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Regional convergence at the county level: The role of commuters*

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Abstract

The growth trajectory of a region is known to be influenced by the economic circumstances of other regions in its proximity. While proximity is often understood in a geographic sense, we consider commuting as a channel for cross-regional economic dependencies. Commuters, who spend a substantial portion of their income in a different place from where they earn it, connect peripheral regions to economic centers. In contrast to geographic measures, commuter flows are inherently asymmetric and heterogeneous, as are the economic dependencies among regions. We estimate a time-space dynamic panel model with German county-level data, and demonstrate a considerable variation in the distribution of shock responses which is hidden by the traditional focus on average marginal effects. In counterfactual experiments, the local spatial multipliers differ substantially depending on the nature of the shock or policy intervention and the assumed network structure, with implications for the growth convergence process.

JEL Classification: R12, C23, J61, O18

Keywords: Regional Convergence, Commuting, Spatial Weight Matrix, Shock Propagation, Time-Space Dynamic Panel Data Model

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1 Introduction

Economic differences can persist over a long time, not just across countries, but also within countries. Whether these differences are becoming smaller over time, and whether a convergence process can be facilitated through government interventions, is of importance for policy makers who have to decide on regulatory frameworks, transfers within and across regions, infrastructure investment, and the provision of public goods. An important aspect of economic development is that regions are often closely interconnected in various ways, and therefore their development is not independent from one another. In the textbook Solow-Swan neoclassical growth model – and many of its extensions – these dependencies are left aside. The speed of convergence is determined by a region's distance from its steady-state equilibrium. Differences in the growth rates can thus be explained by variations in the initial endowments and factors determining the equilibrium growth path.

In recent years, a stronger focus has been placed on cross-sectional dependencies in the form of local and global externalities, often motivated as knowledge spillovers in extensions of the neoclassical growth model. The source of these spillovers can be in the accumulation of physical and human capital in neighboring regions (Carrington, 2003), or in direct contributions to each other's total factor productivity (Egger and Pfaffermayr, 2006). Ertur and Koch (2007) introduce spatial externalities through technological interdependence. In such extended models, the steady-state output per worker becomes a function of the output per worker in the neighboring regions. The speed of convergence therefore depends on the location in space and the strength of the inter-regional linkages. In the empirical literature, the connectivity between spatial units is often modeled in an ad hoc way as a function of their geographic distance, sometimes limited to units sharing a common border (Anselin, 1988; Anselin and Bera, 1998). This is based on the rationale that geographic distance is a good proxy for underlying economic linkages.

However, the geographic connectivity measures cannot account for the heterogeneity in the economic relationships, which may themselves be a function of the state of the economic development. Economic activity is often geographically clustered due to comparative advantages of a certain region – such as the availability of skilled workers, a business-friendly regulatory framework, and existing infrastructure – or the logistical complexities of just-in-time production with interconnected supply chains. Some regions are gravitational centers which substantially influence the surrounding satellite regions, without much feedback in the opposite direction. The resulting asymmetry of the spillover effects cannot be captured by geographic contiguity. Instead, connectivity measures should reflect the gravitational forces. While those forces are inherently latent, it is often possible to find economic or socio-economic proxies for the connectivity strength.

In this paper, we propose approximating the regional linkages by commuter flows. Commuting plays an important role in urban economics and regional science; see Proost and Thisse (2019) for an overview. The classical case is commuting within cities in the canonical Alonso-Mills-Muth model (Alonso, 1964; Mills, 1967; Muth, 1969) and its extensions (Duranton and Turner, 2011; Desmet and Rossi-Hansberg, 2013; Ahlfeldt et al., 2015). Yet, commuting across regions is also increasingly becoming the subject of the theoretical literature. In models of the New Economic Geography literature, regions are not only connected by trade flows and spatial knowledge spillovers, but also by commuter flows (Allen et al., 2015). Monte et al. (2018) demonstrate that spatial interactions through commuting can determine local economic effects of labor market shocks. Commuters, who earn their money in one place and spend a significant portion of it in another place, constitute important links between regions. A commuter flow network implies a shock transmission mechanism which is predominantly one-way, with limited feedback to the origin of the shock; and it allows for substantial geographic heterogeneity.

Commuting is an everyday phenomenon of modern life. In many countries, an increasing number of people work in a different place from where they live. Aside from the workers who commute from the outskirts of a city to the urban center, there are a considerable number of inter-regional commuters. Particularly in countries where economic activity is relatively decentralized, the distances are not too large, and the infrastructure is solid, commuter flows are sizable. In 2019, 24% of workers (16 years and over) in the US commuted to a different county in the same state, and 4% across state borders. Mega commuting – travel times of at least 60 minutes (each way) – amounts to almost 10% of those not working at home. This is about 2 percentage points more than in 2010.[1] In the EU, on average 6% of the employed working-age (15–64 years) population commuted to a different NUTS 2 region (nomenclature of territorial units for statistics) in 2020. Yet, there are large differences across countries. Belgium topped the list with 21% country-wide, and up to 49% for some Belgian provinces.[2] At the smaller county level – NUTS 3 regions – these numbers are considerably higher. As there is no EU-wide data collection on commuting at this disaggregation level, we restrict our attention to Germany, for which suffciently long origin-destination commuter flow time series can be obtained.

We investigate the different shock transmission implications of commuter-based and geography-based spatial linkages with panel data on German counties, covering the time span from 2002 to 2017. Germany is a suitable case in point for the role of commuters in

[1]Source for US commuting data: US Census Bureau, American Community Survey, table S0801 (commuting characteristics by sex).

[2]Source for EU commuting data: Eurostat, online data code LFST_R_LFE2ECOMM (employment and commuting by sex, age and NUTS 2 regions).

regional convergence. It is a territorial state with a number of economic centers, though with considerableregional variation in terms of prosperity. The eastern part experienced strong catch-up growth in the 1990s and 2000s, but as a whole is still lagging behind. Meanwhile, there are both economic hubs as well as poorer regions in the south and west (Kosfeld and Lauridsen, 2004; Kosfeld et al., 2006; Juessen, 2009; Colavecchio et al., 2011). In the period covered by our data set, between 3% and 31% of a county's population was commuting to a different county. For the most attractive commuter destinations, the incoming commuter numbers even totalled up to 78% of their own population size.[3]

The empirical literature on regional convergence is huge; see for instance Sala-i-Martín (1996) and Boucher Breuer et al. (2014) for the United States, Badinger et al. (2004) and Arbia et al. (2008) for Europe, and Gennaioli et al. (2014) for a worldwide analysis. The often rather coarse classification of regional units masks a considerable degree of heterogeneity and intra-regional spillovers. The ties to other regions (relative to the size), and therefore the spatial convergence effects, tend to increase at a deeper level of disaggregation. This is also reflected in the observed commuting patterns. Only a small share of commuters travel across states, and among those many commute between nearby counties which lie on either side of the state border. It thus appears to be a natural choice to use counties as the units of observation. While there have been previous convergence studies at the county level – for example Kosfeld et al. (2006) for Germany, Young et al. (2008) for the U.S., and Cheong and Wu (2013) for China – these either did not explicitly model the dependencies across counties, or relied on geographic proximity measures.

Analyzing cross-sectional spillover effects at the county level is also beneficial from a policy perspective. Government interventions can have quite different local effects within a state, depending on the economic conditions in a county and its interconnectedness with other counties. The multiplier effects of an intervention in an economic center are typically stronger due to the spillover effects to economically dependent counties. While it may seem desirable to directly intervene in disadvantaged areas, this is unlikely to achieve the highest value for taxpayers' money. Conversely, targeting already prospering counties – with the aim to maximize the aggregate effect of an intervention – raises distributional concerns. This differential response to an initial stimulus is often overlooked in empirical studies, where it is common practice to report average effects. Importantly, these distributional effects can differ substantially depending on the assumed spatial network. With geography-based connectivity, economic centers and their periphery would be treated symmetrically. In contrast, spillovers generated by commuter flows (or other measures of economic dependence) can be very heterogeneous, and tend to provide a more accurate picture of the economic reality.

[3] We provide more details on the data in Section 3.

Using the bias-corrected maximum likelihood estimator of Yu et al. (2008), we estimate a time-space dynamic growth convergence model with spatial weight matrices based on either commuter flows or geographic connectivity. Subsequently, we compute spatial multipliers for counterfactual experiments in which we assign treatment to small groups of counties. We distinguish between spatial multipliers for the treated and untreated counties, and we analyze the distributional effects of various treatments. Our experiments highlight that the distributional effects of an intervention (or, more generally, an economic shock) depend considerably on which counties receive the treatment and on the assumed spatial spillover network. When spillovers are realized through commuter flow connections, the strongest effects are achieved by assigning treatment to counties that are characterized by a high per-capita income, high population density, or high value-added share of the financial sector. This is in line with the argument that such counties act as gravitational centers. In contrast, with geographic spatial weights, the economic characteristics of the treated counties are irrelevant (other than being the basis for the treatment selection); and the strength of the multiplier effects is solely determined by the location and proximity of the treated counties.

2 Econometric model and methods

For the empirical growth convergence analysis, the estimation of a time-space dynamic panel data model is becoming increasingly popular. Previous applications include Bouayad-Agha and Védrine (2010), Parent and LeSage (2012), Yu and Lee (2012), Bouayad-Agha et al. (2013), Ho et al. (2013), Evans and Kim (2014), and Fischer and LeSage (2015). The econometric model is as follows:

$$\ln \mathbf{y}_t = \theta \ln \mathbf{y}_{t-1} + \lambda \mathbf{W}_N \ln \mathbf{y}_t + \rho \mathbf{W}_N \ln \mathbf{y}_{t-1} + \mathbf{X}_t \boldsymbol{\pi} + \gamma_t \boldsymbol{\iota}_N + \boldsymbol{\alpha} + \boldsymbol{\varepsilon}_t, \qquad (1)$$

$t = 1, 2, \ldots, T$, where $\mathbf{y}_t = (y_{1t}, y_{2t}, \ldots, y_{Nt})'$ is a vector of real GDP per capita for counties $i = 1, 2, \ldots, N$ at time t. The $N \times N$ matrix $\mathbf{W}_N$ is a spectrally normalized spatial weight matrix that governs the links between counties. The scalar coefficients θ, λ, and ρ determine the strength of the temporal and spatial dependence. $\mathbf{X}_t$ is an $N \times K$ matrix of strictly exogenous covariates with coefficient vector $\boldsymbol{\pi}$. $\boldsymbol{\iota}_N$ is an $N \times 1$ vector of ones and the coefficients γ_t are common time effects to be estimated. The county-specific effects $\boldsymbol{\alpha} = (\alpha_1, \alpha_2, \ldots, \alpha_N)'$ account for any unobserved time-invariant characteristics. $\boldsymbol{\varepsilon}_t$ is an $N \times 1$ vector of idiosyncratic shocks.

2.1 Spatial weight matrices

We estimate the model with different spatial weight matrices. While spatial weights based on geographic proximity - either in the form of direct contiguity or inverse distances - have a long history in empirical spatial analyses (Anselin, 1988; Anselin and Bera, 1998; LeSage and Pace, 2009) and continue to be regularly used, alternative approaches to capture the spatial spillover effects became more and more prominent in recent years. Bavaud (1998), Fingleton and Le Gallo (2008), and Corrado and Fingleton (2012) recognize that there is no one true spatial weight matrix that is adequate in all situations, and that spatial interactions are often determined by relative economic distance rather than geographic boundaries or distances. An example of such economic weights are trade flows capturing international interdependencies, as in Ertur and Koch (2011), Asgharian et al. (2013), and Ho et al. (2013). Amarasinghe et al. (2018) consider weights based on socio-economic distance such as ethnic links and road networks, and Incaltarau et al. (2021) use travel times. Fingleton (2001), Carrington (2003), Fingleton and Le Gallo (2008), and Zhang and Wang (2017) combine geographic distance with a measure of relative economic importance.[4]

In urban economics, commuter flows constitute a particularly important transmission mechanism (Allen et al., 2015; Monte et al., 2018). Commuting can be an individually optimal decision when there are differences in local amenities and job opportunites across counties, also taking into account constraints at the household level. By earning their income in one region and spending a significant part of it in another region, commuters constitute vital economic linkages between those regions. A county's susceptibility to income shocks originating in another county can be reasonably modeled as an increasing function of the share of residents working in that other county.

Geographic spatial weight matrices fail to capture these dependencies because they do not account for the heterogeneity of the counties. Economic activity is often clustered in certain regions. A thriving economy in these counties radiates to a larger area depending on the strength of the linkages. Conversely, the economic center is often largely insulated against adverse developments in surrounding counties. This asymmetric dependence cannot be characterized by geographic measures, but it is an inherent characteristic of commuter flows. There are certainly other aspects that determine the strength of the linkages between counties, such as the cross-county interconnections along the value chain. While we do not claim that commuter flows are a perfect proxy for the economic inter-county links, they reflect the economic reality better than geography-based spatial weights, at least when the unit of observation is small-scale regions where commuting is a significant phenomenon.

We initially construct the weights w_{ij} in row i and column j of our commuter-based spatial weight matrix $\mathbf{W}_N$ as the commuter outflow C_{ij} from county i to county j rela-

[4]Another approach that we do not pursue here is estimating the spatial weights (Getis and Aldstadt, 2004; Beenstock and Felsenstein, 2012; Bhattacharjee and Jensen-Butler, 2013; Bailey et al., 2016) rather than constructing them from observed variables.

tive to the population size P_i of county i. Following standard convention, the diagonal elements are set to zero:

$$w_{ij} = \begin{cases} \frac{C_{ij}}{P_i}, & i \neq j \\ 0, & i = j \end{cases}.$$

Asymmetry of $\mathbf{W}_N$ thus follows from different absolute commuter levels $C_{ij} \neq C_{ji}$ or different population sizes $P_i \neq P_j$. For the spatial lag coefficient λ to be on a similar scale irrespective of the spatial weights, a standardization of the weights is conventionally applied. We apply a spectral standardization; that is a division of all weights by the absolute value of the largest eigenvalue of $\mathbf{W}_N$. This implies a convenient upper bound on the parameter space, $\lambda < 1$, for $\mathbf{S}_N(\lambda)$ to be invertible.[5] The same upper bound could be achieved with a row standardization; that is a division of all weights by the respective row sum $\sum_{j=1}^{N} w_{ij}$. However, the latter would not preserve the underlying network structure. As Kelejian and Prucha (2010) and Neumayer and Plümper (2016) point out, this would generally result in a misspecified model. In our case, the weights would no longer be relative to the population size P_i because the latter is constant within each row. As a consequence, comparatively isolated counties with few commuter links and counties that are strongly connected to others would appear to have similarly strong commuter links after applying a row standardization.

