# Regional Dependencies and Local Spillovers: Insights From Commuter Flows (*Journal of Regional Science*, 2025)

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Supporting Information

## Appendix A Details on the data set

A major hurdle for the data collection at the county level have been several local government reforms that led to a consolidation of several administrative districts (counties). This happened mostly, but not exclusively, in the eastern part of Germany. Major reforms relevant to our data sample, 2002–2017, occurred 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. 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 and required adjustment work on our part.[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. We combined it 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 obtained from the

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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.

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.

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 appendix sections.

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

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 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.

[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.

### A.1.3 Regional price index

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).[5] 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.

## A.2 Descriptive statistics

In Tables A.2 to A.5, we provide some summary statistics for our data. Panel (a) of Figure A.1 highlights the wealth concentration in the top quartile of the counties, and panel (b) illustrates the negative correlation of the average annual growth rate with the initial level of real GDP per capita. 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. For local spatial autocorrelation, Table A.7 lists the top-3 and bottom-3 counties according to the local version of Moran's $I$.

[5] 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.

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 minimum (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 minimum (min) and the maximum (max), the skewness, kurtosis, and the Gini coefficient.

Table A.4: Summary statistics for regression variables

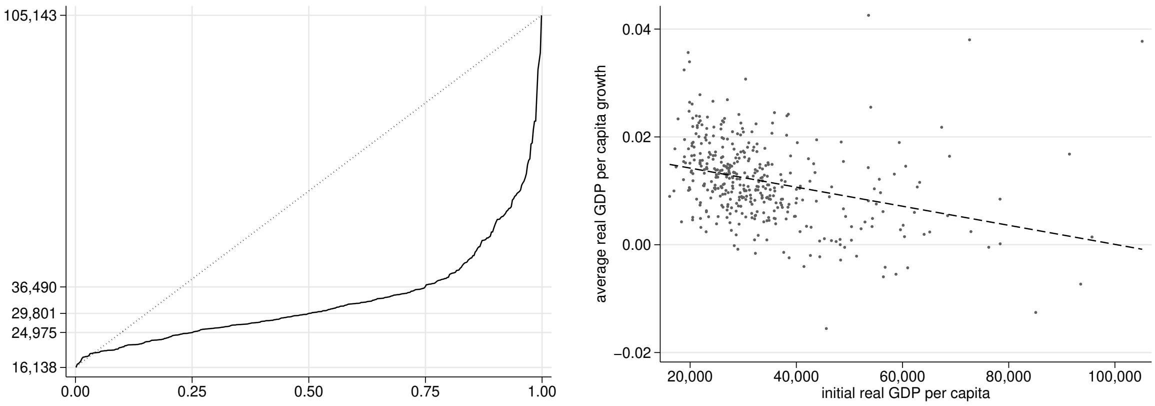
| | obs | mean | sd | min | max |
|---|---|---|---|---|---|
| ln(real gross domestic product per capita) | 6,416 | 10.418 | 0.330 | 9.664 | 12.191 |
| ln(real investment per capita) | 6,015 | 6.386 | 0.770 | 2.375 | 9.715 |
| population growth rate | 6,015 | -0.001 | 0.009 | -0.072 | 0.058 |
| share of employees with professional qualifications | 6,015 | 0.636 | 0.061 | 0.438 | 0.813 |
| share of employees with academic qualifications | 6,015 | 0.088 | 0.043 | 0.023 | 0.329 |
| 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 minimum (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 initial 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 minimum (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.




