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Agglomeration Spillover Effects in German Land and House Prices at the City and County Levels*

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Abstract

We estimate spatial German land price effects using the county-level residential land prices from 2014 to 2018. We show that county-level spatial agglomeration effects play a large and significant role in explaining the cross-county variations in land prices. For example, a 1 % increase in the median income has an increase of 3.45 % in land prices, whereas a 1 % increase in the population density accounts for an increase of 5.47 % increase in land prices. We find that similar empirical patterns also hold for house prices but less so for the seven major German cities. Moreover, housing supply factors such as the available land to build and housing stocks are crucial factors in explaining land and house prices. Furthermore, we show that the land price spillover effects are among the dominating factors in the formation of regional house prices. These results suggest that changes in agglomeration variables such as median income (productivity) and population density cannot completely explain disparate local land and house prices. Lastly, estimating two different land price measurements for Germany shows that direct and indirect agglomeration spillover effects can explain more variation in residential land prices than vacant land prices. (JEL: R0; R11; R14; R21; R31)

Keywords: German Land prices; Land values; German Housing prices; Housing values; Spatial Effects.

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1. Introduction

Figure 1 shows robust growth in house and land prices for the seven biggest German cities[1] that outpaced both New York and London since 2014.

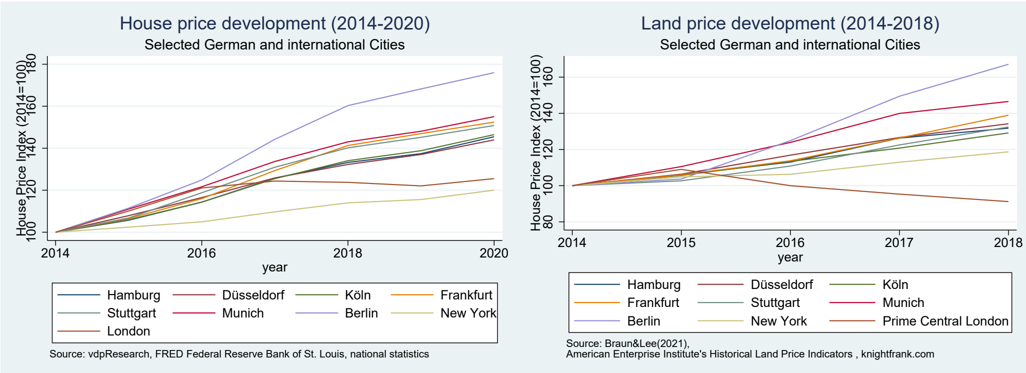

FIGURE 1. Development of house prices (2014-2020) and land prices (2014-2018) - Selected German and international cities

Surrounding areas for these seven cities have also experienced a similar growth pattern in house and land prices from 2014 to 2018.[2] The average real house price appreciation for these German cities' first contiguous surrounding areas ranges between 11 percent and 34 percent. For the same surroundings, the land prices appreciated between 12 percent to 31 percent, whereby both the house and land prices for Munich had the highest and Leipzig had the lowest growth.[3] Figure 2, which plots the Moran scatterplots that measure spatial correlation for house and land prices in 2014, shows clear positive spatial correlations for 378 German counties including these cities and their surrounding areas: the first order contiguity spatial correlations for house and land prices are 0.66 and 0.58, respectively.

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1. We use the Big 8 cities that are also chosen by Gröbel et al. (2020) as the biggest residential markets. But, given their spatial proximity, we combine Cologne and Düsseldorf to represent the biggest German agglomeration. Consequently, we either speak of Top 7 cities or agglomerations in this paper.

2. German house prices have been appreciating at a much faster rate than both New York and London since 2010. However, the analysis starts from 2014 as we use the German land price dataset from Braun and Lee (2021) at the county level that begins from 2014 to 2018.

3. Tables A.4 and A.5 in the Appendix show house and land price development for the first three tiers of the seven cities from 2014 to 2018.

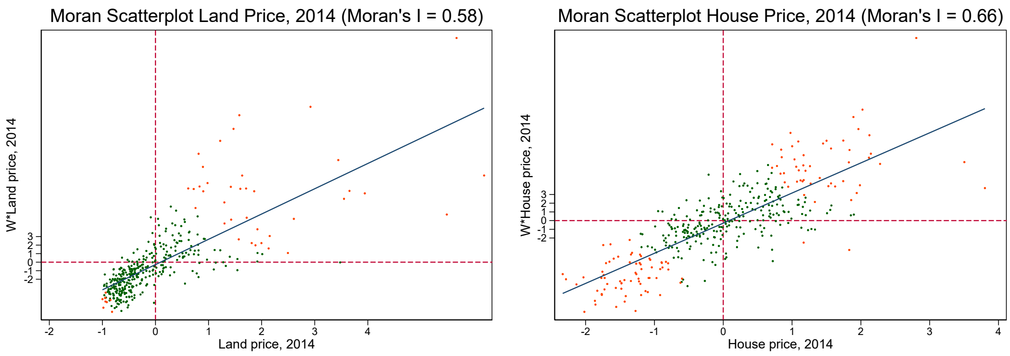

FIGURE 2. Moran scatterplot for land and house prices - First order contiguity matrix

These apparent regional house price spatial spillover effects are well documented for various geographical regions.[4] The main take-away message from the spatial correlation literature is clear: the spatial spillover effects matter in understanding real estate markets. Yet, the economic causes for these spillovers in house prices are less understood as most of the studies focus on the mechanisms of the spatial and temporal lags on housing prices.

The objective of this paper is to analyze the impact of agglomeration effects on spatial price variations for German real estate markets in 378 administrative counties and cities from 2014 to 2018.[5] While most spatial correlation literature focuses on the spatial interaction effects in house prices, the focus of this paper is on the spatial spillovers in land prices affected by the clustering of production and workers, also known as agglomeration economies. Consequently, one of the distinguishing characteristics of this papers' framework is the role played by land prices. We focus on land prices as recent studies on the U.S. land prices such as Ahlfeldt and McMillen (2020), Albouy et al. (2018), Davis et al. (2021), and Braun and Lee (2021), on German land prices, with different objectives in mind, have shown that most of the variations in house prices are due to the underlying land values and shares. For the international evidence, Knoll et al. (2017) also document that rising land values and shares mainly drive house price increases for many developed economies since World War II. For example, Figure 3 that plots the quarterly time series for housing, imputed land, and construction cost indexes for Germany, the U.K., and the U.S., from 2000 to 2020:q3 also informally shows the importance of land price development for housing markets.

4. For example, among others, Otto and Schmid (2018) and Möller (2009) for Germany, Gong et al. (2020) and Guo and Qu (2019) for China, Fingleton (2008) and Baltagi et al. (2014) for the U.K., and Brady (2014) and Cohen et al. (2016), Pijnenburg (2017) for the U.S.