While we postpone discussing estimation methods for model (1) until Section 2.3, it is worth mentioning here that our employed estimator requires a constant spatial weight matrix over time. We thus restrict ourselves to the initial commuter flows in the year 2002, which also helps to address potential endogeneity concerns. The variability of commuter flows over time is relatively low such that the potential adverse consequences of using constant spatial weights are expected to be small, especially with a short time horizon. As a measure of variability, we consider the Frobenius norm of the matrix difference between two years, relative to the Frobenius norm of the initial-period weight matrix:

$$\frac{\|\mathbf{W}_{N,2002} - \mathbf{W}_{N,t}\|_F}{\|\mathbf{W}_{N,2002}\|_F} = \frac{\sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} |w_{ij,2002} - w_{ij,t}|^2}}{\sqrt{\sum_{i=1}^{N} \sum_{j=1}^{N} |w_{ij,2002}|^2}},$$

where all weights have been spectrally standardized. The relative Frobenius difference from 2002 to 2003 is only 2.4 percent. This figure remains relatively stable for subsequent one-year differences. For the whole time span, from 2002 to 2017, the difference becomes

[5] Some authors advocate to divide by the largest singular value instead of the largest eigenvalue. The two approaches are equivalent for symmetric matrices. For asymmetric matrices, the largest singular value is greater than the largest eigenvalue. As a consequence, the upper bound for λ after a standardization with the singular value is greater than 1, which hampers the interpretation. The partial effects discussed in Section 2.2 are invariant to the choice of the scaling factor.

15.3 percent. By itself, this number is hard to interpret but it becomes more meaningful when we compare the commuter flow matrix to alternative spatial weight matrices below.

While there are strong arguments in favor of economically motivated spatial weights, we also compare the results to the traditional spatial weight matrices based on geographic weights. We consider both a binary contiguity matrix with weights equal to 1 if two counties share a common border, and an inverse-distance matrix with weights inversely proportional to the Euclidean distance between any two counties. Common variations are to also give nonzero weights to second-order neighbors in the contiguity matrix, or to define a cut-off distance in the inverse-distance matrix after which all weights are set to zero. Here, we restrict ourselves to the basic versions of the geographic spatial weight matrices to keep the analysis parsimonious. As before, we again apply a spectral standardization. This preserves the relative importance of the network links and the symmetry of these matrices, which would not be the case with a row standardization. While we argued before that symmetry is not a desired feature for the spatial weight matrices in the context of our analysis, the asymmetry induced by row standardizing the weights is merely a technical artifact rather than theoretically motivated.

The relative Frobenius difference of the spectrally normalized contiguity matrix to the initial commuter flow matrix is 90.1 percent. For the inverse-distance matrix it is even higher with 128.7 percent. These differences are considerably larger than those comparing commuter flows for different years, which highlights that the variation in commuter flows over time is much less of a concern than choosing the appropriate type of weights. It must be noted that not only are the Frobenius differences sizeable, but also the Frobenius norms $\|\mathbf{W}_N\|_F$ themselves are quite different. For the commuter-based weight matrix it is 10.2, for the contiguity matrix 7.2, and for the inverse-distance matrix just 1.8. This is important for the comparison of the regression results. Similar to the scaling of an ordinary regressor, a larger Frobenius norm is expected to result in a smaller spatial lag coefficient (in absolute value).[6]

2.2 Partial effects and spatial multipliers

The spatial lag $\mathbf{W}_N \ln \mathbf{y}_t$ induces contemporaneous spillover effects among counties. Thus, the partial effect of a change in the exogenous regressors $\mathbf{X}_t$ on the vector $\ln \mathbf{y}_t$ is not just given by $\boldsymbol{\pi}$ but $\mathbf{S}_N(\lambda)\boldsymbol{\pi}$, where $\mathbf{S}_N(\lambda) = (\mathbf{I}_N - \lambda \mathbf{W}_N)^{-1}$ is the short-run spatial multiplier matrix. The resulting effects will be heterogeneous across counties. As summary measures, it is common practice to report average partial effects, differentiated between direct, indirect, and total effects (LeSage and Pace, 2009). The direct effects are

[6]There is no exact proportional relationship between the magnitude of the spatial lag coefficient and the Frobenius norm of the spatial weight matrix because changing the latter also alters the network structure.

governed by the main diagonal elements of the spatial multiplier matrix. They capture the response to a shock originating in the same county, taking into account the feedback effects while the shock propagates through the network. The average short-run direct spatial multiplier is

$$\bar{s}_N^d(\lambda) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{s}_i'\mathbf{S}_N(\lambda)\mathbf{s}_i = \frac{1}{N}\operatorname{tr}\left(\mathbf{S}_N(\lambda)\right),$$

where $\mathbf{s}_i$ is a selection vector with 1 as the i-th element and 0 elsewhere.

The off-diagonal elements of the spatial multiplier matrix capture the indirect effects; that is the responses to shocks originating in another county j. The average short-run indirect spatial multiplier is defined as

$$\bar{s}_N^{ind}(\lambda) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{s}_i'\mathbf{S}_N(\lambda)\mathbf{s}_{-i} = \frac{1}{N}\sum_{i=1}^{N} \mathbf{s}_{-i}'\mathbf{S}_N(\lambda)\mathbf{s}_i,$$

where $\mathbf{s}_{-i} = \boldsymbol{\iota}_N - \mathbf{s}_i$ is a vector with 0 as the i-th element and 1 elsewhere. Thus, the average indirect effect can either be seen as the average response to a shock of equal size in all other counties, or as the average of the cumulative effects on all other counties, depending on whether we first sum across rows or columns of the spatial multiplier matrix. The average short-run total spatial multiplier is then the sum of the direct and indirect multipliers:

$$\bar{s}_N^{tot}(\lambda) = \bar{s}_N^d(\lambda) + \bar{s}_N^{ind}(\lambda) = \frac{1}{N}\sum_{i=1}^{N} \mathbf{s}_i'\mathbf{S}_N(\lambda)\boldsymbol{\iota}_N = \frac{1}{N}\sum_{i=1}^{N} \boldsymbol{\iota}_N'\mathbf{S}_N(\lambda)\mathbf{s}_i = \frac{1}{N}\boldsymbol{\iota}_N'\mathbf{S}_N(\lambda)\boldsymbol{\iota}_N.$$

When the partial effects are very heterogeneous across counties, averaging them provides only little insight. For our counterfactual analyses, we are interested in the impact of a shock that originates in a selected subset of N_{tr} counties that share some common characteristics. These are the treated counties. Let $\boldsymbol{\zeta}$ be the treatment vector which contains elements 1 for all treated and 0 for all untreated counties, and $\boldsymbol{\zeta}_- = \boldsymbol{\iota}_N - \boldsymbol{\zeta}$ the selection vector for the untreated counties. We define the average short-run multiplier for the treated counties as

$$\bar{s}_N^{tr}(\lambda) = \frac{1}{N_{tr}}\boldsymbol{\zeta}'\mathbf{S}_N(\lambda)\boldsymbol{\zeta},$$

and the average short-run multiplier for the untreated counties as

$$\bar{s}_N^{untr}(\lambda) = \frac{1}{N - N_{tr}}\boldsymbol{\zeta}_-'\mathbf{S}_N(\lambda)\boldsymbol{\zeta}.$$

Instead of averages, we can also compute specific quantiles and other quantities of interest from the distribution of multipliers collected in the $N \times 1$ vector $\mathbf{S}_N(\lambda)\boldsymbol{\zeta}$.

These short-run effects generally do not provide a complete picture if there are significant adjustment effects over time. If θ or ρ are nonzero, then there is only a partial contemporaneous adjustment of the dependent variable. There can be a short-run overshooting that is corrected in the following periods, or a gradual build-up of the effects over time. It is thus often more interesting to analyse the effects on the long-run equilibrium. The long-run spatial multiplier matrix is given by $\mathbf{L}_N(\theta, \lambda, \rho) = ((1-\theta)\mathbf{I}_N - (\lambda+\rho)\mathbf{W}_N)^{-1}$. The average long-run multipliers $\bar{l}_N^{d}(\theta, \lambda, \rho)$, $\bar{l}_N^{ind}(\theta, \lambda, \rho)$, $\bar{l}_N^{tot}(\theta, \lambda, \rho)$, $\bar{l}_N^{tr}(\theta, \lambda, \rho)$, and $\bar{l}_N^{untr}(\theta, \lambda, \rho)$ are defined analogously to their short-run counterparts above.

2.3 Estimation methods

Treating $\boldsymbol{\alpha}$ in the econometric model (1) as a vector of fixed effects causes an incidental-parameters problem since the time dimension in our data set is relatively short. After applying a suitable transformation to remove these time-invariant effects from the model, such as first differencing, the transformed lagged dependent variable will be correlated with the idiosyncratic error term (Nickell, 1981). To account for this resulting bias in addition to the endogeneity of the contemporaneous spatial lag $\mathbf{W}_N \ln \mathbf{y}_t$, we apply the Yu et al. (2008) bias-corrected QML estimator. They first apply a within-groups transformation to model (1) to remove the incidental parameters $\boldsymbol{\alpha}$, then estimate the transformed model by QML conditional on the initial observations $\ln \mathbf{y}_0$, and finally apply an analytical bias correction to the coefficient estimates. While their bias correction was developed under asymptotics where both T and N go to infinity, simulation evidence reveals that it works remarkably well even for short T.[7] A shortcoming of the QML estimator is the requirement of a constant spatial weight matrix over time. Otherwise, the bias correction would become unfeasible. In principle, explicitly modeling the feedback from economic growth to commuter flows and accounting for such endogenous feedback in the econometric approach would be desirable. In the current context, however, the limitations of the data prevent a more sophisticated approach.

As an alternative to QML estimation, the coefficients in model (1) could be estimated by the generalized method of moments (GMM), as discussed by Lee and Yu (2014), among others. Following the suggestion of Arellano and Bover (1995), the county-specific effects $\boldsymbol{\alpha}$ are removed with a forward-orthogonal deviation, i.e. by subtracting the mean of the future observations. Subsequently, given that $\boldsymbol{\varepsilon}_t$ is assumed to be serially uncorrelated, the lagged values $\ln \mathbf{y}_{t-s}$ and $\mathbf{W}_N \ln \mathbf{y}_{t-s}$, $s \geq 1$, can be used as instrumental variables in this transformed equation. Higher-order spatial lags, $\mathbf{W}_N^q \ln \mathbf{y}_{t-s}$ with $q \geq 2$, can be

[7] If our time dimension was considerably longer, we should also treat the time effects γ_t as incidental parameters. Lee and Yu (2010) extend the estimator of Yu et al. (2008) in that direction.

valid instruments as well, but they may not be very informative if the spatial spillover effects are small. For the strictly exogenous regressors $\mathbf{X}_t$, all lags and leads can be used as instruments, although in practice leads are rarely considered. Without such leads, the instruments remain valid when those covariates are predetermined with respect to the idiosyncratic shocks. Spatial lags of $\mathbf{X}_t$ could possibly also be used as instruments.

The advantage of the GMM approach is its flexibility to accommodate different assumptions regarding the exogeneity of $\mathbf{X}_t$. It also allows for time-varying spatial weights. On the other hand, the potential weakness of the instruments poses identification challenges, in particular when the persistence of the process is high, which we expect for our application. Additional instruments in the spirit of Blundell and Bond (1998) are often used to overcome potential identification problems. However, they require the assumption that there are no systematic differences across counties regarding their initial growth path. Given the historical divide of Germany and the fact that the catching-up process of the eastern part is still ongoing, this assumption is hard to justify. Figure 2 in Section 3 strongly reinforces this point.

Further challenges are the curse of too many instruments. If all theoretically valid instruments are employed, their number can easily become large relative to the number of counties in our sample. This can lead to severe finite-sample biases and weakened specification tests, calling for appropriate measures to reduce the instrument count (Roodman, 2009). However, the choice of which instruments to retain is often very arbitrary and leads to substantial researcher degrees of freedom, with the risk of selectively reporting the most favorable results. For our application, we found large differences in the estimation results under different sets of instruments and conflicting evidence from overidentification tests, even when the underlying exogeneity assumptions were left unchanged. Because of this lack of internal robustness, we decided not to report GMM estimation results. Moreover, the GMM standard errors were relatively large compared to those from the QML approach, making any inferential attempts quite uninformative.

3 Data

For our analysis, we combine data from several sources. Most macroeconomic data are available in *GENESIS-Online* and the *Regionaldatenbank Deutschland*, two data bases hosted by Germany's federal and regional statistical offices. In a few instances, some data had to be gathered directly from the regional statistical offices. Data on employees and commuters has been obtained from the federal employment agency. The geodata used for visualization purposes and the construction of the geography-based spatial weights is provided by the geodata center of the federal agency for cartography and geodesy. For a full description of the data sources and necessary data adjustments, as well as summary statistics, see the Supplementary Appendix.

3.1 Data assembly

Our unit of observation is German counties (rural and urban districts), equivalent to the NUTS 3 level of the Nomenclature of Territorial Units for Statistics. In the past decades, German states have undergone several local government reorganizations that lead to a consolidation of counties or redrawn district borders. This happened mostly, but not exclusively, in the eastern part of Germany. Major reforms relevant to our data sample, 2002–2017, occured in Saxony-Anhalt (2007), Saxony (2008), and Mecklenburg-Vorpommern (2011). In addition, North Rhine-Westphalia (2009) and Lower Saxony (2016) saw the consolidation of two counties each. These reforms reduced the total number of German counties from 439 to 401, of which there are 107 urban and 294 rural districts. While some of the time series data were subsequently revised by the statistical authorities, that is not the case for all of our variables of interest or in some cases not for the whole time span. To maximize the time horizon for our empirical analysis and because our econometric approach requires a balanced panel data set, we undertook substantial data assembly work to recreate the time series for the district structure as present at the end of our sample period. Details can be found in the Supplementary Appendix.