(a) Initial real GDP per capita, quantile plot

(b) Growth versus initial real GDP per capita

Figure A.1: Distribution of real GDP per capita of the 401 German counties in 2002 and its average annual growth rate from 2002 to 2017

Table A.6: Moran's $I$ measure of global spatial autocorrelation in real GDP 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.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

Table A.7: Moran's $I$ measure of spatial autocorrelation in real GDP 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.
$^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

# Appendix B  Additional empirical results

## B.1  Different years for commuter flows

Table B.1: Bias-corrected QML estimation with commuter flows from different years

| | commuter $\mathbf{W}_{N,2002}$ | | | commuter $\mathbf{W}_{N,2017}$ | | | commuter $\mathbf{W}_{N,\text{avg}}$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
| $\mathbf{y}_{t-1}$ | 0.892*** | 0.856*** | 0.827*** | 0.887*** | 0.856*** | 0.827*** | 0.888*** | 0.855*** | 0.827*** |
| | (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** | 0.394*** | 0.058*** | 0.051*** | 0.370*** | 0.050*** | 0.044*** |
| | (0.016) | (0.019) | (0.018) | (0.016) | (0.019) | (0.019) | (0.016) | (0.018) | (0.018) |
| $\mathbf{W}_N\mathbf{y}_{t-1}$ | -0.288*** | 0.008 | 0.002 | -0.313*** | -0.002 | -0.008 | -0.292*** | 0.004 | -0.003 |
| | (0.018) | (0.020) | (0.020) | (0.018) | (0.021) | (0.020) | (0.018) | (0.020) | (0.019) |
| $\text{inv}_t$ | 0.006*** | 0.005*** | 0.004*** | 0.006*** | 0.005*** | 0.004*** | 0.006*** | 0.005*** | 0.004*** |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| $\text{pop}_t$ | -0.377*** | -0.218*** | -0.212*** | -0.359*** | -0.219*** | -0.214*** | -0.368*** | -0.219** | -0.213** |
| | (0.070) | (0.083) | (0.082) | (0.069) | (0.083) | (0.082) | (0.070) | (0.083) | (0.082) |
| $\text{prof}_{t-1}$ | 0.115*** | 0.088** | 0.046 | 0.109*** | 0.087** | 0.045 | 0.110*** | 0.085** | 0.044 |
| | (0.023) | (0.036) | (0.036) | (0.023) | (0.035) | (0.036) | (0.023) | (0.036) | (0.036) |
| $\text{acad}_{t-1}$ | 0.351*** | -0.013 | 0.103* | 0.317*** | -0.013 | 0.101* | 0.336*** | -0.012 | 0.103* |
| | (0.035) | (0.059) | (0.060) | (0.036) | (0.059) | (0.060) | (0.035) | (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 |

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. The spatial weight matrices are constructed from commuter flows in 2002, 2017, or the average over all years from 2002 to 2017, respectively.

All regressions use a total of 6,015 observations for 401 counties.

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

Because the QML methodology for short-$T$ time-space dynamic panel models cannot accommodate time-varying spatial weight matrices, we used the commuter flows from the initial year 2002 to construct the spatial weights in the main paper. Table B.1 compares our baseline estimates, for convenience reprinted in columns (1)–(3), with those using commuter flows from the final year 2017 in columns (4)–(6) or the average commuter flows over the whole sample period in columns (7)–(9). The results confirm our expectation that the results are robust to this choice.[6] Especially compared to the different estimates obtained with geographic spatial weight matrices, the differences from varying the year for the commuter flows are largely negligible.

[6] More detailed results on the spatial multiplier effects are available upon request.