5. The official number of administrative counties in Germany is 401 as of 2019. Given the territorial boundaries from 2016, we use 378 counties due to the lack of data for the rest.

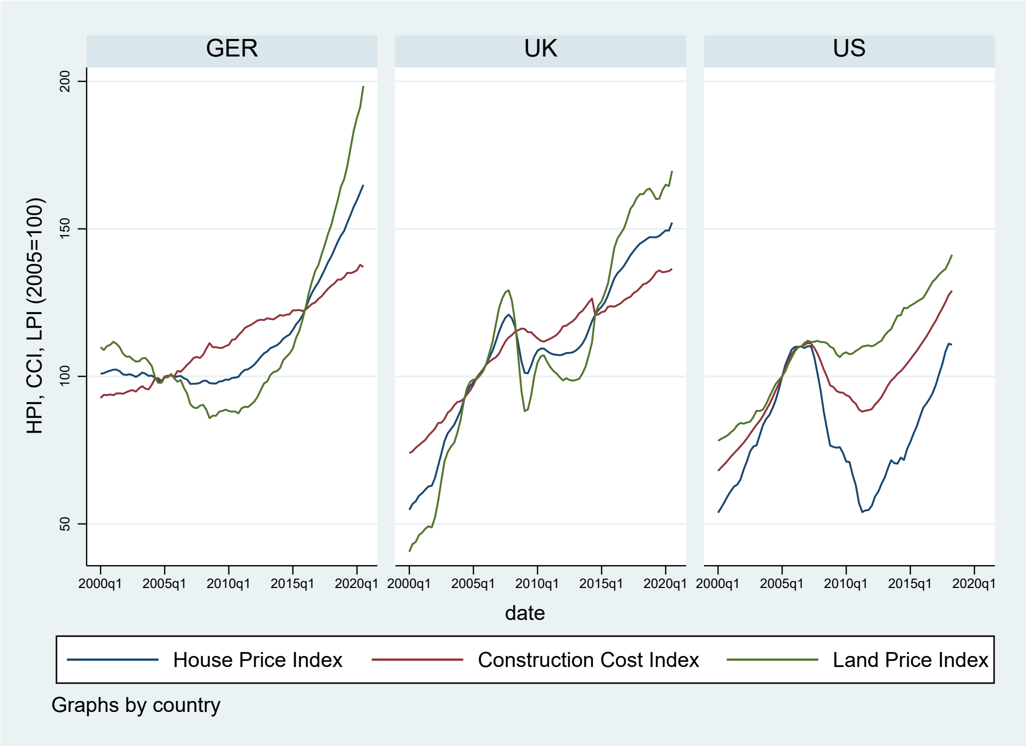

FIGURE 3. Housing market decomposition by country - 2000-2020q3
Source: The sources are listed in Table A.2. The imputed land value is calculated according to Knoll et al. (2017) with $\alpha = 0.5$.

We use the German residential land price dataset from Braun and Lee (2021) for two reasons. First, Figure 3 shows that although German housing prices have been sharply increasing since 2010, the residential land share in total wealth has increased but the structure share in total wealth has been steadily decreasing. Moreover, it shows that residential land prices have increased significantly more than the structure costs and house prices in most of the German counties from 2014 to 2018. Consequently, the findings from Braun and Lee (2021) imply that cycles in the German land values are more likely to affect house prices in the future. Second, Braun and Lee (2021), that construct the German residential land prices at a county level, provides the first and only publicly available dataset. Previously available land price datasets are from the Federal Statistical Office, which only provides the vacant land prices on a national level from 2010 and from the Statistical Offices of the Federal and State Governments, which provide the vacant land prices on a county level from 1995.[6]

6. Appraiser assessed land values are available from regional Independent Surveyor Commissions at costs. However, these Surveyor Commissions use independent appraisal methods. Despite being based on detailed guidelines, these existing land price valuations rely on surveyors' knowledge and expertise. For more details on German land price measurements see Braun and Lee (2021).

The other main focus is the impact of spatial agglomeration effects on real estate markets. Well established empirical evidence that supports the existence of agglomeration economies are the positive relationships between population density and productivity (wages) as well as between population density and real estate prices. Figure 4 shows positive relationships between the log of population density versus the log of GDP per capita (0.59), the log of median income (0.60), the log of house price index (0.55), and the log of land price per square meter (0.60) for German counties in 2014.

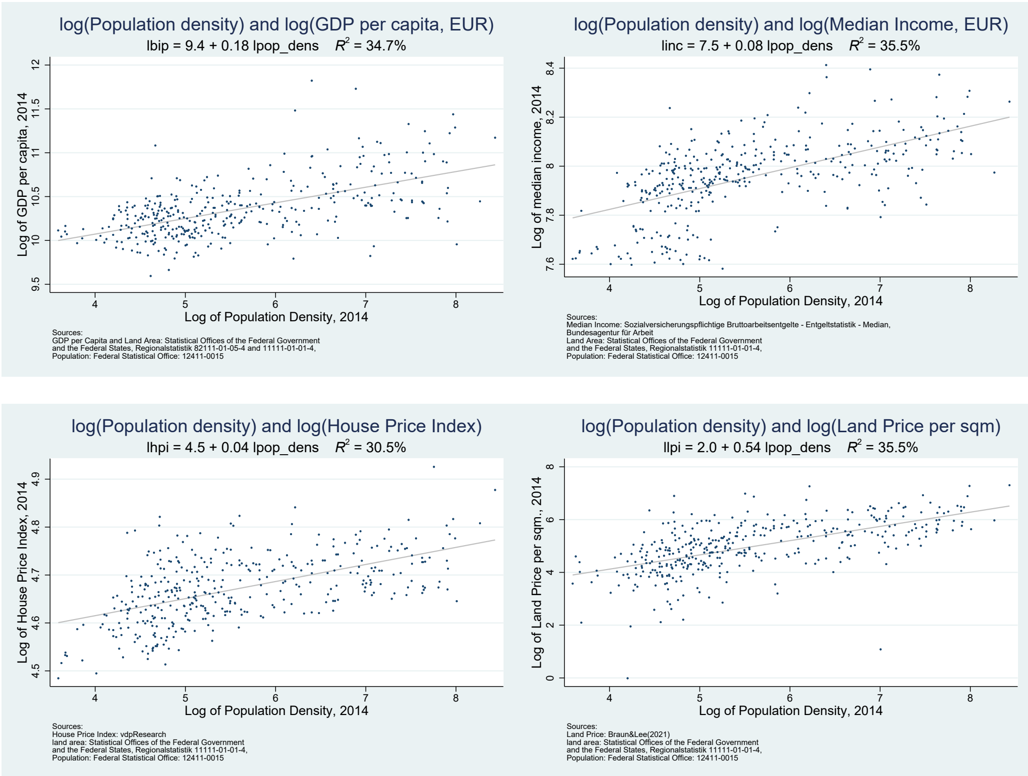

FIGURE 4. Measuring agglomeration - German counties in 2014

These positive relationships informally indicate the well-documented density-productivity relationship in the United States by Ciccone and Hall (1996) and in Europe by Ciccone (2002). Consequently, the spatial equilibrium framework by Rosen (1979) and Roback (1982) suggests that these positive correlations between density and real estate prices can either mean that dense places have become more pleasant over time or that dense places have become more productive. The literature on land value estimation also lend an indirect support for the existence of agglomeration effects in house and land markets. For example, Ahlfeldt and McMillen (2020) report that variation in land shares is likely influenced by demand-side factors that are exogenous to the production function of housing and less by inelasticities in housing supply. Albouy et al. (2018) further provide indirect evidence of agglomeration effects on land prices by showing that monocentric cities have spatially varying negative land price gradients with increasing distance to the city center.

