol	Variable	Linear (6)	Nonlinear (7)	Restricted	Linear (6)	Nonlinear (7)
γ_C	$\frac{\partial \ln(Y)}{\partial \ln(C)}$	-0.04*	-0.04	-0.04**	-0.07***	-0.07
		(0.02)	*(0.03)*	(0.02)	(0.02)	*(0.04)*
θ_{WG}	$\frac{\partial \ln(Y)}{\partial \ln(WG)}$	0.26***	0.25***	0.26***	0.28***	0.29**
		(0.05)	*(0.06)*	(0.05)	(0.04)	*(0.06)*
θ_{WC}	$\frac{\partial \ln(Y)}{\partial \ln(WC)}$	-0.14	-0.13**	-0.12	-0.20***	-0.19
		(0.11)	*(0.07)*	(0.11)	(0.05)	*(0.09)*
λ_P	DP	0.18		0.04		
		(0.14)		(0.11)		
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**	-0.34***	-0.32***
		(0.20)	(0.20)	(0.19)	(0.06)	(0.06)
ρ	Spatial AR				0.40	0.40
R^2	R-squared	0.9984	0.9984	0.9893		

Notes: Standard Errors in Brackets;
*, **, & *** relate to significance on the 90, 95, and 99%-Level, respectively
Table 4 (continued): Estimation of Production Function with aggregated Road Quality

		FGLS			GMM	
Estimator	Variable	Linear (8)	Nonlinear (9)	Restricted	Linear (8)	Nonlinear (9)
α_0	Intercept	16.52*** (2.03)	16.00*** (2.21)	15.96*** (2.03)		
β_{L_1}	$\ln(L)$	-0.59* (0.31)	-0.64** (0.31)	-0.71	0.48 (0.30)	0.42 (0.30)
β_{K_1}	$\ln(K)$	-1.07*** (0.15)	-1.04*** (0.14)	-0.95*** (0.16)	-1.18*** (0.11)	-1.14*** (0.11)
β_{H_1}	$\ln(H)$	1.79*** (0.22)	1.85*** (0.22)	1.62*** (0.23)	1.68*** (0.15)	1.81*** (0.15)
β_{LL}	$\ln(L)\ln(L)$	0.15*** (0.03)	0.16*** (0.03)	0.14*** (0.04)	0.06* (0.03)	0.07** (0.03)
β_{KK}	$\ln(K)\ln(K)$	0.06*** (0.01)	0.06*** (0.01)	0.06*** (0.01)	0.07*** (0.01)	0.07*** (0.01)
β_{HH}	$\ln(H)\ln(H)$	0.10*** (0.02)	0.11*** (0.02)	0.09*** (0.02)	0.06*** (0.01)	0.07*** (0.01)
β_{LK}	$\ln(L)\ln(K)$	-0.01 (0.03)	-0.01 (0.03)	-0.02 (0.03)	-0.03 (0.02)	-0.04* (0.02)
β_{LH}	$\ln(L)\ln(H)$	-0.11*** (0.03)	-0.12*** (0.03)	-0.10*** (0.03)	-0.07*** (0.02)	-0.07*** (0.02)
β_{KH}	$\ln(K)\ln(H)$	-0.04** (0.02)	-0.05** (0.02)	-0.03* (0.02)	-0.08*** (0.01)	-0.09*** (0.01)
γ_1	$\ln(G)$	0.01 (0.02)	-0.17*** (0.06)	0.01 (0.02)	0.06*** (0.02)	-0.29*** (0.11)
γ_{A_1}	$\ln(C_A)$	0.01 (0.01)	0.16 (0.12)	0.01 (0.01)	0.00 (0.01)	0.30*** (0.09)
γ_{B_1}	$\ln(C_B)$	-0.02 (0.02)	-0.31** (0.12)	-0.03 (0.02)	-0.06*** (0.02)	-0.28** (0.13)
γ_3	$\ln(G)^2$		0.02*** (0.01)			0.03*** (0.01)
γ_{A_2}	$\ln(C_A)^2$		-0.08 (0.06)			-0.16*** (0.05)
γ_{B_2}	$\ln(C_B)^2$		0.13** (0.06)			0.09 (0.06)
θ_1	$\ln(WG)$	0.22*** (0.05)	0.53 (0.53)	0.22*** (0.05)	0.25*** (0.04)	0.89** (0.44)
θ_{A_1}	$\ln(WC_A)$	0.10 (0.07)	-0.01 (0.20)	0.11 (0.07)	0.09*** (0.03)	-0.66* (0.38)
θ_{B_1}	$\ln(WC_B)$	-0.31*** (0.05)	0.04 (0.84)	-0.30*** (0.05)	-0.31*** (0.04)	0.61 (0.69)
θ_3	$\ln(WG)^2$		-0.02 (0.04)			-0.05 (0.03)
θ_{A_2}	$\ln(WC_A)^2$		0.06 (0.12)			0.39* (0.20)
θ_{B_2}	$\ln(WC_B)^2$		-0.15 (0.37)			-0.39 (0.30)