## B.2 Alternative estimators

Table B.2: Alternative estimators for the dynamic panel models

| | FE | FE-BC | GMM | GMM commuter $\mathbf{W}_{N,t}$ | GMM contiguity $\mathbf{W}_N$ | GMM inverse-distance $\mathbf{W}_N$ |
|---|---|---|---|---|---|---|
| $\mathbf{y}_{t-1}$ | 0.718*** | 0.852*** | 0.911*** | 0.903*** | 0.913*** | 0.905*** |
| | (0.016) | (0.018) | (0.030) | (0.030) | (0.037) | (0.031) |
| $\mathbf{W}_{N,t}\mathbf{y}_t$ | | | | 0.010 | 0.244 | -0.173 |
| | | | | (0.020) | (0.181) | (0.174) |
| $\mathbf{W}_{N,t-1}\mathbf{y}_{t-1}$ | | | | -0.010 | -0.243 | 0.174 |
| | | | | (0.022) | (0.198) | (0.158) |
| $\text{inv}_t$ | 0.006*** | 0.004*** | -0.005 | -0.006 | -0.003 | -0.001 |
| | (0.002) | (0.001) | (0.004) | (0.004) | (0.009) | (0.013) |
| $\text{pop}_t$ | -0.220*** | -0.205*** | -0.142 | -0.040 | -0.129 | -0.180* |
| | (0.068) | (0.069) | (0.089) | (0.206) | (0.089) | (0.095) |
| $\text{prof}_{t-1}$ | 0.083* | 0.057 | 0.053 | 0.074 | 0.038 | 0.071* |
| | (0.047) | (0.037) | (0.042) | (0.046) | (0.053) | (0.042) |
| $\text{acad}_{t-1}$ | 0.055 | 0.125 | 0.116 | 0.097 | 0.098 | 0.112 |
| | (0.105) | (0.079) | (0.072) | (0.073) | (0.103) | (0.080) |
| time effects | yes | yes | yes | yes | yes | yes |
| crisis × sector | yes | yes | yes | yes | yes | yes |
| AB $p$-value | | 0.876 | 0.838 | 0.826 | 0.603 | 0.905 |
| Hansen $p$-value | | | 0.098 | 0.170 | 0.187 | 0.096 |

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). All specifications include 14 time dummies for the years 2004–2017 and interaction effects between a post-financial crisis dummy (years 2008–2017) and the initial sectoral shares in GVA for 4 sectoral groupings. Standard errors robust to heteroskedasticity and intra-county correlation are in parentheses. The considered estimators are the fixed-effects estimator (FE), a bias-corrected fixed-effects estimator (FE-BC; Breitung et al., 2022), and generalized method of moments estimators (GMM). $p$-values are reported for the Arellano and Bond (1991) test (AB) of no second-order serial correlation in the first-differenced residuals, and the Hansen (1982) overidentification test. The commuter-based spatial weight matrix is time-varying.

The GMM estimators are implemented as two-step estimators with instruments $\mathbf{y}_{t-1-s}$, $\mathbf{W}_{N,t-1-s}\mathbf{y}_{t-1-s}$ (if spatial lags are included), $\text{inv}_{t-1-s}$, $pop_{t-s}$ with $s \in [0, 4]$ for the forward-orthogonally transformed model (Arellano and Bover, 1995). Thus, there are 4 overidentifying restrictions for each of these variables, respectively. The variables $\text{prof}_{t-1}$, $\text{acad}_{t-1}$, and the dummy variables for time effects and crisis interaction effects are instrumented by themselves for the model in deviations from within-group means. Nonlinear moment conditions valid under no serial error correlation are included as well (Ahn and Schmidt, 1995). The first-step estimator used to compute the optimal GMM weighting matrix is the conventional two-stage least squares estimator.

All regressions use a total of 6,015 observations for 401 counties.

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

Table B.2 presents additional estimation results. In the first three columns, spatial spillover effects are ignored. A comparison of the first two columns illustrates the Nickell (1981) bias of the conventional fixed-effects (FE) estimator. As expected given the still relatively short number of time periods, the bias-corrected fixed-effects estimator (FE-BC) of Breitung et al. (2022) yields a significantly higher coefficient for the lagged dependent variable. The impact of the bias correction on the other coefficients is less substantial, although still noticeable.