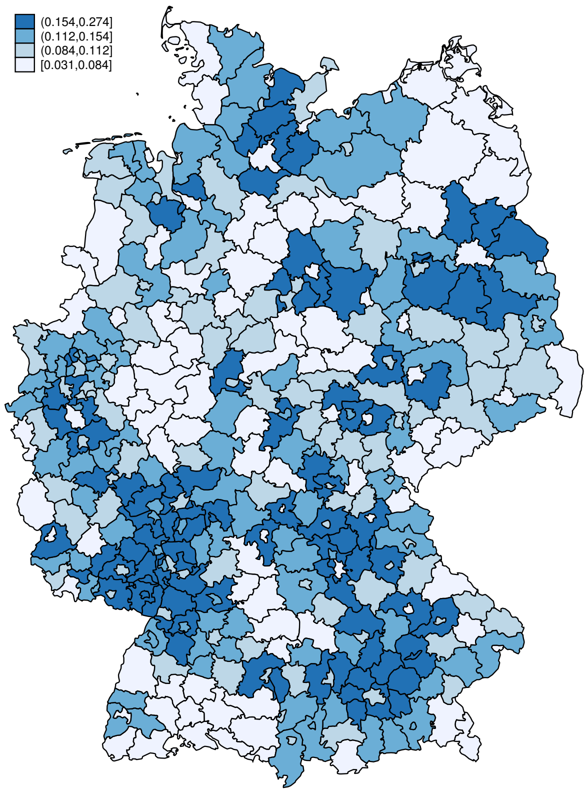
Time series data for prices at the local level are unavailable. We construct a county-level index for deflating the nominal variables, where necessary, by adjusting the German consumer price index with a regional price index constructed by the Bundesinstitut für Bau-, Stadt- und Raumforschung (2009).[8] The latter is an attempt to measure relative consumer price differences across German counties in the year 2009. Because it represents these differences only at a single point in time, we have to implicitly assume that the price distribution across counties is constant throughout our sample period. This assumption does not appear to be too problematic given the finding by Vortmann et al. (2013) that price disparities between East and West Germany have been fairly stable since 2000.

3.2 Commuter flows

For our purpose, commuters are defined as all employees whose place of work is located in a different county than their main residence.[9] This includes individuals with a secondary residence at or near their place of work who may not commute from their main residence on a daily basis. Weekend commuters might still spend a substantial part of their income

[8] We construct our deflator from the German consumer price index because the regional price index is only available for consumer prices. With the inclusion of year dummies in our panel data regression model, the choice of the deflator becomes irrelevant.

[9] We only have commuter flow data for employees who are subject to social security contributions. This excludes civil servants and self-employed people. It also excludes German residents who commute to a workplace abroad.



(a) Commuters per capita, outflow

(b) Commuters per capita, inflow

Figure 1: Spatial distribution of the per capita flow of commuters from and to the 401 German counties in 2002

at their main residence, in particular if they are a family's main breadwinner. Even long-distance commuter linkages thus can be potentially relevant for the shock transmission in the network.

In 2002, on average 12.1% of the residents in a county were commuting to a different county. 69.2% of the commuters lived in an adjacent county to their place of work, and another 16.9% had to cross two county borders. Until 2017, the commuter share of the average county rose to 15.9%, with 66.1% of commuters working in a neighboring county and another 17.4% having to cross one additional border. There is thus a slight tendency towards increasing commuter distances over our sample period.

Commuter flows are quite heterogeneous across Germany. Moreover, they are highly asymmetric. In the two panels of Figure 1, it is apparent that urban areas – identifiable by their comparatively small area – attract a large number of commuters relative to their population size from the surrounding rural areas, but less so in the opposite direction. Yet, the picture is not uniform across the country. As firms in suburban areas often face a cost advantage but can still access the large pool of workers who prefer living in an urban environment, these suburban counties both send a lot of commuters out to the urban center and also welcome relatively high commuter numbers. The larger the distance to the next urban center, the smaller the commuter flows in both directions. Commuter flows are therefore a suitable proxy for the gravitational force that connects large economic centers to the surrounding areas.

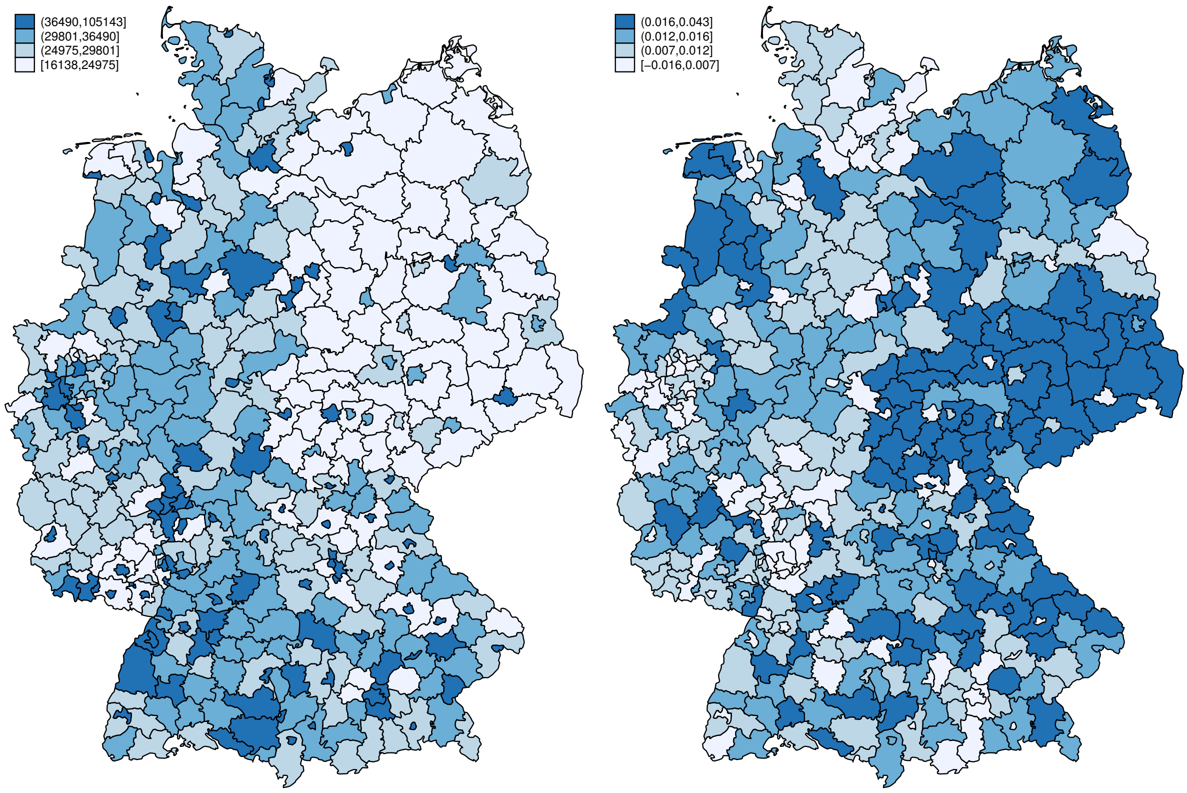
3.3 Distribution and evolution of real GDP per capita

The dependent variable in our regression analysis is the natural logarithm of real GDP per capita. From 2002 to 2017, the mean and median real GDP per capita rose from 33,424 and 29,801 Euro to 39,672 and 35,519 Euro, respectively. However, the gap between the rich and poor counties increased substantially. While real GDP per capita in the poorest county – the rural region Südwestpfalz – grew by 14.4% from 16,138 to 18,461 Euro, for the wealthiest county – the urban region Wolfsburg – it rose over the same time by 76.1% from 105,143 to 185,187 Euro. Compared to 2002, the distribution over the 401 counties in 2017 was more spread out, more skewed, and had fatter tails. In contrast, the Gini coefficient slightly improved from 0.197 to 0.182, driven by the growth of the median county.[10] Juessen (2009) and Eggert et al. (2007) find strong evidence for bimodality in the German GDP per capita distribution in the 1990s just after the reunification. This became much weaker around the turn of the century as many East German counties caught up. For our sample, Silverman's (1981) test cannot reject the hypothesis of an unimodal distribution. Even with the tendency of the richest counties to pull away, this does not manifest itself in a separate mode.

There is considerable heterogeneity in the characteristics of the German counties. The richest counties tend to be major industrial centers, large cities, and their suburban areas. While the 44 richest counties are consistently located in West Germany, this is also the case for the 4 poorest counties throughout our sample period. Moreover, there is very little mobility at the top and bottom of the distribution. For the whole distribution, Spearman's rank correlation between real GDP per capita in 2002 and 2017 is 0.936. From one year to the next, the rank correlation is always higher than 0.988.

Panel (a) of Figure 2 shows the spatial distribution of real GDP per capita at the beginning of our sample in 2002. We see not only that the richer counties tend to be located in the geographic west and south, but also that numerous rich urban counties – which are easily identifiable by their comparatively small area – are surrounded by poorer rural counties. However, when we look at the average real GDP per capita growth rate from 2002 to 2017 in panel (b) of Figure 2, we note that many initially poor East German regions had experienced strong catch-up growth, and that there is hardly any

[10] Detailed summary statistics are provided in the Supplementary Appendix.



(a) Initial real GDP per capita

(b) Average real GDP per capita growth

Figure 2: Spatial distribution of real GDP per capita of the 401 German counties in 2002 and its average annual growth rate from 2002 to 2017

notable difference between rural and urban areas.[11] This already gives a good indication that convergence is indeed happening. But this picture is not uniform across Germany. There are also some poorer regions that have not experienced high growth rates and thus have become even more left behind over time. Yet others have experienced high growth rates despite an already high starting level.

19 counties were less wealthy in per capita terms at the end of our sample period than at the beginning. All but 2 of them were initially above the median. 15 of the counties experiencing negative growth are urban regions, including prominent examples such as the former West German capital Bonn and the financial center Frankfurt am Main. The latter was hit hard by the 2008 global financial crisis and its aftermath. This crisis also hit the adjacent rural counties Hochtaunuskreis and Main-Taunus-Kreis, which still had not fully recovered in 2017. Only one of the counties with negative average growth – the city of Eisenach – is located in East Germany. Nevertheless, Eisenach remains the

[11]The growth rate of real GDP per capita is approximated by the first difference in the natural logarithm.

wealthiest East German county. It also took a substantial hit during the financial crisis, although not as a financial center but because of its dominant manufacturing sector that also saw a slowdown.

Figure 2 suggests the presence of spatial dependence. We observe that many counties have similar real GDP per capita levels and growth rates as those in close geographic proximity. This suggests positive spatial autocorrelation that one might be tempted to model with the conventional geographic spatial weight matrices. However, there is also a substantial number of (mostly urban) counties that are markedly different to their (rural) neighbors, indicating the presence of negative spatial autocorrelation in parts of the network. This heterogeneity makes it difficult to meaningfully interpret summary measures for global spatial autocorrelation based on geographic spatial weights. Moran's I, computed as

$$I_t = \frac{N}{\left(\sum_{i=1}^{N}\sum_{j=1}^{N} w_{ij}\right)} \frac{(\mathbf{y}_t - \bar{y}_t \boldsymbol{\iota}_N)' \mathbf{W}_N (\mathbf{y}_t - \bar{y}_t \boldsymbol{\iota}_N)}{(\mathbf{y}_t - \bar{y}_t \boldsymbol{\iota}_N)'(\mathbf{y}_t - \bar{y}_t \boldsymbol{\iota}_N)}$$

(Moran, 1950; Cliff and Ord, 1981), where $\bar{y}_t$ is the cross-sectional average at time t, yields very different results for geographic spatial weights compared to commuter-based weights. At the beginning of our sample, we obtain $I_{2002} = 0.106$ and $I_{2002} = 0.011$ with contiguity weights and inverse-distance weights, respectively. Both are positive and statistically significantly different from the expected value under no global spatial autocorrelation, $-(N-1)^{-1} = -0.002$, at the 1% and 5% significance levels, respectively. This reflects the similarity of the majority of geographically proximate counties. In contrast, commuter-based spatial weights yield $I_{2002} = -0.074$, significant at the 5% level. The negative sign is a consequence of the stronger emphasis on links between relatively poor rural counties and relatively rich urban centers. As shown in Figure 3, the positive global spatial autocorellation with geographic weights became smaller over time and eventually insignificant. On the other hand, with commuter-based weights, the negative autocorrelation strengthened to $I_{2017} = -0.108$, with an intermediate peak at $I_{2014} = -0.131$, indicating that some counties might be left even further behind. The gap between Moran's I obtained with the three different spatial weight matrices remains relatively constant over time. This indicates that the observed trend reflects changes in the distribution of real GDP per capita, and that it is not driven by changes in the commuter behavior. It thus appears justified to base our econometric analysis on constant 2002 commuter flows.[12]

As a global measure of spatial autocorrelation, Moran's I hides a lot of heterogeneity.

[12]We report Moran's I and the respective standardized z-score for all years and all three spatial weight matrices in the Supplementary Appendix.