This paper estimates spatial land price and agglomeration spillovers using a standard spatial econometrics framework that accounts for the effects of localization and network externalities as well as spatial spillovers in house and land prices. We first estimate panel data with fixed effects as a benchmark. Then, the analysis is extended using a spatial framework that accounts for spatial lags of dependent (house and land prices) and agglomeration variables, the so-called Spatial Durbin Model (SDM). We also estimate the Spatial Lag of X Model (SLX) and the Spatial Autoregressive Model (SAR) that account for either only exogenous spillovers or endogenous spillovers, respectively. More specifically, we address the following questions: First, can cross-county agglomeration spillovers explain variation in land and house prices for Germany, including the seven largest German cities and their surrounding counties?[7] Second, to what extent can clustering patterns in house prices be attributed to spatial variations in land prices? Lastly, how do spillover effects on house price variations differ between the residential land prices and the land prices on vacant land, which are provided from the Statistical Offices of the Federal Government and the German States?

One of the main results is that there are large and significant local and spatial agglomeration effects on land and house prices. For example, if there is an one percent increase in the median income the land price changes by 2.6 percent, ceteris paribus. A corresponding one percent increase in median income of the neighboring counties raises land prices by 0.85 percent in the county of interest. A one percent change in the population density of the county itself and its neighboring counties has a similar effect on land prices, with land price increases of 3.48 percent and 1.99 percent, respectively. We find that comparable empirical patterns also hold for house prices, but less so for the seven major German cities. This result suggests, unlike Gyourko et al. (2013), that the Big 7 German cities do not exhibit the characteristics of the so-called Superstar Cities. Although the direct median income and population density effects are significant for all seven cities, the indirect (spatial) effects for the variables are significant for only four out of seven cities.

Moreover, housing supply factors such as the available land to build and a proxy for the restrictiveness of housing supply also significantly affect land and house prices on county and city levels. Furthermore, we show that the land price spillover effects are among the dominating factors in the formation of regional house prices. These

7. Figure 5 shows those seven cities (Tier 1) as well as their surrounding counties that we assigned into Tier 2 and 3. The upper right map highlights the new German Federal States (Former ”East Germany” and before 1990, part of the German Democratic Republic (GDR).).

results, as in Gyourko et al. (2013), suggest that disparate local land and house prices can be driven by other housing variables and cannot be explained entirely by the agglomeration effects such as median income (productivity) and population density levels in those areas. Lastly, estimation on two different land price measurements for Germany shows that direct and indirect agglomeration spillover effects can explain more variation in residential land values than in vacant land prices from the Statistical Offices of the Federal Government and the German States.

The rest of this paper is organized as follows. In Section 2, we overview the literature on spatial effects in housing prices. Section 3 outlines a simple baseline framework on network spillovers in housing and land prices across counties for the empirical analysis. Section 4 presents the empirical model specifications and outlines the data sources. In Section 5, we present the empirical findings that include various robustness analysis. Section 6 concludes, followed by the Appendix.

2. Previous Literature on Spatial Spillovers in House Prices, Agglomeration, and Land Prices

This paper combines three strands of literature: Literature on spatial spillovers in house prices, agglomeration effects on real estate prices, and land prices. This section, thus, provides a literature review on the significance of spatial correlation in regional housing markets, the agglomeration effects on real estate markets, and the upward trend in land prices.

The literature on spatial interaction in real estate markets is clear in the importance of spatial correlation in determining property values. These so-called spatial spillover effects in house prices are widely studied in the literature using spatial econometric methods for different countries and different geographic aggregation levels.

Prior to 2007, spatial econometrics mostly focused on models that contained one type of spatial spillover effect. These models that contain either an endogenous interaction effect (i.e., a spatially lagged dependent variable) or correlated effects (i.e., spatially autocorrelated error terms were introduced in the seminal work by Anselin (1988)). After 2007, the literature includes model estimation with several types of interaction effects. Kelejian and Prucha (1998); Kelejian et al. (2004) and Kelejian and Prucha (1999) developed estimation techniques for models that contain both spatially lagged dependent variables and autocorrelated error terms. Whereas, LeSage and Pace (2009) introduced the Spatial Durbin Model (SDM) that incorporates both endogenous as well as exogenous interaction effects, where a exogenous interaction effect supposes that the house price of a region depends on other regions' explanatory variables (Elhorst, 2010).

Many studies use hedonic house price analysis that incorporates spatial interaction effects to investigate mechanisms for spillovers between prices of neighboring houses. On the least aggregated (MSA) level, Can (1990, 1992) shows that for Columbus, Ohio, USA, accounting for different spatial effects using spatial econometric models is superior to simple hedonic pricing models. Dubin (1988) examines spatial autocorrelation in hedonic house price residuals using a Maximum Likelihood procedure for data on 221 property transactions of homes in Baltimore sold in 1978. She extends her earlier work in Dubin (1992) by presenting an alternative approach to model spatial autocorrelation in hedonic house price residuals. Based on structural characteristics of properties and the average of hedonic residuals of nearby properties, she predicts market values for homes by Kriging. Other studies that examine spatial autocorrelation in house prices within Metropolitan areas using similar methodologies to Can (1990, 1992) and Dubin (1988, 1992) are for example Basu and Thibodeau (1998) that use transaction data of home sales in Dallas 1991:4-1993:1 and Clapp and Tirtiroglu (1994) that use data for the Hartford area, 1982-1988. Helbich et al. (2014) and Pijnenburg (2017) emphasize the importance of comparing different estimation techniques (parametric, non-parametric, and non-linear spatial effects) to account for the presence of spatial heterogeneity in hedonic house prices in Austria and the U.S.