The third column present results from a GMM estimator. 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 the idiosyncratic error component $\boldsymbol{\varepsilon}_t$ is assumed to be serially uncorrelated, the lagged values $\ln \mathbf{y}_{t-1-s}$ and $\mathbf{W}_N \ln \mathbf{y}_{t-1-s}$, $s \geq 0$, can be used as instrumental variables in this transformed equation. In a similar way, regressors in $\mathbf{X}_t$ can be instrumented by using appropriate lags as well.[7] Here, we relax the strict exogeneity assumption for investment and population growth by treating the former as endogenous and the latter as predetermined. Instruments for them (and the lagged dependent variable) are selected by exploiting the fact that past observations of endogenous variables are uncorrelated with the error term, once the latter is transformed by removing its "forward mean". For predetermined variables, the contemporaneous observation yields a valid instruments as well under this transformation. Instruments for the strictly exogenous professional/academic qualifications and the dummy control variables are chosen analogously to the fixed-effects estimator.

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 3 in Section 3.3 of the main text strongly reinforces this point. Further challenges are the curse of too many instruments, which we account for by "collapsing" and "curtailing" ($s \in [0, 4]$) the instruments (Kiviet, 2020).[8]

As a remedy for potential identification problems due to the high persistence of the dependent variable, we add the nonlinear moment conditions proposed by Ahn and Schmidt (1995), which are valid under the absence of serial correlation in the idiosyncratic error term. The estimated autoregressive coefficient is even higher than with the FE-BC estimator and our QML estimators in Table 1 of the main paper. As a consequence, most of the variation in the dependent variable is explained by its own past. In such a situation, it is not unusual to find that the remaining coefficients are statistically insignificant, as

[7] Higher-order spatial lags, $\mathbf{W}_N^q \ln \mathbf{y}_{t-1-s}$ with $q \geq 2$, can be valid instruments as well, but they may not be very informative if the spatial spillover effects are small. Spatial lags of $\mathbf{X}_t$ could possibly also be used as instruments.

[8] 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.

it is the case here. A potential weakness of the instruments, as partly reflected in higher standard errors, possibly also contributes to these results.

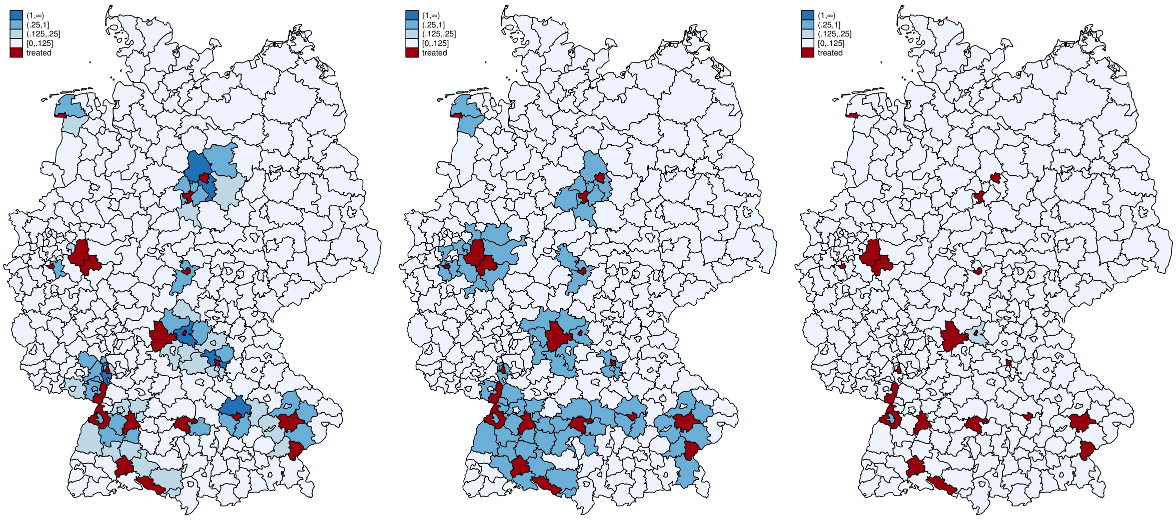
The last three columns show GMM results for models with a contemporaneous spatial lag and a spatial time lag of the dependent variable. These spatial lags are instrumented analogously to the lagged dependent variable by using appropriate lags for the forward-orthogonally transformed model. The GMM estimator has the advantage that it can accommodate time-varying spatial weights, which we exploit here for the commuter flows. However, both additional coefficients are statistically insignificant, and their point estimates offset each other in the calculation of long-run effects. While the nonlinear Ahn and Schmidt (1995) moment conditions can help with the identification for the coefficient of the lagged dependent variable, it is unclear whether this applies as well to the coefficients of the spatial lags or whether a potential weak-instruments problem remains here.