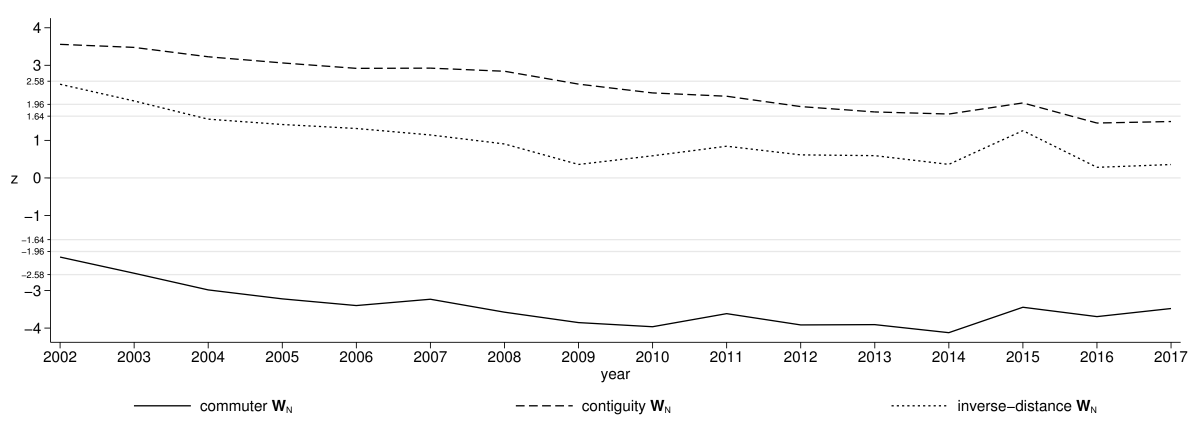


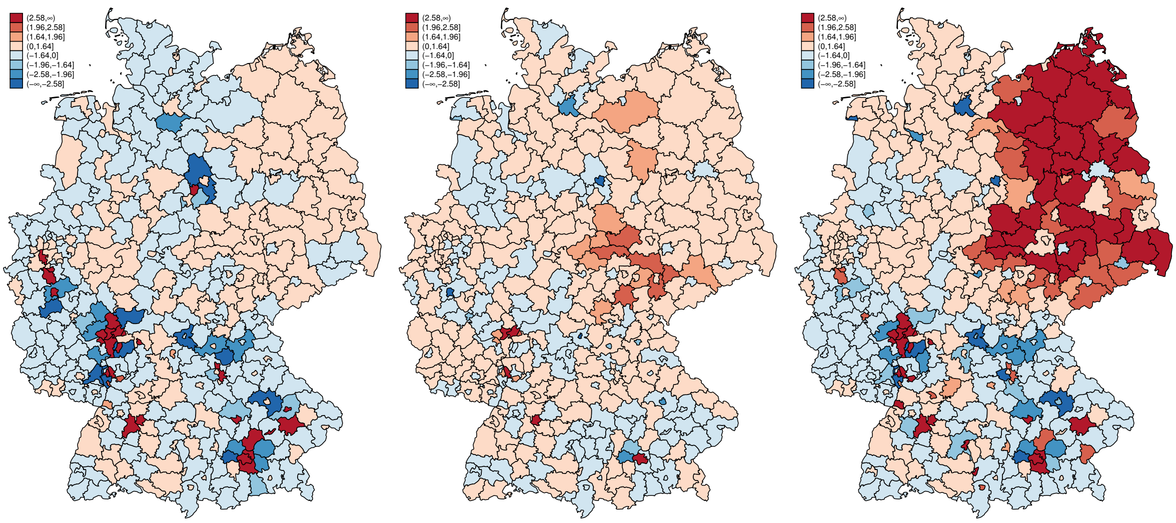
Figure 3: Moran's I global spatial autocorrelation over time, standardized z-score

The local version of Moran's I,

$$I_{it} = (y_{it} - \bar{y}_t) \sum_{j=1}^{N} w_{ij}(y_{jt} - \bar{y}_t)$$

such that $\sum_{i=1}^{N} I_{it}$ is proportional to I_t (Anselin, 1995), summarizes for every county i to what extent it is linked to others of similar or dissimilar real GDP per capita. Not surprisingly, among the 401 German counties there are some with strongly negative and some with strongly positive local spatial autocorrelation. Figure 4 displays the spatial distribution of the respective standardized z-scores for the start of our sample. There are commonalities across the three different spatial weight matrices but also marked differences. The majority of the counties do not exhibit a statistically significant local spatial autocorrelation even at the 10% significance level. In line with the global Moran's I, the sign of the local measure is predominantly positive with the geographic weights and predominantly negative with the commuter weights. This reflects the strong commuting ties between relatively poor rural counties and relatively rich urban counties, which is not fully captured by the geography-based spatial weights.

Irrespective of the spatial weight matrix, large parts of East Germany are characterized by positive spatial autocorrelation. Especially with inverse-distance weights, this positive autocorrelation is highly statistically significant, reflecting the similar economic development across this sparsely populated area. The inverse-distance weights and the commuter weights yield very similar spatial autocorrelation patterns in the south and southwest of Germany with negative signs in rural counties vicinal to strong economic centers. Some of the latter centers exhibit large positive spatial autocorrelation, as they form spatial clusters comprising multiple counties that are also deeply interconnected by



(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

Figure 4: Moran's I local spatial autocorrelation in 2002, standardized z-score

commuter flows. As shown in Table 1, the regions with the strongest positive spatial autocorrelation are the Frankfurt am Main and Munich metropolitan areas. In contrast, the wealthy city of Wolfsburg in the northern state of Lower Saxony has by far the strongest negative spatial autocorrelation based on the geographic weights, given that it is surrounded by relatively poor counties along the former inner-German border. However, commuter flows constitute a strong link between Wolfsburg and the metropolitan area Hanover-Braunschweig-Göttingen, giving rise to positive local spatial autocorrelation, albeit statistically insignificant. The strongest negative spatial autocorrelation with commuter weights is instead observed for Gifhorn in Wolfsburg's commuter belt. It is evident from Table 1 that some counties exhibit strong spatial autocorrelation, either positively or negatively, with any of the spatial weight matrices, while for others the picture depends on the chosen weights. The former capital city Bonn is a case in point. With commuter weights, it exhibits statistically significantly positive spatial autocorrelation, while with contiguity weights it has the second-strongest negative autocorrelation (in terms of the standardized z-score). Conversely, the rural district of Munich, which is adjacent to the same-named Bavarian capital city, is among the top 3 counties with positive spatial autocorrelation under commuter and inverse-distance weights, while close to the bottom under contiguity weights.

3.4 Sectoral decomposition

The global financial crisis disparately affected firms in different sectors. In our regressions, we account for different post-crisis growth trajectories as a function of the sectoral

Table 1: Moran's I measure of spatial autocorrelation in real gross domestic product per capita, 2002

	commuter $\mathbf{W}_N$		contiguity $\mathbf{W}_N$		inverse-distance $\mathbf{W}_N$	
	rank	z-score	rank	z-score	rank	z-score
global Moran's I		-2.108**		3.559***		2.496**
local Moran's I (top 3)						
Frankfurt am Main (u)	**2**	11.964***	**1**	5.238***	**1**	12.574***
München (u)	**1**	12.207***	**2**	4.178***	**3**	9.055***
Main-Taunus-Kreis (r)	9	5.909***	**3**	3.651***	7	5.232***
München (r)	**3**	11.586***	385	-1.160	**2**	10.392***
local Moran's I (bottom 3)						
Bonn (u)	13	4.376***	**400**	-3.787***	117	0.839
Hamburg (u)	49	0.992	397	-2.438**	**400**	-5.389***
Wolfsburg (u)	55	0.889	**401**	-7.763***	**401**	-18.976***
Gifhorn (r)	**401**	-5.765***	367	-0.856	143	0.495
Helmstedt (r)	**399**	-5.064***	372	-0.933	177	0.234
Schweinfurt (u)	351	-1.147	**399**	-3.761***	371	-1.737*
Rhein-Pfalz-Kreis (r)	**400**	-5.106***	386	-1.267	**399**	-4.710***

Note: The counties are ranked in terms of their standardized z-score for local Moran's I. (r) and (u) indicate rural and urban districts, respectively. Listed are counties that are in the top 3 or bottom 3 of the rank distribution (bold-faced rank numbers) for at least one spatial weight matrix. The ordering in the table is by average rank. The significance levels refer to a two-sided test of no local/global spatial autocorrelation.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

decomposition by adding interaction terms between a post-crisis dummy for the years from 2008 onwards and the shares in gross value added (GVA) of four sectoral groupings, broadly defined based on the Classification of Economic Activities (WZ 2008) of the Federal Statistical Office of Germany. These are the *industrial sector* (WZ sections B–E), the *construction sector* (WZ section F), a *services sector* that includes trade, transportation, information, and communication services (WZ sections G–J), and the *financial sector* that includes financial, insurance, real estate, and business services (WZ sections K–N). While there is some variation in sector shares over time, for our empirical analysis we restrict ourselves to the sector shares at the beginning of our sample. This is for the reason that these sector shares cannot be regarded as exogenous when the dependent variable is real GDP per capita. We believe that these endogeneity concerns weigh stronger than any biases due to the neglected time variation of these shares.

Overall, the largest distortions to the sectoral decomposition at the county level occured in parallel to the global financial crisis, from the year 2008 onwards, and remained fairly stable in the years before. In Frankfurt am Main, the share of the financial sector (as defined above) remained relatively stable between 46 and 48 percent until 2009 before it slid down towards 41 percent. In the adjacent Hochtaunuskreis, the drop was even more pronounced, from 50 percent in 2008 to 42 percent in 2010, and eventually even 38 percent in 2017, which shows the lasting effect of the crisis. In the East German manufacturing lighthouse Eisenach, the share of the industrial sector decreased only slowly from 51 to 47 percent before the crisis onset, but then plummeted to 27 percent in 2008. Since then, the industrial sector recovered and reached again 43 percent by 2014. These examples illustrate that the German counties experienced quite heterogeneous consequences of the financial crisis. Fully accounting for the differential timing and magnitude of the initial impact and the recovery from the crisis in an endogeneity-robust way is beyond the scope of this paper. Including further interaction effects would risk overfitting the data, and finding additional relevant control variables at the quite disaggregated county level is challenging.

The reference group in our regressions is the *public sector* (WZ sections O–U) that includes public administration, education, health and social services, entertainment, and other services. We do not control for the *aggricultural sector* (WZ section A) in our regressions due to its negligible relevance. However, we still use it for an illustrative example in our counterfactual analysis, in which we simulate the spillover effects from shocks that originate in counties that are characterized by comparatively large shares of particular sectors.

3.5 Determinants of economic growth

Capital and labor are the key input factors in textbook production functions. The transitional dynamics of output per worker are thus a function of capital investment and the growth rate of the labor force. We only observe investment data for firms in the mining and quarrying industry and the manufacturing industry, which serves as a proxy for overall investment. This is a valid approximation as long as the sectoral shares in GVA remain stable over time, assuming that investment in different sectors follows similar business cycles. Any cross-sectional variations in relative sectoral shares can then be captured by the county-specific fixed effects in our regression model. As discussed in Section 3.4, the global financial crisis had a differential effect on the sectoral decomposition across counties. While we cannot entirely account for these distortionary effects, we are confident that our approach of including interaction terms between a post-crisis dummy and the initial sectoral shares captures a sufficiently large share of these distortions.

As a proxy for labor force growth, we use the population growth rate. While we could compute a growth rate for the labor force from the number of employees who are subject to social security contributions, this would also be an imperfect approximation. Moreover, it could be quite volatile, in particular in times of economic turmoil. Given that business cycle fluctuations are not the scope of our analysis, population growth is thus a more stable proxy for the change in the labor force potential. We also control for human capital differences with the shares of employees who either have a professional qualification or an academic qualification, which is common practice in the literature (Goldin and Katz, 2008). The base group is low-skilled workers without higher qualifications, including workers whose qualifications are unknown. The average share of employees with a professional qualification is 64%, while it is 9% for academic qualifications. Because we use end-of-year data for educational attainment, these variables enter our regressions with a one-period lag.

4 Empirical results

We now present the results from our time-space dynamic panel data regressions with the bias-corrected QML estimator of Yu et al. (2008). The dependent variable is the natural logarithm of real GDP per capita. All specifications contain a time lag $\mathbf{y}_{t-1}$, a contemporaneous spatial lag $\mathbf{W}_N\mathbf{y}_t$, and a spatial time lag $\mathbf{W}_N\mathbf{y}_{t-1}$, as in equation (1). The exogenous regressors in $\mathbf{X}_t$ are the natural logarithm of real investment per capita, the population growth rate, and the shares of employees with professional or academic qualifications. These independent variables serve as proxies for the physical capital, labor, and human capital inputs in the production of goods and services. Due to the dynamic nature of the model, their coefficients $\boldsymbol{\pi}$ can be interpreted as short-run effects on the GDP per capita growth rate, conditional on the initial state and prior to accounting for any spillover effects.

We provide the regression results in Table 2. For each of the three spatial weighs matrices, we estimate three different model specifications. In columns (1), (4), and (7), no time effects are included. In macro applications such as ours, this rarely yields reliable results. Time effects account for global shocks that affect all counties simultaneously. These can be changes to the economic environment such as interest rates or commodity prices, or any political developments that affect the business climate. Accounting for these global shocks is particularly important in spatial econometric models because otherwise the spatial spillover effects could become conflated with them. This is indeed what we observe when we compare the estimates with those in columns (2), (5), and (8) that have time dummies included. The spatial lag coefficients shrink substantially, and we notice some significant changes in the estimated coefficients of the exogenous regressors as well. We thus do not pay much attention on the results without time effects.[13]

The global financial crisis fell right into the middle of our data set's time span. While time dummies can capture any common crisis effects, they do not account for the heterogeneity of the impact the crisis had on different counties. In columns (3), (6), and (9), we thus add interaction terms between a post-crisis dummy for the years from 2008 onwards and the shares in GVA of the industrial sector, the construction sector, some service sectors, and the financial sector. Despite our observation that the financial crisis shook up considerably the sectoral decomposition in some counties, it is reassuring to see that the results are largely unaffected by the addition of these interaction terms. We

[13] While the standardization of the spatial weight matrices should ensure that the upper bound for the spatial lag coefficient is unity, estimates above 1 can occur as an artifact of the bias correction procedure, as happened here in column (7) of Table 2.