Spatial interactions of house prices, however, do not only occur within urban housing markets. They also appear between aggregated housing markets, such as between different counties, cities, or states. Many studies used spatial autoregressive models that include endogenous interaction effects to investigate house price interaction effects. Fingleton (2008) motivates this type of interaction by displacement effects in supply and demand. Fingleton (2008) finds evidence for endogenous house price spillovers among 353 districts in the U.K. estimating a spatial autoregressive model (SAR) model in 2001. Also for the U.K., Baltagi et al. (2014) support this finding even after using random nested error terms with panel data from 2000-2007 for the 353 districts. Gong et al. (2020) also show endogenous cross-region spillover effects for the Chinese housing markets. Another mechanism that a SAR model empirically estimates is yardstick competition, which assumes that participants of the demand and supply side of a housing market take actions of neighboring housing markets into account when forming their buying and selling strategies (Brady, 2014; Gong et al., 2020). For the U.S., Brady (2014, 2011) find persistent spatial diffusion processes by estimating spatial impulse response functions based on a SAR model for California counties for the period, 1995-2002 and across the U.S. States for the period, 1975-2011. Similarly, using a spatial-temporal model Holly et al. (2010) examine to what extent movements in house prices can be explained by fundamentals for the States of the U.S. For regions in the U.K., Holly et al. (2011) analyze spatial and temporal diffusion processes of shocks in a dominant region (London) in a spatial-temporal setting.

For Germany, Otto and Schmid (2018) find evidence for the existence of cross-county house price spillovers estimating dynamic spatial panel data models for their dataset on German real estate prices in 412 counties. The found ripple effect is timely delayed and diminishes with distance to the region a shock occurred. Möller (2009) also finds similar spatial effects for vacant land ready for development when analyzing the relationship between the regional German labor market and the market for building land.

Endogenous spillover effects are not the only cause of cross-county interactions considered in the literature. Cross-county spillovers can also emerge due to exogenous interaction mechanisms such as network effects in a county or city grid. The presence of agglomeration effects between counties, was first implemented by Krugman (1991) in the new economic geography theory (NEG). The existence of this type of spatial spillover effects is, for example, supported by Gong et al. (2020) who applies the spatial lag of X model (SLX) using cross-sectional housing market data on an urban network in eastern China. They also find common shocks to cause cross-city dependence of housing prices, estimating the Spatial Durbin Error Model (SDEM). Some other studies that show evidence for network spillover effects in housing markets use different market potential measures. For 136 European large urban zones, Camagni et al. (2017) find a significant impact of static and dynamic agglomeration economies on house prices. For U.S. counties, Partridge et al. (2009) analyze the impact of hierarchical geographic proximity and market potential on median earnings and housing costs. They find especially housing costs to be higher with closer proximity to higher-tier urban cores.

While most of this literature focuses on spatial interaction effects in house prices, this papers' goal is to analyze spatial spillovers in land prices. The literature on land prices shows the upward trend in land prices and large land shares in housing wealth for many developed economies. Most of these studies equate house prices to the cost of putting up the structure plus the value of land, where the latter is often seen as pricing any geographical and regulatory barriers to housing supply, as well as amenities accessible at a given location (Glaeser et al., 2006; Davis and Heathcote, 2007; Davis and Palumbo, 2008). Studies such as Davis and Heathcote (2007), Davis and Palumbo (2008), and Davis et al. (2017), Davis et al. (2021) have shown, for the U.S., that most of the variations in house prices are due to the underlying land value. In Braun and Lee (2021), we argue that movements in the land - and structure values are crucial for understanding the development of German housing markets and policy measures that accompany these movements. Studies that estimate land values and shares via spatial transaction based approaches such as Albouy et al. (2018) and

Ahlfeldt and McMillen (2020) support the presence of network externalities in land values. For example, Albouy et al. (2018)'s land value estimates indirectly support the monocentric city theory as they increase with decreasing distance to the center of an agglomeration. Ahlfeldt and McMillen (2020) argue that the factors to the demand side that are exogenous to the housing production function such as higher income and larger preferences for certain amenities are positively correlated with high land values.

3. Baseline Model

The main empirical interest lies in the spatial interaction patterns of land prices both of endogenous and exogenous nature and the clustering patterns in house prices that can be contributed to spatial variations in land prices. Rather than simply presenting spatial lag models for the empirical analysis, we present a simple reduced form of the spatial housing market which captures variables that affect both supply and demand functions.

As in Fingleton and Le Gallo (2008), consider an economy with n counties. In this economy, the determination process of house price within a region i may not assume to be only a function of demand and supply factors of that region but also of regions within commuting distance from county i. Consequently, we assume that demand for real estate (q_i) reacts to changes in income (w_i) of both region i and surrounding regions to reflect the travel-to-work patterns that require to cross county borders. Moreover, I assume that demand for real estate depends on natural attributes of a county (E_i) such as green coverage as well as two types of externalities: 1) local externalities formed by agglomeration economies (l_i) and 2) network externalities from cross-county connections (Wl_i, where W is a spatial weighting matrix). A prime example for agglomeration economies is that higher population density counties can increase the likelihood of enjoyable social contacts and meet like-minded peers, especially attracting young single people. Also, so-called higher-order amenities, such as opera, expensive restaurants that require substantial scales of economies to be sustained, can mostly be found in higher population density places. We also include the size of land (Combes et al., 2010) and median income (Ciccone and Hall, 1996; Combes and Gobillon, 2015) to measure the agglomeration effect.

One can further link the local externality to its agglomeration level in economic activities. Mechanisms that support this connection are, for example, a shared and larger labor pool that improves firm-worker matching and knowledge spillovers through shared information during face-to-face meetings (Glaeser et al., 2001; Gong et al., 2020; O'sullivan, 2007). Switching from the single county to a network of counties,[8] the previously mentioned connection can cause the same benefits resulting from agglomeration economies within such a network. For example, higher-order amenities can be used by people from less dense populated nearby counties in order for them to complement their shopping and entertainment facilities. But these amenities also need to be demanded by those people in order to support and maintain the higher population density counties' functionality and local externalities (Gong et al., 2020; Meijers et al., 2016; Meijers and Burger, 2017).[9] Finally, while demand in region i is assumed to negatively depend on the region's house price p_i, this reduced demand spills over to neighboring regions (displaced demand effect: $\sum_{i\neq j}^{n} W_{ij}p_j$). Consequently, the demand function for housing is[10]

$$\begin{aligned} q_i \quad = \quad & a_0 + a_1 w_i + \overline{a}\sum_{i\neq j}^{n} W_{ij}w_j + a_2 E_i + a_3 l_i + \widehat{a}\sum W_{ij}l_i \qquad (1) \\ & -a_4 p_i + \widetilde{a}\sum_{i\neq j}^{n} W_{ij}p_j + \omega_i, \end{aligned}$$

where W_{ij} spatially links counties with each other. ω_i is the error term that contains other unmodelled demand factors.

The corresponding supply function for housing takes the following form

$$q_i = b_0 + b_1 p_i + b_2 H_i - b\sum_{i\neq j}^{n} W_{ij}p_j + \eta_i, \qquad (2)$$

where η_i is the unobserved supply error term. The supply of housing is assumed to increase in the price level of housing in region i. High real estate prices attract real estate developers and it may be more likely that homeowners are offering their properties for sale. However, this also means that high property prices in neighboring counties "steal" away supply of housing from region i (displaced supply effect: $\sum_{i\neq j}^{n} W_{ij}p_j$). As in Gong et al. (2020), supply is assumed to depend on the restrictiveness of housing supply, H_i.