Table 5: Estimation of Production Function with disaggregated Road Quality

		FGLS			GMM	
Estimator	Variable	Linear (8)	Nonlinear (9)	Restricted	Linear (8)	Nonlinear (9)
β_L	$\frac{\partial \ln(Y)}{\partial \ln(L)}$	1.00***	1.00***	0.80***	0.83***	0.84***
		(0.05)	*(0.05)*	*(0.00)*	*(0.08)*	*(0.08)*
β_K	$\frac{\partial \ln(Y)}{\partial \ln(K)}$	0.22***	0.22***	0.20***	0.23***	0.22***
		(0.02)	*(0.02)*	*(0.00)*	*(0.03)*	*(0.03)*
β_H	$\frac{\partial \ln(Y)}{\partial \ln(H)}$	0.37***	0.37***	0.39***	0.27***	0.27***
		(0.02)	*(0.02)*	*(0.00)*	*(0.04)*	*(0.04)*
γ_G	$\frac{\partial \ln(Y)}{\partial \ln(G)}$	0.01	0.03	0.01	0.06***	0.09**
		(0.02)	*(0.02)*	(0.02)	(0.02)	*(0.03)*
γ_{C_A}	$\frac{\partial \ln(Y)}{\partial \ln(C_A)}$	0.01	0.01	0.01	0.00	0.01
		(0.01)	*(0.02)*	(0.01)	(0.01)	*(0.03)*
γ_{C_B}	$\frac{\partial \ln(Y)}{\partial \ln(C_B)}$	-0.02	-0.01	-0.03	-0.06***	-0.06**
		(0.02)	*(0.03)*	(0.02)	(0.02)	*(0.03)*
θ_{WG}	$\frac{\partial \ln(Y)}{\partial \ln(WG)}$	0.22***	0.21***	0.22***	0.25***	0.26***
		(0.05)	*(0.06)*	(0.05)	(0.04)	*(0.07)*
θ_{WC_A}	$\frac{\partial \ln(Y)}{\partial \ln(WC_A)}$	0.10	0.10*	0.11	0.09***	0.10
		(0.07)	*(0.06)*	(0.07)	(0.03)	*(0.08)*
θ_{WC_B}	$\frac{\partial \ln(Y)}{\partial \ln(WC_B)}$	-0.31***	-0.31***	-0.30***	-0.31***	-0.29***
		(0.05)	*(0.07)*	(0.05)	(0.04)	*(0.09)*
λ_P	DP	0.22	0.23*	0.08		
		(0.13)	(0.13)	(0.11)		
λ_U	DU	0.77**	0.77**	0.47*		
		(0.33)	(0.33)	(0.29)		
λ_E	DE	-0.56	-0.53	-0.95**		
		(0.44)	(0.45)	(0.38)		
λ_S	DS	-0.04**	-0.04**	-0.04**	-0.06***	-0.06***
		(0.01)	(0.01)	(0.02)	(0.00)	(0.00)
λ_{PD}	ln(PD)	-0.63***	-0.63***	-0.51***	-0.36***	-0.36***
		(0.19)	(0.19)	(0.19)	(0.06)	(0.06)
ρ	Spatial AR				0.38	0.38
R^2	R-squared	0.9984	0.9984	0.9896		

Notes: Standard Errors in Brackets;
*, **, & *** relate to significance on the 90, 95, and 99%-Level, respectively
Table 5 (continued): Estimation of Production Function with disaggregated Road Quality

Appendix E: Robustness of Spatial Specification

The specification of the spatial weighting matrix W can have a significant influence on the estimation results of spatial models. We therefore calculated our models using several specifications and compared the results to those of the baseline model. Figure 3 shows the GMM estimation results for model (6) with a common condition variable, comparing the baseline model (gravity-model specification of W with $\rho_3 = 2$) to three alternatives: A gravity-model with $\rho_3 = 1.5$, a gravity-model with $\rho_3 = 2.5$, and a distance-decay model with $\rho = 2$. While this is only a limited selection of the models we estimated, the results represent the general patterns we found in our analysis (in which we also used the restricted and unrestricted FGLS specification, as well as model (8) with separate quality variables B_A and B_B).