Table 2: Bias-corrected QML estimation of time-space dynamic panel models

	commuter $\mathbf{W}_N$			contiguity $\mathbf{W}_N$			inverse-distance $\mathbf{W}_N$		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
$\mathbf{y}_{t-1}$	0.892***	0.856***	0.827***	0.862***	0.850***	0.825***	0.858***	0.864***	0.832***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
$\mathbf{W}_N\mathbf{y}_t$	0.361***	0.044**	0.037**	0.500***	0.144***	0.136***	1.006***	0.319***	0.301***
	(0.016)	(0.019)	(0.018)	(0.017)	(0.022)	(0.022)	(0.018)	(0.069)	(0.069)
$\mathbf{W}_N\mathbf{y}_{t-1}$	-0.288***	0.008	0.002	-0.399***	-0.068***	-0.088***	-0.368***	-0.304***	-0.277***
	(0.018)	(0.020)	(0.020)	(0.020)	(0.026)	(0.026)	(0.023)	(0.078)	(0.078)
inv_t	0.006***	0.005***	0.004***	0.005***	0.004***	0.004***	-0.001	0.004***	0.004***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
pop_t	-0.377***	-0.218***	-0.212***	-0.304***	-0.197**	-0.198**	-0.179***	-0.213**	-0.211**
	(0.070)	(0.083)	(0.082)	(0.067)	(0.082)	(0.082)	(0.065)	(0.083)	(0.082)
prof_{t-1}	0.115***	0.088**	0.046	0.103***	0.080**	0.042	-0.051**	0.108***	0.061*
	(0.023)	(0.036)	(0.036)	(0.022)	(0.035)	(0.035)	(0.021)	(0.035)	(0.035)
acad_{t-1}	0.351***	-0.013	0.103*	0.307***	0.031	0.125**	-1.087***	-0.019	0.097
	(0.035)	(0.059)	(0.060)	(0.034)	(0.059)	(0.061)	(0.045)	(0.059)	(0.060)
time effects	no	yes	yes	no	yes	yes	no	yes	yes
crisis × sector	no	no	yes	no	no	yes	no	no	yes
observations	6015	6015	6015	6015	6015	6015	6015	6015	6015
counties	401	401	401	401	401	401	401	401	401

Note: The dependent variable $\mathbf{y}_t$ is ln(real GDP per capita). The independent variables are ln(real investment per capita) (inv), population growth (pop), and the shares of employees with professional qualifications (prof) or academic qualifications (acad). Some specifications include 14 time dummies for the years 2004–2017, and some include interaction effects between a post-financial crisis dummy (years 2008–2017) and the initial sectoral shares in GVA for 4 sectoral groupings. Standard errors are in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

observe a lower growth effect for the share of employees with a professional qualification, and a larger effect for those with an the academic qualification. Because the educational level is substantially correlated with the sectoral decomposition, it is not surprising that controlling for the sectoral shares particularly affects these two coefficients. Importantly, in these final specifications the effect of a higher share of academically-trained employees is positive and larger than that for those with professional qualifications, which is in line with the expected benefits of human capital accumulation.

In all specifications, the coefficients of investment and population growth have the expected sign in accordance with the neoclassical growth model, and changing the spatial weight matrix hardly affects them. Likewise, the coefficient of the pure time lag remains fairly stable across all specifications. It indicates a substantial degree of persistence over time, and therefore a slow speed of adjustment. The interpretation of the spatial lag and spatial time lag coefficients is less straightforward. Their magnitude varies noticeably with the choice of the spatial weight matrix. Not surprisingly, they tend to be larger in absolute value the smaller the Frobenius norm of the underlying weight matrix is.

In the following, we restrict our attention to the specifications with post-crisis interaction terms. Due to the difficulties in interpreting the spatial lag coefficients themselves, it is more instructive to focus on the short-run and long-run multipliers, which are shown

Table 3: Average short-run and long-run spatial multipliers

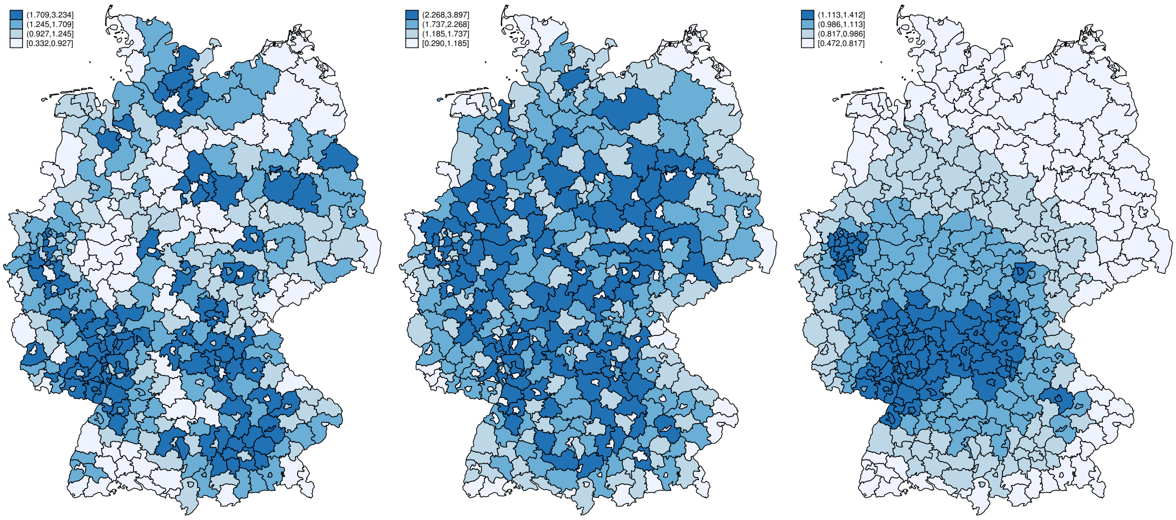
	commuter $\mathbf{W}_N$			contiguity $\mathbf{W}_N$			inverse-distance $\mathbf{W}_N$		
	direct	indirect	total	direct	indirect	total	direct	indirect	total
short-run	1.000	0.033**	1.033**	1.003***	0.127***	1.129***	1.001**	0.407***	1.408***
	(0.000)	(0.017)	(0.017)	(0.001)	(0.024)	(0.024)	(0.000)	(0.133)	(0.133)
long-run	5.825***	1.345***	7.169***	5.787***	1.718**	7.505***	5.954***	0.968	6.922***
	(0.307)	(0.556)	(0.693)	(0.303)	(0.758)	(0.879)	(0.319)	(1.817)	(1.846)

Note: The multipliers are computed for the regressions in columns (3), (6), and (9) of Table 2. Standard errors (in parentheses) are computed with the Delta method. The p-values correspond to a one-sided test of equality to unity for the direct and total multipliers, and a one-sided test of equality to zero for the indirect multiplier.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

in Table 3. The short-run direct spatial multiplier estimates are hardly distinguishable from unity, even though the difference is statistically significant for the geography-based spatial weight matrices. Consequently, for the direct effects of a change in one of the exogenous regressors on output growth in the same county, the respective coefficients can be interpreted in the same way as in the absence of any spatial spillover effects. Yet, the statistically significant indirect multipliers give rise to relevant externalities on other counties. Regarding the magnitudes of the indirect and total multipliers, the choice of the spatial weight matrix is anything but innocuous. Assuming a commuter-based network structure, the externalities amount to just 3.3 percent of the direct effect, while under an inverse-distance spillover regime they rise above 40 percent.

From a policy perspective, the cumulative long-run effects are usually more relevant than the contemporaneous short-run effects. These are considerably higher due to the strong intertemporal persistence. It takes time until the benefits (or detriments) of a policy change or shock fully materialize. The average direct long-run multiplier is very similar across the three spatial weight matrices. The indirect multiplier is now lowest (and not even statistically significant) for the model with the inverse-distance spatial weights. This is because the contemporaneous spillover effects are almost completely offset by the one-period lagged spillover effects. Just focusing on the short-run effects could thus be very misleading.

The average multipliers are still masking the heterogeneity of the effects. For individual counties, we can distinguish between spill-in and spill-out multipliers, depending on whether we are summing over the rows or columns of the spatial multiplier matrix. Figure 5 shows the spatial distribution of the indirect long-run spill-in multipliers; that is the response to a shock that occurs in all other counties. Figure 5(a) closely resembles Figure 1(a) because the spill-in effects for a county are directly linked to its commuter outflows. Similarly, the distribution of the indirect spill-out multipliers – that is the reponse by all other counties to a shock that originates in the respective county – is hardly



(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

Figure 5: Indirect long-run spill-in multipliers

distinguishable from Figure 1(b).[14] With contiguity weights, the decisive factor for the effect size is the number of adjacent counties. Therefore, urban counties that are often surrounded by only one or two rural counties show the smallest spill-in response. When using inverse-distance weights, the effect size is largest in regions where many small-area counties are clustered and therefore the distances between those counties are small. Due to their symmetry, for the geography-based spatial weight matrices the distributions of the spill-in and spill-out multipliers are identical.

To further uncover the heterogeneity of the spatial multipliers, we consider some counterfactual experiments. We do this by assuming that a certain group of counties is treated with a unit shock, while all other counties are only indirectly affected through the cummulative spillover effects. We report the average long-run spatial multipliers for the treated and the untreated counties in Table 4. In each counterfactual scenario, 20 counties – the top or bottom 5 percent of the distribution according to some treatment indicator – are directly affected by the hypothetical treatment. The average multiplier for the treated is conceptually comparable to the conventional average total multiplier. The two would be identical if the treatment was applied to all 401 counties. The average multiplier for the untreated has a similar interpretation as the average indirect multiplier, although it applies only to a subsample. Both multipliers are necessarily smaller than those in Table 3 because the spillover effects originate in fewer counties.

In our first counterfactual exercise, we consider the 20 counties with the highest GVA share of the financial sector (in the year 2002) as the treated counties. Some of them are

[14]For brevity, we do not show a separate figure for the spill-out multipliers.

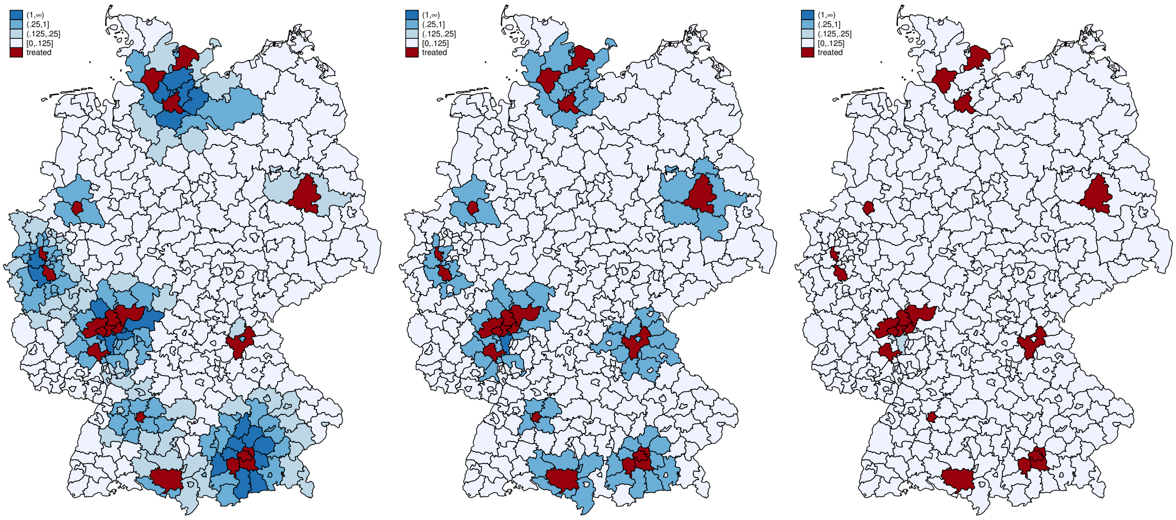
Table 4: Average counterfactual long-run spatial multipliers

	commuter $\mathbf{W}_N$		contiguity $\mathbf{W}_N$		inverse-distance $\mathbf{W}_N$	
	treated	untreated	treated	untreated	treated	untreated
financial centers	6.540***	0.228**	6.134***	0.081**	6.024***	0.050
	(0.478)	(0.102)	(0.366)	(0.036)	(0.343)	(0.094)
	[5.856, 7.940]	[0.019, 2.311]	[5.759, 6.941]	[0.000, 1.221]	[5.977, 6.100]	[0.022, 0.153]
industrial centers	5.867***	0.092***	5.838***	0.070**	6.004***	0.051
	(0.311)	(0.037)	(0.308)	(0.031)	(0.333)	(0.097)
	[5.806, 6.026]	[0.000, 1.789]	[5.746, 6.089]	[0.000, 0.616]	[5.976, 6.023]	[0.019, 0.278]
agricultural centers	5.908***	0.022***	6.274***	0.076**	6.001***	0.042
	(0.315)	(0.009)	(0.401)	(0.034)	(0.330)	(0.079)
	[5.800, 6.133]	[0.000, 0.611]	[5.773, 7.048]	[0.000, 1.237]	[5.983, 6.016]	[0.021, 0.204]
high GDP per capita	6.171***	0.311**	5.824***	0.058**	6.020***	0.055
	(0.376)	(0.134)	(0.306)	(0.026)	(0.343)	(0.104)
	[5.850, 7.756]	[0.025, 2.293]	[5.734, 6.128]	[0.000, 0.616]	[5.977, 6.078]	[0.019, 0.386]
low GDP per capita	5.877***	0.024***	6.008***	0.094**	6.010***	0.047
	(0.312)	(0.009)	(0.342)	(0.041)	(0.335)	(0.088)
	[5.799, 6.137]	[0.000, 0.440]	[5.759, 6.427]	[0.000, 0.932]	[5.978, 6.029]	[0.023, 0.146]
high population density	6.340***	0.317**	6.139***	0.071**	6.077***	0.054
	(0.416)	(0.137)	(0.369)	(0.032)	(0.389)	(0.102)
	[5.887, 7.149]	[0.022, 1.921]	[5.759, 6.976]	[0.000, 1.538]	[5.975, 6.185]	[0.021, 0.255]
low population density	5.993***	0.014***	6.575***	0.054**	6.012***	0.036
	(0.325)	(0.005)	(0.493)	(0.025)	(0.334)	(0.067)
	[5.806, 6.234]	[0.000, 0.553]	[6.023, 7.362]	[0.000, 1.231]	[5.984, 6.034]	[0.018, 0.123]

Note: The multipliers are computed for the regressions in columns (3), (6), and (9) of Table 2. Standard errors (in parentheses) are computed with the Delta method. The p-values correspond to a one-sided test of equality to unity for the average multiplier on the treated, and a one-sided test of equality to zero for the average multiplier on the untreated. The minimum and maximum multipliers are shown within the square brackets. In each counterfactual, there are 20 treated and 381 untreated counties.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

located geographically close to each other. For example, 6 out of the 20 treated counties are in the Rhein-Main area, with Frankfurt am Main as a center of gravity. These counties are strongly interlinked, both from a commuter perspective and in a purely geographic network. These counties thus benefit from their own treatment and the treatment of their neighboring counties. It is therefore not surprising to find a comparatively large average multiplier on the treated. Given that not all of the treated counties are located in treatment clusters, there is also considerable heterogeneity remaining within the treated group. The strongest long-run effect is close to 8-fold the size of the initial treatment, while it is less than 6-fold for more isolated treated counties.