8. We focus on network connections between counties located in geographical proximity to each other. As mentioned in Camagni et al. (2017), network externalities can, however, also emerge between regions located far from each other but linked through a horizontal, non-hierarchical network given a similar size.

9. The productivity of counties with smaller urban cores can be increased given the so-called "borrowed size" effect, when located next to counties with major urban cores, by borrowing their technological externalities. Moreover, proximity to larger consumer and supplier markets increases productivity by saving transportation costs and often correlates with higher wage levels (Gong et al., 2020).

10. In the empirical analysis, we also include unemployment, housing stock, and open accommodation as control variables.

Rewriting the supply function by solving for p_i, we have

$$p_i = \frac{1}{b_1} q_i - \frac{b_0}{b_1} - \frac{b_2}{b_1} H_i + \frac{1}{b_1} b \sum_{i \neq j}^{n} W_{ij} p_j - \frac{\eta_i}{b_1}. \tag{3}$$

Substituting for q_i yields

$$p_i = c_1 \left[a_0 + a_1 w_i + \overline{a} \sum_{i \neq j}^{n} W_{ij} w_j + a_2 E_i + a_3 l_i + \widehat{a} \sum_{i \neq j}^{n} W_{ij} l_i - a_4 p_i + \widetilde{a} \sum_{i \neq j}^{n} W_{ij} p_j + \omega_i \right] \\ - c_0 - c_2 H_i + c_3 \sum_{i \neq j}^{n} W_{ij} p_j - \nu_i. \tag{4}$$

Simplifying the equation further gives the empirical form that includes spatial effects as

$$\begin{aligned} p_i = {} & d_0 + d_1 w_i + \overline{d} \sum_{i \neq j} W_{ij} w_j + d_2 E_i + d_3 l_i + \widehat{d} \sum_{i \neq j} W_{ij} l_i + \\ & + d_4 H_i + \widetilde{d} \sum_{i \neq j} W_{ij} p_j + u_i, \end{aligned} \tag{5}$$

where $u_i = c_1 \omega_i + \nu_i$.

Since the focus is on land prices, we modify Equation (5) by including construction costs. As Davis and Heathcote (2007) and Davis and Palumbo (2008), Glaeser et al. (2006) argue that the determination of house price is more complex in a sense, that the costs of new construction consist of the cost of putting up the structure in addition to any geographical or regulatory barriers to housing supply. While the former can be assumed to be supplied highly elastically, the latter can cause housing supply to be highly inelastic depending on locations. Following the residual approach in Braun and Lee (2021)[11], we decompose house value into a physical cost of construction and the land value. Therefore, from the housing supply perspective, the price of housing will be determined by the cost of new construction, defined above as the sum of construction cost and land value, in places where demand is sufficiently large to justify new construction. Incorporating this decomposition into Equation (5), the land value is defined as:

$$\begin{aligned} lp_i = {} & d_0 + d_1 w_i + \bar{d} \sum_{j \neq i} W_{ij} w_j + d_2 E_i + d_3 l_i + \\ & \hat{d} \sum_{j \neq i} W_{ij} l_j + d_4 H_i + \tilde{d} \sum_{j \neq i} W_{ij} p_j + \lambda cc_i + u_i \end{aligned} \tag{6}$$

11. The two-step residual approach has been used in Davis and Heathcote (2007); Davis and Palumbo (2008) and Braun and Lee (2021)

where lp_i is the land value per m^2 in county i, cc_i is a county-specific construction cost factor and λ measures the effect of county-specific construction cost on land value. In the next section we outline the empirical methodology.

4. Empirical Framework and Data

We are interested in two types of spatial spillover effects in land and house prices: First, exogenous interaction effects within the explanatory variables. Second, endogenous interaction effects within the dependent variable.

There are different types of spatial regression model specifications that include spatial lags of the dependent variable. But Anselin (1988); LeSage and Pace (2009) argue that one specification, the spatial Durbin model (SDM), stands out as superior in a vast number of applied situations. The SDM is shown in Equation (7). It includes a spatial lag of the dependent variable ($ln(P)$) as well as agglomeration variables in (l):

$$ln(P) = \rho M ln(P) + \alpha_0 \mathbf{1} + X\beta + Wl\theta + \varepsilon, \varepsilon \sim N\left(0, \sigma^2\right) \tag{7}$$

where, $\mathbf{P}_{n\times 1}$ is the vector of land values or house prices, $\mathbf{X}_{n\times r}$ incorporates the county-specific characteristics and agglomeration economies and $\mathbf{Wl}_{n\times r}$ represents the network externalities. In the empirical analysis, we use the same weight matrix for $\mathbf{M}_{n\times n}$ and $\mathbf{W}_{n\times n}$ (Anselin, 1988; LeSage and Pace, 2009). $\mathbf{W}$ $\mathbf{(M)}$ is the spatial weight matrix that defines how counties are spatially connected. This matrix allows for local externalities $\mathbf{l}$ to spillover between spatially linked counties and hence spillover effects can be modeled as $\mathbf{Wl}$.

Apart from estimating the model in Equation (7), we also estimate three other models. We first start with a panel fixed effects model ($\rho = \theta_{1\times r} = 0$), and then add two other spatial lagged models, namely the Spatial Autoregressive Model (SAR: $\theta = 0$) and the Spatial Lag of X Model (SLX: $\rho = 0$).

The latter is seen as more appropriate for applied studies and superior to SAR-type specifications as it does not suffer from identification problems (Halleck Vega and Elhorst, 2015; Gibbons and Overman, 2012; Gong et al., 2020). Also, next to the SDM, this model provides a flexible way to model exogenous interaction effects among the explanatory variables.

However, for economic reasons we use the SDM as the main model of interest as the likelihood of displacement effects in land and house prices causing cross-county spillovers being present in the process of house price determination is pretty high. For example, high house prices in one region cause demand for housing to decrease. However, this demand is likely to be displaced to regions nearby. Another mechanism that can explain this type of spillover effect is ”yardstick competition”.

For example, house sellers and buyers might take into account price signals from house price transactions in a neighboring county, spatially linking house prices with each other (Brady, 2014; Gong et al., 2020).