As can be seen, an increase of the decay parameter leads to a slight increase of the local effects and a stronger decrease of the spatial effects. This is not surprising, as a higher decay parameter corresponds to a lower weighting of distant counties, shifting the focus of this variable to close-by neighboring regions. This lower impact of supra-regional effects (and the relatively higher importance of the local variables) is represented by the estimation results.

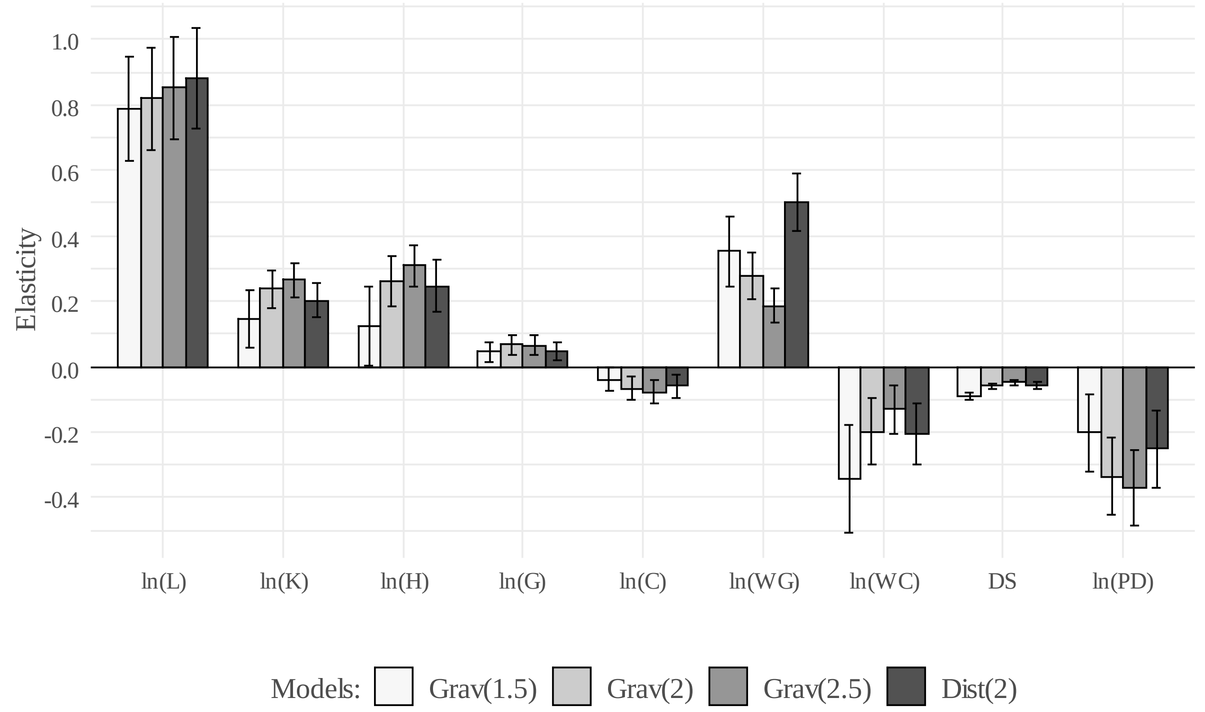

Figure 3 - Robustness Check Models: Elasticities for GMM of Specification (6) with 95% CIs

Comparing the gravity model specification with the distance decay one, no systematic changes of the coefficients are apparent. While an increase of the labor input effect is accompanied by a slight decrease of the coefficients relating to capital and human capital inputs, the effect of the highway condition, both locally and supra-regionally, is identical in the two models. The only notable changes in this as well as in other specifications are a slight decrease of the impact of the local highway quantity and a stronger increase of the spatial highway quantity effect. In all cases, the statistical significance of the coefficients mirrors the one in the baseline model.

Overall, we conclude that our models are robust to changes of the spatial weighting matrix W. The changes we find are rather small in size, leaving the sign and significance of our findings unaffected, and following expected behavior.