There are pronounced differences between the multipliers from the three spatial weight matrices. While the lower bound for the multiplier is quite stable across network structures and counterfactual scenarios, the upper bound varies substantially. Under the first counterfactual treatment scenario, the effects are strongest based on the commuter links, which one may not have expected from the estimated spatial lag coefficients. For the untreated counties, those closely linked to clusters of treated counties reach a multiplier of up to 2.3, which is considerable given that these are entirely indirect effects. This



(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

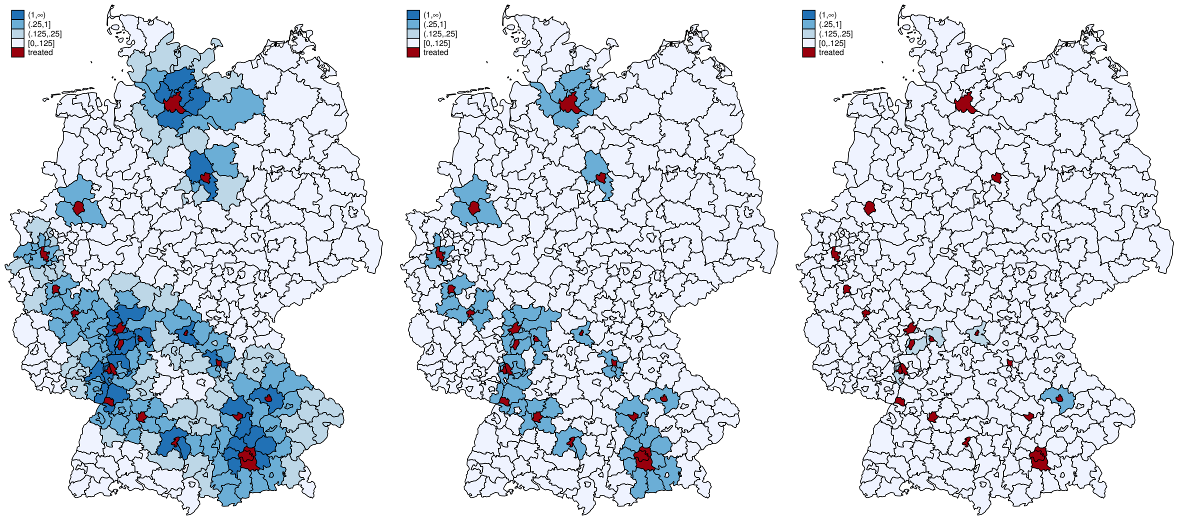
Figure 6: Counterfactual long-run spatial multipliers for treatment of financial centers

maximum multiplier for the untreated is roughly halved under the contiguity network, and it is almost negligible when inverse-distance weights are used, even for those counties in close proximity to the treated ones. In Figure 6, it is evident that also under the more favorable network schemes any noticable indirect effects remain local. For the majority of untreated counties, there is hardly any measurable response.

In our second counterfactual scenario, we apply the treatment to the 20 counties with the highest share of the industrial sector in their GVA. While most of those counties are located in the south of Germany, they are not strongly clustered and hardly any of them shares a common border with another treated county. Consequently, the feedback effects are smaller than in the first scenario and there is not much variation of the long-run multiplier effect on the treated, with the highest multiplier barely exceeding 6. The differences are also much less pronounced across spatial weight matrices.

In the third scenario, we use the GVA share of the agricultural sector as an indicator to select 20 counties that are predominantly rural. These are largely clustered in the north-east of Germany. The geographic proximity yields comparatively large multiplier effects from a contiguity network. In contrast, when we use commuter weights, the multipliers on the treated and untreated are both relatively low as there are no substantial commuter flows between these counties. The long-run multipliers from the inverse-distance spatial weights remain small due to the offsetting effects of the contemporaneous and one-period-lagged spatial spillovers.

In the next two scenarios, we consider a treatment of the 20 richest and 20 poorest counties (in 2002), respectively. The former can be mainly found in the south and south-



(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

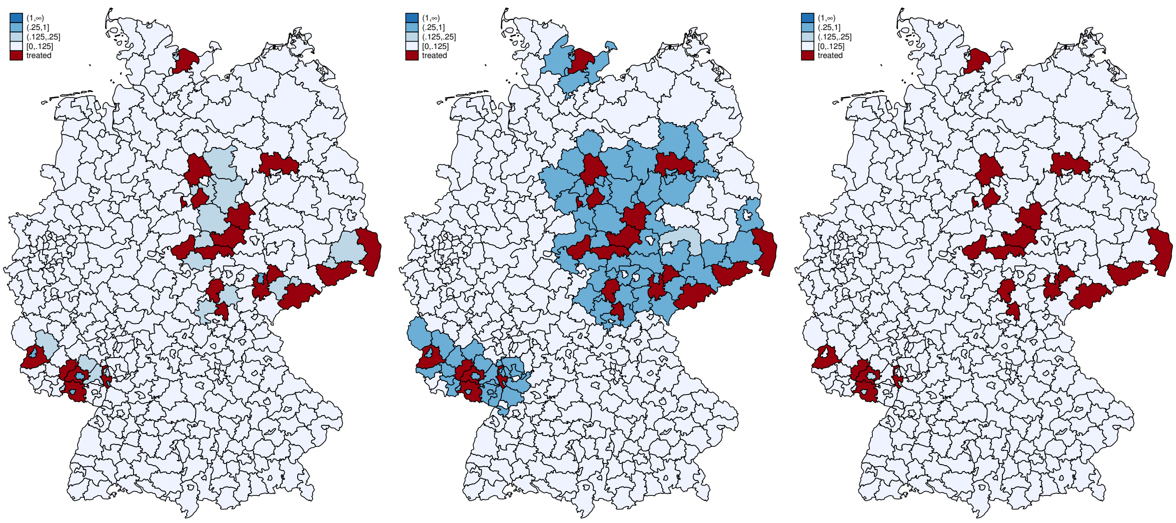
Figure 7: Counterfactual long-run spatial multipliers for treatment of rich counties

west of Germany, while many of the latter are clustered in the east and along the former intra-German border. The different implications of commuter-based or contiguity-based spatial weights become quite apparent when comparing these two treatment scenarios. Under the former regime, the long-run spatial multipliers are higher when the richest counties are treated because the surrounding counties tend to have strong commuter linkages with them. With contiguity weights, the reinforcement of the spillover effects is stronger from a treatment of the poorest counties, simply because of the geographic clustering. The resulting differential spatial multipliers on the untreated are apparent in Figures 7 and 8.[15]

The situation is similar when we contrast the treatment scenarios for the counties with the highest and lowest population densities. Many of the latter are the same rural counties in the northeastern part that we considered earlier under the agricultural centers scenario. Many of the high-density counties, on the other hand, are found in the Rhein-Ruhr metropolitan region. There is considerable geographic clustering at both ends of the population density spectrum, contributing to strong multiplier effects when using contiguity weights. In contrast, commuting is a driving force for the spillover effects primarily in densely populated regions.

There are important policy consequences of these findings. If it was the objective of a policy maker to maximize the total benefit for the whole country from an intervention in a limited number of counties, a commuter-based propagation mechanism would need

[15]For the remaining counterfactual scenarios, the graphical illustration of the long-run spatial multipliers on the untreated can be found in the Supplementary Appendix.



(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

Figure 8: Counterfactual long-run spatial multipliers for treatment of poor counties

to target more densely populated areas, many of which are also among the wealthiest regions. Yet, this would aggravate existing inequalities as remote regions would be left behind even further. Conversely, directly targeting the poorest regions would require a stronger stimulus in order to achieve the same aggregate effect due to the small local multipliers. On the other hand, with a purely geographic shock propagation, there would be hardly any guidance to the policymaker as to where to deploy the limited resources.

5 Conclusion

This paper demonstrates that commuter flows can be an important factor in the analysis of regional convergence when the geographic units are sufficiently disaggregated. Commuter flows link regions in which commuters earn their income – often comparatively rich urban areas – to those where they spend a substantial part of it – often comparatively poor rural areas – and they do so in an asymmetric way. While commuter flows are correlated with geographic proximity, they are based on workers' observed behavior and thus better reflect the economic dependencies among regions. In contrast, when dependencies are proxied merely by the relative geographic location of the regions, such asymmetric shock propagation mechanisms cannot be adequately captured.

With data on German counties, we illustrate that varying assumptions on the spatial network structure result in significantly different local adjustment dynamics. Importantly, the regression coefficients in a time-space dynamic panel data model can be highly misleading about the magnitude of the effects. The spatial lag coefficients are not directly comparable across specifications with different spatial weight matrices, even if the latter are appropriately standardized. Moreover, the heterogeneity of the spatial multiplier effects is masked by traditionally reported average effects. We highlight that the propagation of an initial stimulus not only depends on the place in which it originates, but also on the assumed network structure. The local multiplier effects can substantially vary across counties, depending on their position in the spatial network and the nature of the considered treatment or shock.

From a policy perspective, our results emphasize that the differential regional impacts of an intervention should be carefully considered. In our counterfactual experiments, directly treating the poorest regions hardly creates any spillover effects under a commuter flow network structure, while large gains can be realized by treating the well-connected richer counties. This creates a potential trade-off between maximizing the aggregate welfare gains from an intervention and reducing the inequality across regions. We expect that these conclusions continue to hold under alternative measures of economic dependence, while the less realistic geographic linkages do not reveal such policy implications.

References

Ahlfeldt, G. M., S. J. Redding, D. M. Sturm, and N. Wolf (2015). The economics of density: Evidence from the Berlin Wall. *Econometrica 83*(6), 2127–2189.

Allen, T., C. Arkolakis, and X. Li (2015). Optimal city structure. Working Paper, Yale University.

Alonso, W. (1964). *Location and Land Use: Toward a General Theory of Land Rent.* Cambridge: Harvard University Press.

Amarasinghe, A., R. Hodler, P. A. Raschky, and Y. Zenou (2018). Spatial diffusion of economic shocks in networks. Working Paper 7001, CESifo.

Anselin, L. (1988). *Spatial Econometrics: Methods and Models.* Dordrecht: Kluwer Academic Publishers.

Anselin, L. (1995). Local indicators of spatial association—LISA. *Geographical Analysis 27*(2), 93–115.

Anselin, L. and A. K. Bera (1998). Spatial dependence in linear regression models with an introduction to spatial econometrics. In A. Ullah and D. E. A. Giles (Eds.), *Handbook of Applied Economic Statistics*, Chapter 7, pp. 237–289. New York: Marcel Dekker.

Arbia, G., J. Le Gallo, and G. Piras (2008). Does evidence on regional economic convergence depend on the estimation strategy? Outcomes from analysis of a set of NUTS2 EU regions. *Spatial Econometric Analysis 3*(2), 209–224.

Arellano, M. and O. Bover (1995). Another look at the instrumental variable estimation of error-components models. *Journal of Econometrics 68*(1), 29–51.

Asgharian, H., W. Hess, and L. Liu (2013). A spatial analysis of international stock market linkages. *Journal of Banking & Finance 37*(12), 4738–4754.

Badinger, H., W. Müller, and G. Tondl (2004). Regional convergence in the European Union, 1985–1999: A spatial dynamic panel analysis. *Regional Studies 38*(3), 241–253.

Bailey, N., S. Holly, and M. H. Pesaran (2016). A two-stage approach to spatio-temporal analysis with strong and weak cross-sectional dependence. *Journal of Applied Econometrics 31*(1), 249–280.

Bavaud, F. (1998). Models for spatial weights: A systematic look. *Geographical Analysis 30*(2), 153–171.

Beenstock, M. and D. Felsenstein (2012). Nonparametric estimation of the spatial connectivity matrix using spatial panel data. *Geographical Analysis 44*(4), 386–397.

Bhattacharjee, A. and C. Jensen-Butler (2013). Estimation of the spatial weights matrix under structural constraints. *Regional Science and Urban Economics 43*(4), 617–634.

Blundell, R. and S. R. Bond (1998). Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics 87*(1), 115–143.

Bouayad-Agha, S., N. Turpin, and L. Védrine (2013). Fostering the development of European regions: A spatial dynamic panel data analysis of the impact of cohesian policy. *Regional Studies 47*(9), 1573–1593.

Bouayad-Agha, S. and L. Védrine (2010). Estimation strategies for a spatial dynamic panel using GMM. A new approach to the convergence issue of European regions. *Spatial Economic Analysis 5*(2), 205–227.

Boucher Breuer, J., W. Hauk, and J. McDermott (2014). The return of convergence in the US states. *Applied Economics Letters 21*(1), 438—467.

Bundesinstitut für Bau-, Stadt- und Raumforschung (2009). *Regionaler Preisindex*. Bonn: Bundesamt für Bauwesen und Raumordnung.

Carrington, A. (2003). A divided Europe? Regional Convergence and neighbourhoud spillover effects. *Kyklos 56*(3), 381–393.

Cheong, T. S. and Y. Wu (2013). Regional disparity, transitional dynamics and convergence in China. *Journal of Asian Economics 29*, 1–14.

Cliff, A. D. and J. K. Ord (1981). *Spatial Processes: Models & Applications.* London: Pion.

Colavecchio, R., D. Curran, and M. Funke (2011). Drifting together or falling apart? The empirics of regional economic growth in post-unification Germany. *Applied Economics 43*(9), 1087–1098.

Corrado, L. and B. Fingleton (2012). Where is the economics in spatial econometrics? *Journal of Regional Science 52*(2), 210–239.

Desmet, K. and E. Rossi-Hansberg (2013). Urban accounting and welfare. *American Economic Review 103*(6), 2296–2327.

Duranton, G. and M. A. Turner (2011). The fundamental law of road congestion: Evidence from US cities. *American Economic Review 101*(6), 2616–2652.

Egger, P. and M. Pfaffermayr (2006). Spatial convergence. *Papers in Regional Science 85*(2), 199–215.

Eggert, W., M. von Ehrlich, R. Fenge, and G. König (2007). Konvergenz- und Wachstumseffekte der europäischen Regionalpolitik in Deutschland. *Perspektiven der Wirtschaftspolitik 8*(2), 130–146.

Ertur, C. and W. Koch (2007). Growth, technological interdependence and spatial externalities: Theory and evidence. *Journal of Applied Econometrics 22*(6), 1033–1062.

Ertur, C. and W. Koch (2011). A contribution to the theory and empirics of Schumpeterian growth with worldwide interactions. *Journal of Economic Growth 16*(3), 215–255.