Note that a significant estimate of ρ could either be attributed to pure spatial spillover effects in house prices or reflect information picked up from omitted variables such as network externalities (Corrado and Fingleton, 2012; Gibbons and Overman, 2012; Gong et al., 2020). However, one can statistically justify estimating Equation (7) by evaluating the role of network externalities when testing the SDM model against the SAR model with the restriction $\theta = 0$.[12]

4.1. Direct vs. Indirect Effects

In spatial econometrics, due to the presence of the spatial weights matrix, the interpretation of point estimates as spatial spillover effects is misleading in some models (Elhorst, 2010; LeSage and Pace, 2009). To circumvent delusive conclusions from hypothesis tests based on point estimates, LeSage and Pace (2009) present the partial derivative approach for finding the impact of a change in variables for different model specification as being more valid. Given this approach, the direct effect represents the effect of a change in a county-specific variable on that counties' land value. We however, interested in cross-county spillovers. By definition this refers to the indirect effect, the impact of a change in a county-specific variable on land values of other counties (Gong et al., 2020; LeSage and Pace, 2009; Elhorst, 2010).

We briefly outline the direct and indirect effects below, but the interested reader may refer to LeSage and Pace (2009) and Elhorst (2010) for more details. Equation (7) can be written as

$$ln(P) = (I - \rho M)^{-1} (X\beta + Wl\theta + R), \tag{8}$$

where R includes intercept and the error terms. The marginal effect of agglomeration on the land or house prices can be clearly seen by taking the derivatives of $ln(P)$ with respect to the rth l :

$$\frac{\partial ln(P)}{\partial l}_{n \times r} = (I - \rho M)^{-1} (1_{n\times 1}\beta_{1\times r} + W_{n\times n} 1_{n\times 1}\theta_{1\times r}).$$

For the SDM, the diagonal elements of $(I - \rho M)^{-1} (1_{n\times 1}\beta_{1\times r} + W_{n\times n} 1_{n\times 1}\theta_{1\times r})$ represent direct effect and the off-diagonal elements are the indirect effects. For the SLX, $\beta_{1\times r}$ and $\theta_{1\times r}$ are the direct and indirect effects, respectively. Lastly, for the SAR, the diagonal elements of $(I - \rho M)^{-1} (1_{n\times 1}\beta_{1\times r})$ represent direct effect and the off-diagonal elements are the indirect effects.

12. For more details on the spatial econometric models outlined in this section the reader may refer for example to Anselin (1988) and LeSage and Pace (2009).

4.2. Data

We use the annual (2014-2018) land value per square meter of lot size estimates for German counties and county-free cities from Braun and Lee (2021) as a measure for residential land price. Since one of the main focuses of this paper rests on land prices, the data from Braun and Lee (2021) is briefly summarized here. It estimates changes in the value and price of residential land for the 379 German counties ("Landkreise") from 2014 to 2018 by combining data from several publicly available sources for academic researchers. In doing so, a database for the cost of housing structures and residential land values at the county-level is built. The framework of the approach used is that of Davis and Heathcote (2007), who decompose house value into the value of the structure and land value on the aggregate level for the U.S. Some of the results from Braun and Lee (2021) lend support to this papers' spatial analysis. For example, it shows that residential land price has become relatively more expensive in the majority of German counties. Moreover, the counties around urban centers such as Munich, Stuttgart, Berlin, Hamburg, Dresden, and the Ruhr area cities experienced the highest land price increases. However, we also note that, in general, an upward shift in home values, land values, and residential land share occurred in almost every state.

We use annual house price indexes for single- and double-family houses from vdpResearch at the county and independent city level available for the years 2007-2018 based on transaction data. I control for several county-level characteristics in different model specifications (Table 14). First, we use the following variables to measure the agglomeration economies of each county that are known to generate local and network externalities: the counties' land area in km^2, its median income, and population density (Gong et al., 2020). The latter is calculated by dividing county's population by its land area in km^2 in a given year. That is, population density is equal to 100 in a county with 100 individuals per km^2.[13] Second, we include county-specific natural and economic characteristics in different model specifications. As an indicator for the environmental amenities of a city, we include the green residential area that is used for recreational purposes divided by a county's land area in km^2 (green coverage). We measure amenities of a county in terms of history and culture with the number of available accommodation facilities in that county (e.g., hotels, etc.). Moreover, we include the housing stock of single and double family housing as a measure of housing supply and the arable land per km^2 of land area to measure for the restrictiveness of housing supply (Gyourko et al., 2013; Gong et al., 2020).

13. As land values(/house prices) and population are usually determined simultaneously, population density could cause endogeneity. To circumvent this problem, we use one-year lagged population density.

	Mean	Std.Dev.	Min	Max
House price index	117.5	14.33	88.64	189.5
Land value per m^2 (Braun and Lee, 2021)	252.2	255.3	0.987	2184.2
Land value per m^2 (Vacant land ready for construction)	175.3	231.3	8.960	2737.8
Population density (person per km^2)	516.0	702.0	35.78	4736.1
Median income[14]	3012.5	455.1	1961.8	4896.9
Unemployment rate	5.605	2.629	1.300	15.40
Housing starts[15]	310.1	255.2	10	2708
Open accomodation facilities	131.3	152.0	5	1398
Green coverage (percent of 'green' recreation area within residential areas)	0.0150	0.0207	0	0.121
Land area (km^2)	931.5	722.4	40.02	5495.6
Total housing stock	48924.3	32291.1	6977	326882
Housing stock (Single family houses)	32650.8	20562.1	4235	169251
Housing stock (Double family houses)	8081.0	5250.1	762	30681
Construction cost index	101.3	10.74	65.20	160.3

TABLE 1. Descriptive statistics

Finally, we use the construction cost, income, and unemployment rate as measures for a counties' economic situation as control variables. The data and sources are described in detail in the Appendix in Table A.1. Descriptive statistics are provided in Table 1.

5. Estimation Results

We focus on the first-order contiguity matrix[16] estimation results for land values as spatial baseline results. We estimate the models outlined in Section 4 for the total of 378 counties, 314 counties in the old Federal States, 64 counties in the new Federal States, and the Big 7 German cities, including their surrounding counties. For expositional purpose, we present Figure 5 that shows the counties assigned to each Tier and Table 2 that presents the number of total counties within Tiers 1-3.[17]

As we use an annual panel data set for German counties from 2014-2018 we need to consider both time and cross effects in the estimation methods. However, we only

15. Median of gross financial wages of full-time workers with compulsory social insurance.

16. Construction permits of new residential buildings and apartments in residential buildings, annual sum.

16. To construct spatial weight matrices and maps in this paper, the shape files with coordinates on German states and counties from Bundesamt für Kartographie und Geodäsie, Frankfurt am Main (GeoBasis-DE / BKG) (2019) are used.

17. The states highlighted in red in the map in the upper right corner of Figure 5 denote former East Germany. For a detailed representation of the counties assigned in each tier for the 7 agglomerations, refer to Table A.3 in the Appendix, where counties highlighted in red are missing in the dataset of Braun and Lee (2021) and are therefore not included in the estimation.