The Arellano and Bond (1991) test provides supportive evidence that there are no omitted model dynamics which could lead to serial correlation in the idiosyncratic error term. The Hansen (1982) overidentification test is mildly supportive of the model specification, although the $p$-values are not too comfortable. When we classify population growth as endogenous, or professional/academic qualifications as predetermined or endogenous, the Hansen test does not improve.[9]

## B.3 Additional results for counterfactual scenarios

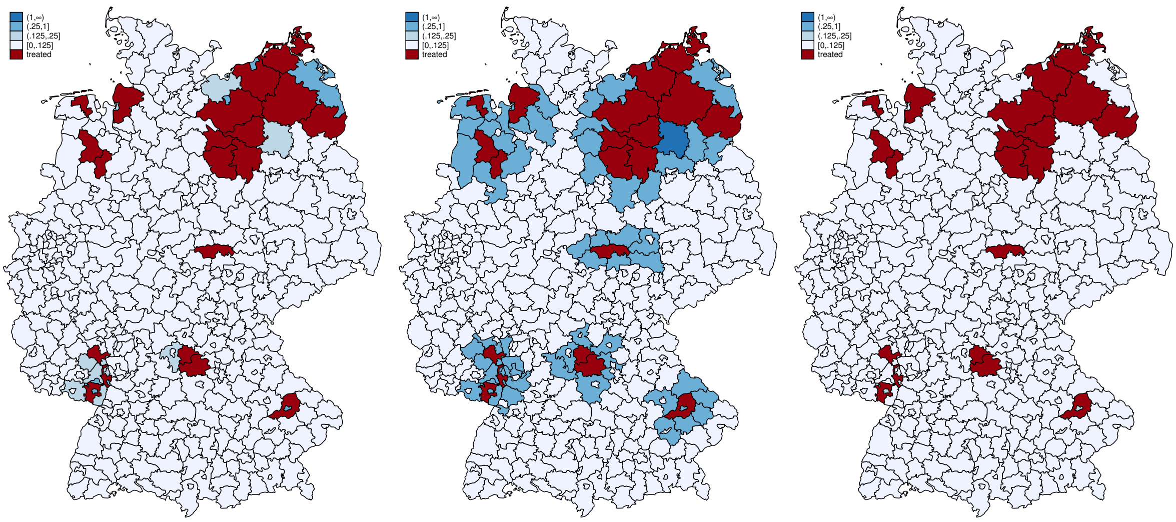
In addition to Figures 7 to 9 in the main paper, Figures B.1 to B.4 visualize the heterogeneity of the long-run spatial multipliers for the untreated counties under the remaining counterfactual treatment scenarios. These results are based on the respective QML estimates.

[9]The additional results under varying classifications of the variables are not shown for brevity.