Evans, P. and J. U. Kim (2014). The spatial dynamics of growth and convergence in Korean regional incomes. *Applied Economics Letters 21*(16), 1139–1143.

Fingleton, B. (2001). Equilibrium and economic growth: Spatial econometric models and aimulations. *Journal of Regional Science 41*(1), 117–147.

Fingleton, B. and J. Le Gallo (2008). Estimating spatial models with endogenous variables, a spatial lag and spatially dependent disturbances: Finite sample properties. *Papers in Regional Science 87*(3), 319–339.

Fischer, M. M. and J. P. LeSage (2015). A Bayesian space-time approach to identifying and interpreting regional convergence clubs in Europe. *Papers in Regional Science 94*(4), 677–702.

Gennaioli, N., R. La Porta, F. López-de-Silanes, and A. Shleifer (2014). Growth in regions. *Journal of Economic Growth 19*(3), 259–309.

Getis, A. and J. Aldstadt (2004). Constructing the spatial weights matrix using a local statistic. *Geographical Analysis 36*(2), 90–104.

Goldin, C. and L. F. Katz (2008). *The Race between Education and Technology*. Cambridge: Harvard University Press.

Ho, C.-Y., W. Wang, and J. Yu (2013). Growth spillover through trade: A spatial dynamic panel data approach. *Economics Letters 120*(3), 450–453.

Incaltarau, C., G. C. Pascariu, A. Duarte, and P. Nijkamp (2021). Migration, regional growth and convergence: a spatial econometric study on Romania. *Annals of Regional Science 66*(3), 497–532.

Juessen, F. (2009). A distribution dynamics approach to regional GDP convergence in unified Germany. *Empirical Economics 37*, 627–652.

Kelejian, H. H. and I. R. Prucha (2010). Specification and estimation of spatial autoregressive models with autoregressive and heteroskedastic disturbances. *Journal of Econometrics 157*(1), 53–67.

Kosfeld, R., H.-F. Eckey, and C. Dreger (2006). Regional productivity and income convergence in the unified Germany. *Regional Studies 40*(7), 755–767.

Kosfeld, R. and J. T. Lauridsen (2004). Dynamic spatial modelling of regional convergence processes. *Empirical Economics 29*(4), 705–722.

Lee, L.-F. and J. Yu (2010). A spatial dynamic panel data model with both time and individual fixed effects. *Econometric Theory 26*(2), 564–597.

Lee, L.-F. and J. Yu (2014). Efficient GMM estimation of spatial dynamic panel data models with fixed effects. *Journal of Econometrics 180*(2), 174–197.

LeSage, J. P. and R. K. Pace (2009). *Introduction to Spatial Econometrics*. London: Chapman.

Mills, E. S. (1967). An aggregative model of resource allocation in a metropolitan area. *American Economic Review 57*(2), 197–210.

Monte, F., S. Redding, and E. Rossi-Hansberg (2018). Commuting, migration and local employment elasticities. *American Economic Review 108*(12), 3855–3890.

Moran, P. A. P. (1950). Notes on continuous stochastic phenomena. *Biometrika 37*(1/2), 17–23.

Muth, R. (1969). *Cities and Housing: The Spatial Patterns of Urban Residential Land Use*. Chicago: University of Chicago Press.

Neumayer, E. and T. Plümper (2016). W. *Political Science Research and Methods 4*(1), 175–193.

Nickell, S. (1981). Biases in Dynamic Models with Fixed Effects. *Econometrica 49*, 1417–1426.

Parent, O. and J. P. LeSage (2012). Spatial dynamic panel data models with random effects. *Regional Science and Urban Economics 42*(4), 727–738.

Proost, S. and J.-F. Thisse (2019). What can be learned from spatial economics? *Journal of Economic Literature 57*(3), 575–643.

Roodman, D. (2009). A note on the theme of too many instruments. *Oxford Bulletin of Economics and Statistics 71*(1), 135–158.

Sala-i-Martín, X. X. (1996). Regional cohesion: Evidence and theories of regional growth and convergence. *European Economic Review 40*(6), 1325–1352.

Silverman, B. (1981). Using Kernel Density Estimation to Investigate Multimodality. *Journal of the Royal Statistical Society, Series B (Methodological) 43*(1), 97–99.

Vortmann, H., J. Goebel, P. Krause, and G. G. Wagner (2013). Zur Entwicklung der Preisniveaus in Ost- und Westdeutschland – Zugleich eine Dokumentation verschiedener Preisniveau-Zeitreihen für das geteilte und für das vereinigte Deutschland. Discussion Paper 1269, DIW Berlin.

Young, A. T., M. J. Higgins, and D. Levy (2008). Sigma convergence versus beta convergence: Evidence from U.S. county-level data. *Journal of Money, Credit and Banking 40*(5), 1083–1093.

Yu, J., R. de Jong, and L.-F. Lee (2008). Quasi-maximum likelihood estimators for spatial dynamic panel data with fixed effects when both n and T are large. *Journal of Econometrics 146*(1), 118–134.

Yu, J. and L.-F. Lee (2012). Convergence: A spatial dynamic panel data approach. *Global Journal of Economics 1*(1), 1250006.

Zhang, H. and X. Wang (2017). Combined asymmetric spatial weights matrix with application to housing prices. *Journal of Applied Statistics 44*(13), 2337–2353.

Regional convergence at the county level: The role of commuters

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Supplementary Appendix

Appendix A Details on the data set

A major hurdle for the data collection at the county level have been several local government reforms, predominantly in the East German states, that led to a consolidation of several administrative rural and urban districts (counties). The total number of counties shrunk from 439 at the beginning of our sample (2002) to 401 at the end (2017). While some data series were reconstructed by the statistical agencies for previous years based on the latest area classification, for example GDP, in general each reform led to a break in the recorded time series.[1] In the following, we provide a detailed account of our data assembly work.

A.1 Data sources and data adjustments

A large portion of the raw data comes from the *Regionaldatenbank Deutschland* (regional data base, RDB), a data base jointly hosted by Germany's federal and regional statistical offices. It is combined with data from the *GENESIS-Online* data base of the Federal Statistical Office of Germany, data from the *Bundesagentur für Arbeit* (federal employment agency, BA), and in some instances with information directly obained from the respective regional statistical offices. The geodata for the construction of geography-based spatial weights and the data and results visualization in map format are provided by the *Geodatenzentrum* (geodata center, GDZ) of the Federal Agency for Cartography and Geodesy. Table A.1 lists the variables and corresponding data sources from which we assembled our data set.

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[1] A few other methodological changes led to slight inconsistencies in the definition of some variables over time. We did not attempt to correct the data for these changes but accounted for them in our regression analysis by the inclusion of year dummy variables.

Table A.1: Variables, data sources, and necessary adjustments

variable	level	source	notes on data source	adjustments
gross domestic product per capita, in Euro	counties	RDB	Table 82111-01-05-4	–
gross value added, in 1000 Euro, by industry	counties	RDB	Table 82111-01-05-4	–
investment, in 1000 Euro	counties	RDB	Table 42231-01-04-4	A.1.1, A.1.2
population, end of year	counties	RDB	Table 12411-01-01-4	A.1.1
territorial area, in km^2	counties	RDB	Table 11111-01-01-4	–
harmonized consumer price index, base = 2015	Germany	GENESIS	Table 61121-0001	–
regional price index, 2009, base = Bonn	counties	BBSR	–	A.1.1
employees subject to social security contributions, commuter interrelations	counties	BA	–	A.1.1
employees subject to social security contributions, with/without professional/academic qualifications, at place of work, end of year (mid-year for 2011)	counties	BA	–	A.1.1
geodata	counties	GDZ	VG2500, UTM32	–

Note: The RDB (*Regionaldatenbank Deutschland*) can be accessed at `https://www.regionalstatistik.de/`. *GENESIS-Online* is maintained by Destatis (*Statistisches Bundesamt*) and accessible via `https://www-genesis.destatis.de/`. The BA (*Bundesagentur für Arbeit*) statistics from 2013 onwards can be obtained from its website, `https://statistik.arbeitsagentur.de/`, while data for earlier years had to be obtained from the BA upon written request. Additional data sources were used for the manual adjustments as explained in Appendix A.1.1. Geodata from the GDZ (*Geodatenzentrum*) of the BKG (*Bundesamt für Kartographie und Geodäsie*) can be downloaded from `https://www.geodatenzentrum.de/`. BBSR is an abbreviation for Bundesinstitut für Bau-, Stadt- und Raumforschung (2009). The RDB, *GENESIS-Online*, and GDZ data were obtained in 2020 under the data licence dl-de/by-2-0 (`https://www.govdata.de/dl-de/by-2-0`). Regarding our adjustments to the data, see the respective appendices.

A.1.1 Local government reorganizations

The following reforms affected our data set since many of the time series were not officially revised retrospectively, or only for a limited number of years. We thus had to manually adjust (some of) the pre-reform data for the counties affected by those reforms where this has not been done by the statistical authorities. In most cases, this meant simply adding up the respective numbers for the consolidated counties. In some instances, when entirely new borders were drawn, we constructed weights based on municipality level population data to proportionally assign the values from the old districts to the new one.

1. **Saxony-Anhalt**: In 2007, the number of administrative districts was reduced by 10. For the affected counties, we had to amend the pre-2006 investment and population data, the pre-2007 data on employees' professional/academic qualifications, the pre-2008 data on commuter flows, and the regional price index. Where weighting was necessary, constant 2005 end-of-year population weights at the municipality level were obtained from the regional statistical office of Saxony-Anhalt.[2]

2. **Saxony**: In 2008, the number of administrative districts was reduced by 16. For the affected counties, we had to amend the pre-2004 investment data, the pre-2008 data on employees' professional/academic qualifications, and the pre-2009 data on commuter flows. For the regional price index, constant 2006 end-of-year population weights were obtained from the RDB.

3. **North Rhine-Westphalia**: In 2009, the rural and urban districts of Aachen were

[2] `https://www.stala.sachsen-anhalt.de/gk/kreform2007/aenderung.dr.html`; last updated on 19 July 2007.

consolidated to the *Städteregion* Aachen. We had to amend the pre-2009 data on investment, population data, and employees' professional/academic qualifications, and the pre-2010 data on commuter flows. For the regional price index, constant 2008 end-of-year population weights were obtained from the RDB.

4. **Mecklenburg-Vorpommern**: In 2011, the number of administrative districts was reduced by 10. For the affected counties, we had to amend the pre-2011 investment[3] and population data, the pre-2012 data on employees' professional/academic qualifications and commuter flows, and the regional price index. Where weighting was necessary, constant 2010 end-of-year population weights at the municipality level were obtained from the regional statistical office of Mecklenburg-Vorpommern.[4]

5. **Lower Saxony**: In 2016, the urban district Osterode am Harz was integrated into the urban district Göttingen. We had to amend the pre-2016 data on investment, population data, and employees' professional/academic qualifications, and the pre-2017 data on commuter flows. For the regional price index, constant 2015 end-of-year population weights were obtained from the RDB.

A.1.2 Investment data

Time series data for investment is not available for all economic sectors at the German county level. As a proxy, we use investment reported by firms in the mining and quarrying industry and the manufacturing industry (sections B and C of the Classification of Economic Activities, WZ 2008, of the Federal Statistical Office of Germany).

Besides the adjustments due to the local government reorganizations, we had to interpolate a few irregularly missing data points. For each county and year, we computed the investment share in the total investment at the next higher administrative district level or statistical region. At this higher level, the data was available without gaps. We then linearly interpolated these shares and subsequently computed the investment level at the county level. Whenever data was missing at the beginning or end of a time series, we have filled the blanks based on a nearest neighbor extrapolation of the investment share.

A.2 Descriptive statistics

In Tables A.2 to A.5, we provide some summary statistics for our data. Table A.6 presents the evolution of Moran's I as a measure of global spatial autocorrelation over the whole sample period for the three different spatial weight matrices considered in the main paper.

[3]For 2011, the Mecklenburg-Vorpommern investment data was missing in the RDB. We instead accessed the data directly from the regional statistical office (statistical report E163 2011 00).

[4]Statistical report A123 2010 22.

Table A.2: Summary statistics for raw data, 2002–2017

	obs	mean	sd	min	max
gross domestic product per capita, in Euro	6,416	30,278	13,787	11,385	180,454
gross value added, in 1000 Euro					
total	6,416	5,929,956	9,184,494	745,121	125,931,874
agricultural sector	6,416	49,585	47,843	122	492,633
industrial sector	6,416	1,527,527	1,867,166	69,926	22,737,816
construction sector	6,416	256,317	275,540	19,276	4,990,538
services sector	6,416	1,235,860	2,406,627	99,258	33,287,606
financial sector	6,416	1,572,484	3,138,810	154,649	38,495,528
public sector	6,416	1,288,184	2,058,654	163,659	39,682,812
investment, in 1000 Euro	6,416	133,007	186,821	1,334	2,398,613
population	6,416	204,240	231,206	33,944	3,613,495
area, in km^2	6,416	891.52	723.26	35.7	5,495.6
harmonized consumer price index, base = 2015	6,416	92.33	6.67	81.5	102.1
regional price index, 2009, base = Bonn	401	91.13	4.91	83.4	114.4
employees subject to social security contributions					
commuters, outflow	6,416	25,735	19,905	2,256	179,911
commuters, inflow	6,416	25,735	38,697	2,208	380,473
total	6,416	71,245	95,986	10,780	1457,214
with professional qualifications	6,416	42,865	48,308	6,710	709,963
with academic qualifications	6,416	8,364	19,072	369	374,425

Note: The table reports the number of observations (obs), the sample average (mean), the standard deviation (sd), the mininum (min) and the maximum (max). The summary statistics are for the data after the adjustments indicated in Table A.1. Sectors are broadly classified according to the Classification of Economic Activities, WZ 2008, of the Federal Statistical Office of Germany. The *agricultural sector* classification (WZ 2008 section A) includes forestry and fishery. The *industrial sector* classification (WZ 2008 sections B–E) excludes construction (WZ 2008 section F). The *services sector* classification (WZ 2008 sections G–J) includes trades, transportation, information, and communication services. The *financial sector* classification (WZ 2008 sections K–N) includes financial and insurance services, real estate services, and business services. The *public sector* classification (WZ 2008 sections O–U) includes public administration, education, health and social services, entertainment, and other services.