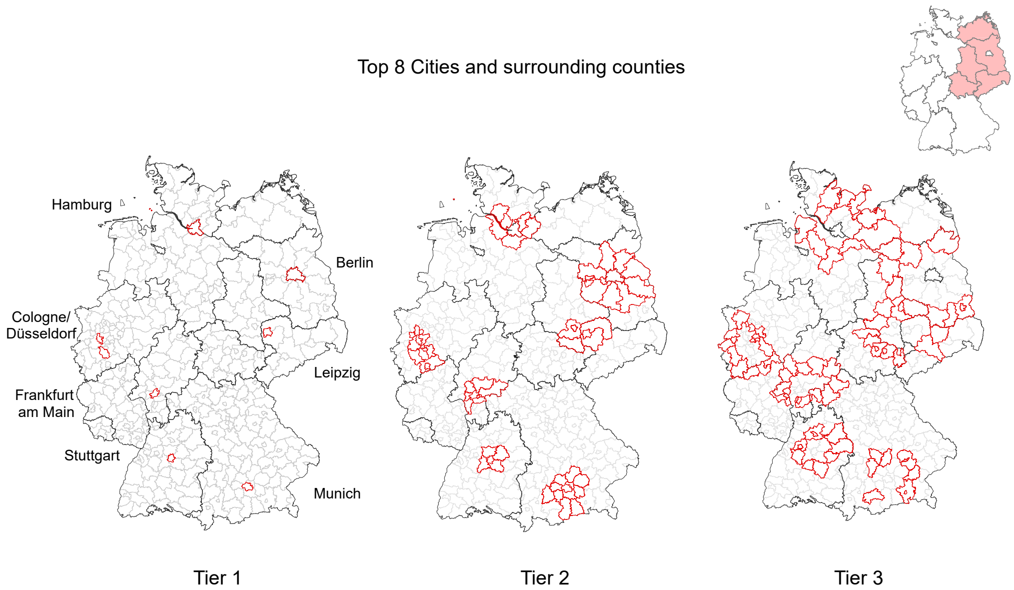

FIGURE 5. Top 7 agglomerations and surrounding counties

City	no. of counties
Berlin	21
Munich	19
Hamburg	19
Cologne/ Düsseldorf	28
Frankfurt am main	22
Leipzig	18
Stuttgart	15

TABLE 2. Sum of counties in Tier 1-3 for each of the Big 7 cities

account for county fixed effects in the estimations for two reasons.[18] First, we observe slight heterogeneity over time due to the short time period. Figures A.1 to A.3 [19] in the Appendix show only little variation in the time-varying explanatory variables by the state over time. Second, including a set of time dummies in column (2) in Table A.6, we find time dummies to be insignificant at all common significant levels except for the year 2018. The results from the $F-Test$ on joint significance of the time variables also do not reject the null that they together are not different from zero ($p-value = 0.27$). Moreover, comparing random and fixed effects estimation results with the Hausman test, we also reject the use of random effects ($p-value = 0.00$). To circumvent various serial autocorrelation issues for short panels, we use the transformation approach

18. Omitting time fixed effects could lead to a significant upward bias in the spatial lag's coefficient (Lee and Yu, 2010b; Halleck Vega and Elhorst, 2015).

19. The data and sources are described in detail in the Appendix in Table A.1.

maximum likelihood (ML) estimation with county fixed effects as in Lee and Yu (2010a).[20]

5.1. Spatial correlation of land and housing prices

Table 3 shows global Moran's I statistics that measure the spatial correlations for house and land prices in 2014. The first correlations use the first-order contiguity and inverse distance weight matrix. Other spatial correlations use three binary weight matrices that assign a weight of one if two counties are located within a certain distance and 0 otherwise. The distance bands for the correlations we use are 0-60km, 60-120km, and 120-180km to reflect the distances between Tier levels. Columns (1) and (2) show a significant positive auto-correlation both in house and land prices, that diminishes with increasing distance of neighboring counties. These spatial correlations lend informal for endogenous interaction of house and land prices.

Other explanatory variables also display similar spatial correlation patterns. Table 3 also provides the global spatial cross-correlation coefficient by Chen (2015), R_c. If exogenous spillover effects in land and housing markets exist, one would expect spatial cross-correlation between housing and land markets with agglomeration variables. We find significantly positive cross-correlations between a county's land and house prices and neighboring counties' median income and population density. However, especially, the cross-correlation with population density quickly vanishes with distance. The land area is negatively cross-correlated with both house and land prices. These spatial correlation patterns also show informal evidence for exogenous spillover effects.

5.2. Non-spatial estimation results

Baseline results for Germany are displayed in Tables 4 and 5. Tables 6 and 7 compare the Spatial Durbin Model results for West and former East Germany and the Big 7 Agglomerations.

We first estimate a non-spatial model as a benchmark. Column (1) of Table 4 reports the estimation results for the non-spatial model accounting for fixed effects. In column (1), all coefficients are statistically significant on the 1 or 10% significance level and have the expected sign. Except for the coefficient on green coverage, we would expect the opposite sign as green coverage proxies local amenities. However, green coverage could also indicate a restriction on available land to build. A city with a higher median income and higher population density is likely to have higher land values, ceteris paribus. Besides income and population density, the variable land area

20. Lee and Yu (2010a) introduce the bias correction procedures for Spatial Error Model (SEM), SDM, SAR and SDEM models to correct for biased parameter estimates in models with spatial fixed effects (and time fixed effects).

	Moran's I	Moran's I	R_c with Income		R_c with Population Density		R_c with Land area (km^2)	
	HPI	Land value	HPI	Land value	HPI	Land value	HPI	Land value
First order contiguity	0.66***	0.58***	0.48***	0.46***	0.29***	0.34***	-0.21***	-0.22***
	(20.87)	(18.35)	(15.14)	(14.59)	(8.92)	(10.70)	(6.45)	(6.69)
Inverse Distance	0.15***	0.14***	0.12***	0.14***	0.04***	0.07***	-0.05***	-0.06***
	(24.29)	(22.77)	(20.13)	(22.00)	(7.58)	(12.04))	(7.13)	(8.82)
Distance 0-60 km	0.46***	0.49***	0.34***	0.40***	0.20***	0.32***	-0.16***	-0.21***
	(23.32)	(24.81)	(17.17)	(19.93)	(10.29)	(15.89)	(7.61)	(10.19)
Distance 60-120 km	0.25***	0.18***	0.22***	0.23***	-0.01	0.02**	-0.04***	-0.04***
	(19.94)	(14.72)	(17.56)	(18.08)	(0.53)	(2.05)	(3.25)	(2.88)
Distance 120-180 km	0.18***	0.08***	0.18***	0.15***	0.01	-0.005	-0.05***	-0.02*
	(17.33)	(8.16)	(16.70)	(14.21)	(1.03)	(0.17)	(4.08)	(1.95)

t statistics in parentheses
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 3. Moran's I (year=2014)