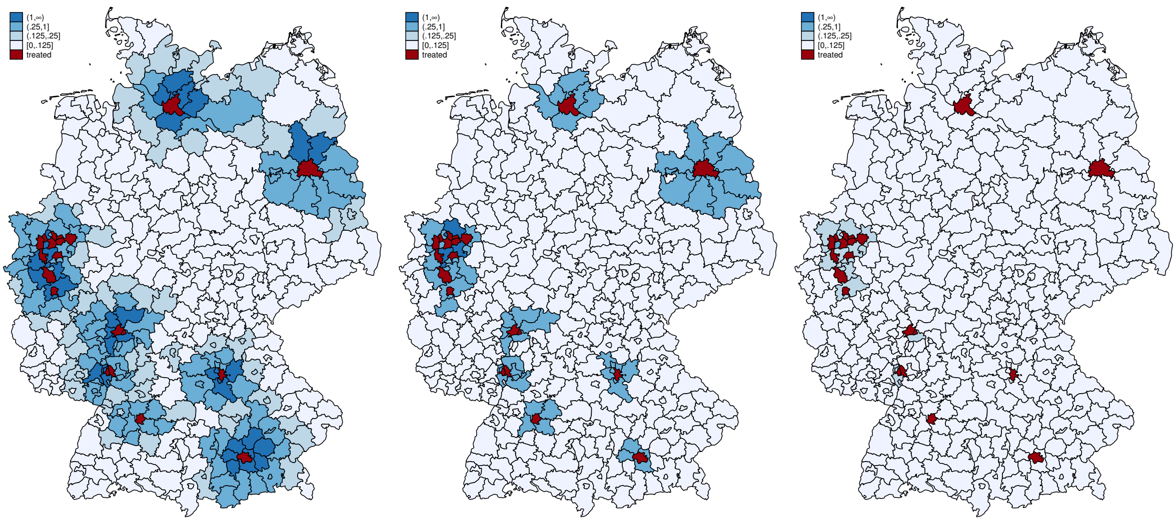

(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

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



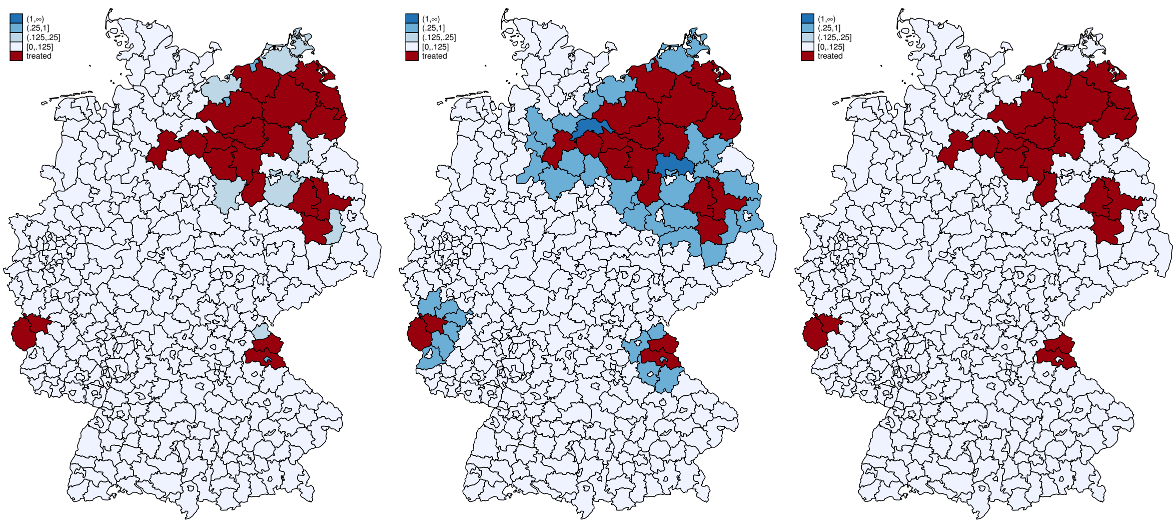

(a) commuter $\mathbf{W}_N$ (b) contiguity $\mathbf{W}_N$ (c) inverse-distance $\mathbf{W}_N$