Table A.3: Summary statistics for real GDP per capita

year	mean	median	sd	min	max	skewness	kurtosis	Gini
2002	33,424	29,801	13,428	16,138	105,143	2.04	8.35	0.1973
2003	33,211	29,545	13,291	15,881	107,786	2.03	8.41	0.1970
2004	33,498	29,786	13,334	15,744	97,453	1.97	7.73	0.1964
2005	33,347	29,501	13,465	15,920	112,165	2.16	9.38	0.1968
2006	34,182	30,143	13,819	16,198	109,969	2.08	8.55	0.1977
2007	35,096	30,791	14,197	16,645	115,979	2.12	8.86	0.1972
2008	34,948	30,856	13,617	16,513	112,274	2.07	8.64	0.1913
2009	33,657	30,116	12,989	15,951	99,460	2.01	7.93	0.1895
2010	35,195	31,440	13,994	16,271	129,546	2.32	10.91	0.1920
2011	36,107	32,230	14,653	16,858	143,790	2.62	13.60	0.1915
2012	36,061	32,372	14,514	17,072	145,142	2.79	15.13	0.1875
2013	36,252	32,759	14,479	17,128	143,336	2.93	16.45	0.1838
2014	37,325	33,933	14,649	17,594	151,038	2.96	17.15	0.1811
2015	37,977	34,327	14,596	18,184	135,821	2.63	13.36	0.1804
2016	39,045	35,079	16,311	18,484	197,078	3.81	28.49	0.1846
2017	39,672	35,519	16,079	18,461	185,187	3.44	23.47	0.1824

Note: For each year, the table reports the sample average (mean), the median, the standard deviation (sd), the mininum (min) and the maximum (max), the skewness, kurtosis, and the Gini coefficient.

Table A.4: Summary statistics for regression variables

	obs	mean	sd	min	max
ln(real gross domestic product per capita)	6,416	10.418	0.330	9.664	12.191
ln(real investment per capita)	6,015	6.386	0.770	2.375	9.715
population growth rate	6,015	-0.001	0.009	-0.072	0.058
share of employees with professional qualifications	6,015	0.637	0.062	0.437	0.813
share of employees with academic qualifications	6,015	0.091	0.045	0.024	0.336
commuters per capita, outflow	6,416	0.137	0.053	0.031	0.310
commuters per capita, outflow, 2002	401	0.121	0.049	0.031	0.274
commuters per capita, inflow	6,416	0.128	0.104	0.018	0.780
commuters per capita, inflow, 2002	401	0.113	0.097	0.018	0.649

Note: The table reports the number of observations (obs), the sample average (mean), the standard deviation (sd), the mininum (min) and the maximum (max). For the dependent variable and the commuter flows, the data are summarized over the years 2002–2017, while for the exogenous regressors they are summarized over the years 2003–2017 as the inital year 2002 is not used for the latter variables. The population growth rate is approximated by the first difference in the natural logarithm.

Table A.5: Summary statistics for counterfactual treatmeant variables

	obs	mean	sd	min	max	5%	95%
gross domestic product per capita	401	25,068	11,142	11,443	85,474	14,207	47,256
share of gross value added							
agricultural sector	401	0.016	0.015	0.000	0.073	0.000	0.046
industrial sector	401	0.264	0.105	0.044	0.731	0.107	0.446
construction sector	401	0.054	0.021	0.009	0.168	0.023	0.091
services sector	401	0.193	0.052	0.078	0.544	0.123	0.283
financial sector	401	0.241	0.053	0.083	0.487	0.174	0.327
public sector	401	0.233	0.068	0.065	0.490	0.134	0.351
population density, per km^2	401	522.5	670.0	42.2	3,973.9	77.3	2,032.1

Note: The table reports the number of observations (obs), the sample average (mean), the standard deviation (sd), the mininum (min) and maximum (max), and the 5% and 95% quantiles. Sectors are classified as in Table A.2. The data are summarized for the year 2002.

Table A.6: Moran's I measure of global spatial autocorrelation in real gross domestic product per capita

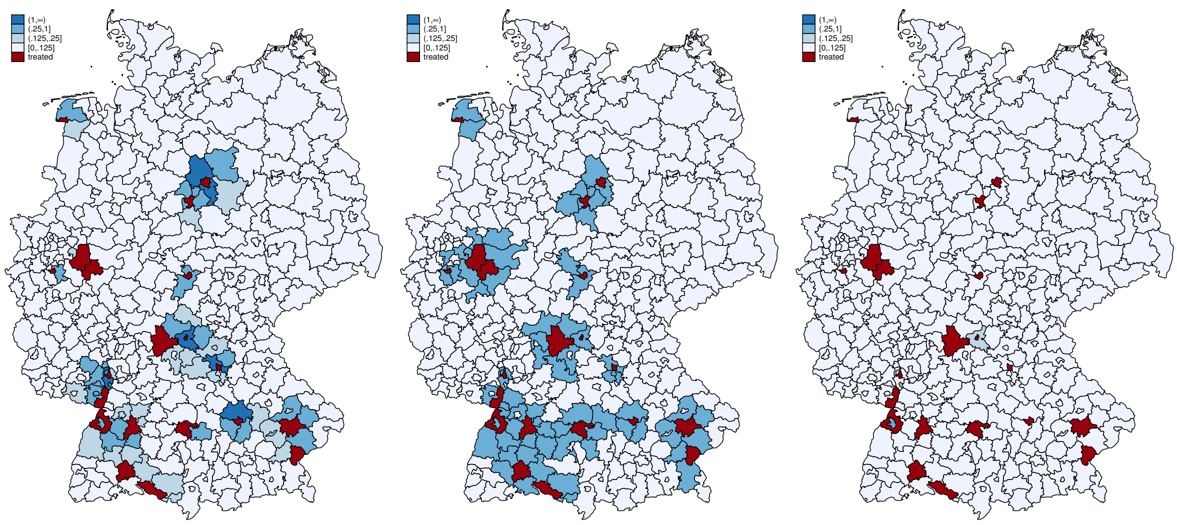
	commuter $\mathbf{W}_N$		contiguity $\mathbf{W}_N$		inverse-distance $\mathbf{W}_N$	
year	Moran's I	z-score	Moran's I	z-score	Moran's I	z-score
2002	-0.074	-2.108**	0.106	3.559***	0.011	2.496**
2003	-0.088	-2.539**	0.103	3.478***	0.009	2.050**
2004	-0.102	-2.983***	0.096	3.228***	0.006	1.566
2005	-0.109	-3.222***	0.090	3.063***	0.005	1.424
2006	-0.114	-3.399***	0.086	2.919***	0.005	1.318
2007	-0.107	-3.576***	0.086	2.926***	0.004	1.145
2008	-0.117	-3.594***	0.084	2.843***	0.002	0.906
2009	-0.125	-3.853***	0.073	2.499**	-0.001	0.359
2010	-0.128	-3.964***	0.066	2.265**	0.001	0.590
2011	-0.116	-3.615***	0.063	2.177**	0.002	0.845
2012	-0.125	-3.916***	0.055	1.901*	0.001	0.615
2013	-0.125	-3.908***	0.050	1.758*	0.001	0.594
2014	-0.131	-4.122***	0.049	1.703*	-0.001	0.361
2015	-0.110	-3.445***	0.058	1.999**	0.004	1.260
2016	-0.114	-3.695***	0.041	1.463	-0.001	0.283
2017	-0.108	-3.479***	0.042	1.502	-0.001	0.358

Note: The expected value of Moran's I under the null hypothesis of no global spatial autocorrelation is -0.002. The significance levels refer to a two-sided test of no global spatial autocorrelation.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

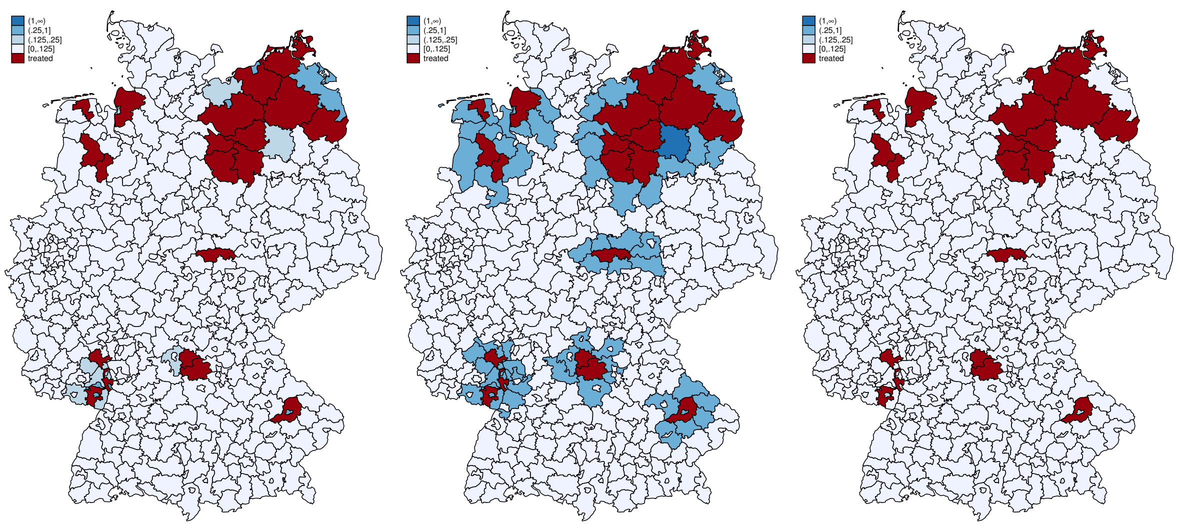
Appendix B Additional empirical results

In addition to Figures 6 to 8 in the main paper, Figures B.1 to B.4 visualize the heterogeneity of the long-run spatial multipliers for the untreated counties under the remaining counterfactual treatment scenarios.



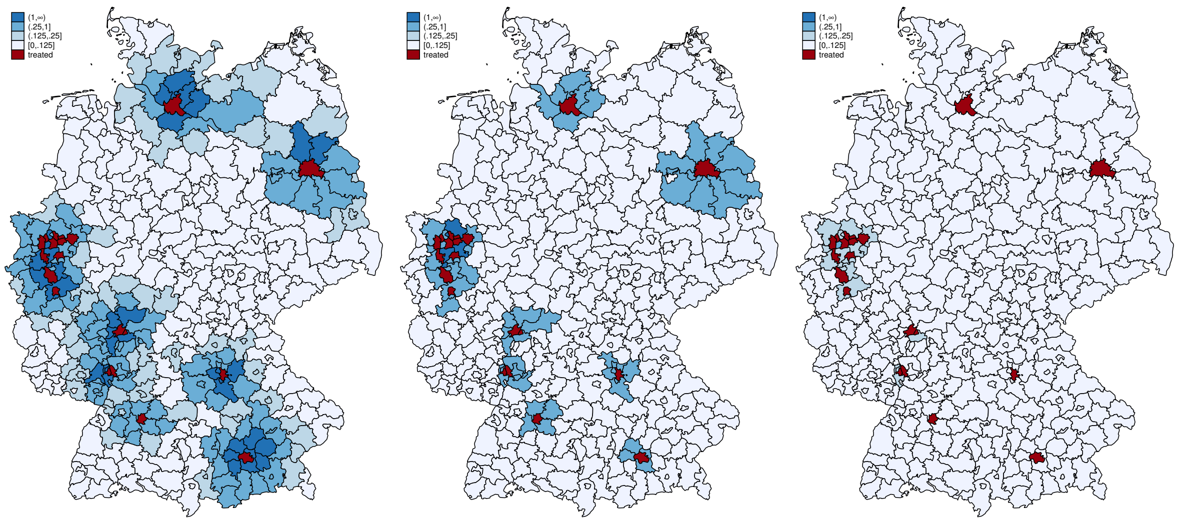
(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

Figure B.1: Counterfactual long-run spatial multipliers for treatment of industrial centers



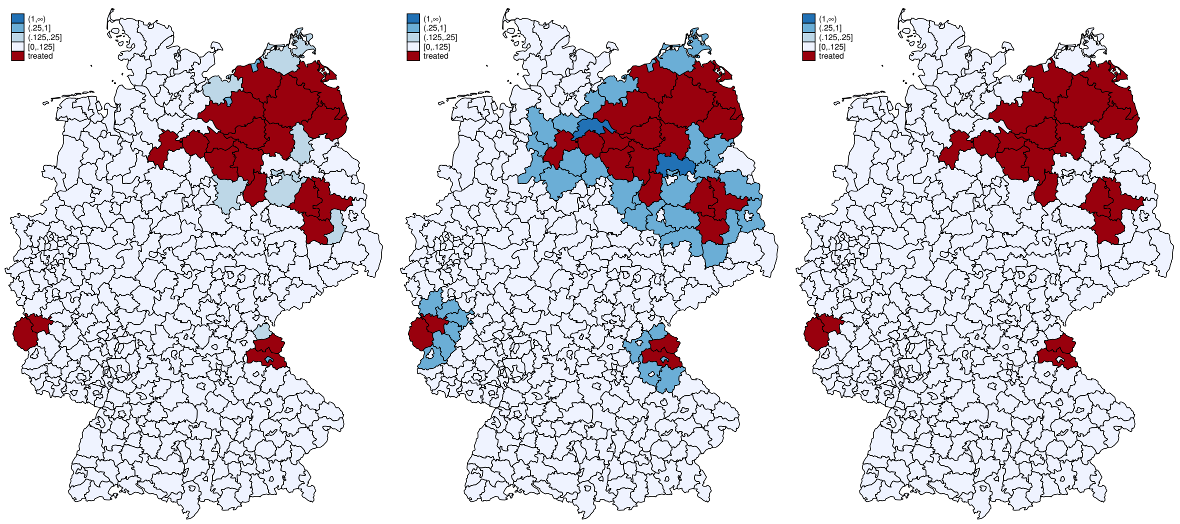
(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

Figure B.2: Counterfactual long-run spatial multipliers for treatment of agricultural centers



(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

Figure B.3: Counterfactual long-run spatial multipliers for treatment of urban counties



(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

Figure B.4: Counterfactual long-run spatial multipliers for treatment of rural counties

References

Bundesinstitut für Bau-, Stadt- und Raumforschung (2009). *Regionaler Preisindex*. Bonn: Bundesamt für Bauwesen und Raumordnung.