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

The analysis in the main text assumed local shocks $\varepsilon_i$ of equal size to the log of real GDP per capita. This may not be desired. If we want to investigate the impact of equally costly policy interventions in different counties, we need to adjust the magnitude of the shocks to account for the size of the counties. Due to differences in the relative importance, an intervention of $x$ Euro in a poor county translates into a much bigger $\varepsilon_i = \ln(x/\text{real GDP}_i + 1)$ than an intervention of the same absolute size in a rich county. In the following, we therefore consider similar scenarios as before, but with

Table B.3: Total counterfactual long-run returns

| | commuter $\mathbf{W}_N$ | | | contiguity $\mathbf{W}_N$ | | | inverse-distance $\mathbf{W}_N$ | | |
|---|---|---|---|---|---|---|---|---|---|
| | treated | untreated | all | treated | untreated | all | treated | untreated | all |
| financial centers | 6.372 | 1.081 | 7.453 | 6.605 | 1.627 | 8.232 | 6.196 | 0.791 | 6.987 |
| industrial centers | 5.882 | 1.106 | 6.988 | 5.898 | 1.535 | 7.432 | 6.049 | 1.220 | 7.269 |
| agricultural centers | 5.970 | 0.570 | 6.539 | 6.427 | 2.643 | 9.070 | 6.069 | 2.214 | 8.284 |
| high GDP per capita | 6.115 | 1.555 | 7.671 | 5.859 | 0.454 | 6.313 | 6.101 | 0.548 | 6.649 |
| low GDP per capita | 5.931 | 0.778 | 6.709 | 6.092 | 4.224 | 10.316 | 6.085 | 2.655 | 8.740 |
| high population density | 6.275 | 1.172 | 7.448 | 6.430 | 0.629 | 7.059 | 6.205 | 0.471 | 6.676 |
| low population density | 6.049 | 0.390 | 6.439 | 6.781 | 2.704 | 9.485 | 6.077 | 1.839 | 7.916 |

Note: Reported are the relative long-run returns for a shock to real GDP in the treated counties, cumulatively for the treated, untreated, and all counties. The returns are computed based on the regressions in columns (3), (6), and (9) of Table 1, with county-specific shock sizes corresponding to a 10m Euro increase in real GDP for each of the 20 treated counties, respectively.

shocks $\varepsilon_i$ corresponding to an intervention of 10m Euro in each of the 20 treated counties, respectively.[10]

In Table B.3, we report the corresponding long-run returns. For example, considering the commuter-based spatial weights, the combined return for the treated counties to an intervention in the 20 largest financial centers is about 6.4 times the size of the intervention. Even though there was no direct intervention in the untreated counties, the cumulative effect (for all 381 untreated counties combined) slightly exceeded the size of the investment.[11] The total long-run return – adding up the returns for the treated and untreated – is about 7.5 times the total initial investment. In other words, the initial investment of 200m Euro adds over time 1.5bn Euro to the economy. This now enables a comparison of alternative interventions in terms of value for money. Based on the shock transmission through the commuter network, larger returns are reaped from an intervention in wealthy and densely populated counties, thanks to them being gravitational centers for commuter flows.

The picture is largely reversed when the shocks are transmitted through geographic networks, which can create large spillover effects independent of any economic linkages. Here, taken together, the untreated counties can benefit from the intervention in the treated counties by as much as 4.2 times the initial investment. This results in a substantial 10.3-fold total return (under contiguity weights) when the 20 counties with the lowest GDP per capita are treated.

[10]Due to the nonlinearity of the log-transformation, the multiplier effects depend on the size $x$ of the intervention, but the differences are small enough to not affect the qualitative conclusions. We calculate the respective innovations $\varepsilon_i$ based on the values of real GDP (in prices of 2015) in the year 2002.

[11]With equally sized shocks $\varepsilon_i$, the total returns for the treated from Table B.3 would be identical to the corresponding average multipliers from Table 3. For the untreated, the total returns would be higher than the average multipliers by factor $381/20 \approx 19$, because the cumulative return for the 381 untreated counties is evaluated relative to the joint intervention in the 20 treated counties.

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