	FE	SLX	SAR	SDM
main				
log(median income)	3.08***	2.52***	2.58***	2.56***
	(23.42)	(11.63)	(16.72)	(10.76)
log(Lag Population density (person per km^2))	4.30***	3.34***	3.70***	3.38***
	(15.74)	(8.98)	(12.30)	(8.28)
green coverage	-6.98*	-7.26***	-7.11***	-7.18***
	(-7.04)	(-7.42)	(-6.64)	(-6.68)
log(construction cost index)	-1.09***	-1.17***	-1.19***	-1.20***
	(-10.78)	(-11.65)	(-10.91)	(-10.90)
log(arable land (sqkm) per capita)	-0.61***	-0.63***	-0.58***	-0.59***
	(-3.49)	(-3.68)	(-3.09)	(-3.12)
log(land area (km^2))	3.90***	2.34	2.94*	2.51
	(2.68)	(1.60)	(1.86)	(1.57)
F				
log(median income)		0.10**		0.01
		(2.63)		(0.26)
log(Lag Population density (person per km^2))		0.37***		0.15
		(4.19)		(1.47)
log(Land value per m^2 (Braun,Lee (2021)))			0.05***	0.04***
			(9.99)	(7.21)
N	1890.00	1890.00	1890.00	1890.00
R2	0.516	0.529	0.522	0.99/0.524
Log-Likelihood	1654.2	1679.8	1680.1	1682.3

t statistics in parentheses
dependent variable: log(landvalue per m^2) Braun&Lee (2021)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4. Baseline estimation results - Germany

per km^2 that is also supposed to measure agglomeration economies has a statistically significant effect on land prices. If population density increases by one percent, land value per m^2 increases land values by 4.3 percent, ceteris paribus. An increase in land area per km^2 by one percent drives up land values by 3.08 percent. If arable land per capita increases by one percent, the land price per m^2 decreases by 0.61 percent. In other words, a less restrictive housing supply is associated with lower land values. Lastly, the independent variables in the model specification (FE) explain around 52 percent of the cross-county land price variation.

5.3. Spatial estimation results

Despite the SDM model being the main model of interest, the first part of this section is divided by the type of spillover effects: First, agglomeration effects are discussed in light of the SLX model, followed by endogenous spillover effects in SDM and SAR models. The subsequent parts focus on the difference in direct and indirect interactions, diagnostics, estimations for the Top 7 agglomerations and house price index as an alternate dependent variable.

	SLX	SAR	SDM
direct			
log(median income)	2.52***	2.62***	2.60***
	(11.63)	(17.11)	(11.10)
log(Lag Population density (person per km^2))	3.34***	3.75***	3.48***
	(8.98)	(12.44)	(9.04)
indirect			
log(median income)	0.10***	0.95***	0.85***
	(2.63)	(7.48)	(3.56)
log(Lag Population density (person per km^2))	0.37***	1.35***	1.99***
	(4.19)	(6.70)	(3.43)
Observations	1890	1890	1890

t statistics in parentheses
dependent variable: log(landvalue per m^2) Braun&Lee (2021)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 5. Baseline estimation results - Germany (direct and indirect effects)

5.3.1. Exogenous spillover effects: SLX model. For the SLX model, the choice of the spatial weights matrix is important as it determines the structure of spatial spillovers across counties. Although LeSage and Pace (2014) suggest that spatial estimation results are not as sensitive to the choice of spatial weights as commonly believed in literature, we capture the nature of spatial interaction with two spatial weight matrices. First, we estimate the spatial models outlined in Section 4 using a first-order binary contiguity matrix as the network externalities are highest among neighboring counties.[21] Second, to allow for network externalities between counties further apart, the models are re-estimated using an inverse distance matrix (See Section 5.4.2). Inverse distance matrices depict spatial interaction by weights that diminish with distance.

We find empirical support for the presence of network externalities for the model in column (2). The coefficients on the spatial lag of a counties' population density and median income are positive and significant. For example, an increase in the population density in a neighboring county of one percent increases land values per m^2 in the county of interest by 0.37 percent, ceteris paribus. The direct effects of median income and population density are smaller compared to the fixed effects specification (1). For income, the coefficient falls by 0.56, and the coefficient on population density falls by 0.96. The other explanatory variables, if at all, change only slightly and are all still highly significant in model (2) compared to the non-spatial model specification. The effect of a county's scale is lower in column (2) compared to column (1) and statistically insignificant.

21. Table 3 shows both higher auto-correlations and cross-correlations coefficients for the global Moran's I statistics using a first-order contiguity matrix compared to an inverse distance matrix.

Although we present statistical support for network spillover effects in land values, the spatial dependence may also be caused by pure spatial spillovers in land values. For this reason, we compare the SLX results with the SAR and SDM models below.

5.3.2. Endogenous spillover effects: SAR and SDM models. If spatial dependence is still present after accounting for network externalities, it can be attributed to pure land value spillovers or common shocks. Consequently, if pure land value spillovers cause the remaining spatial dependence, then the SDM would be a more valid specification.

Column 4 and 5 in Tables 4 and 5 show the QMLE estimates of the SAR and the SDM models for the first order contiguity matrix. The significant estimated coefficient (0.05 and 0.04 for the SAR and SDM, respectively) on WY_t in both columns (3) and (4) support pure land value spillovers.

Except for land area, the coefficients in the SAR model (3) and SDM model (4) remain highly significant and increase either slightly or stay almost the same compared to column (2). When including exogenous spillover effects into the model in column (4), the coefficient estimate of the spatial lags for median income and population density becomes insignificant. However, as discussed in Section 4.1, this interpretation may be misleading in the Spatial Durbin Model as there might be some network effects, which are more discussed in the following section. Compared to column (2), the SAR model slightly decreases explanatory power but comparing models (4) and (3), we find the SDM to be slightly superior. Moreover, the Likelihood Ratio (LR) tests, where the SDM is defined as the unrestrictive model, clearly reject the null-hypothesis that both the SLX and SAR are significantly preferred to the SDM.[22]

5.3.3. Network effects. As discussed in Section 4.1, spatial regressors' point estimates in spatial models (2)-(4) do not exactly show the direct and indirect spillover effects. We use the partial derivative approach to calculate direct and indirect spatial effects (See Table 5). It shows both evidence for a direct and indirect effect of population density and median income on a counties' land value. For example, a one percent increase in median income and population density in neighboring counties increases land values in the SLX model in a given county by 0.10 and 0.37 percent, respectively, ceteris paribus. On the other hand, the total (direct plus indirect) effects of a one percent increase in median income and population density in neighboring counties increase land values in a given county for median income and population density on land prices are 2.62 percent and 3.71 percent, respectively.

22. For example, the likelihood ratio test of $LR = 2ln\left(\frac{unrestrictive}{restrictive}\right)$ for SLX vs. SDM gives $LR = 2\,(1682.3 - 1679.8) = 5$ with the critical $\chi^2_{0.95,8} = 2.73$

Overall, the direct effects of population density and median income stay relatively robust across non-spatial and spatial models. In contrast, spillover effects vary between model specifications. Taking a closer look at Table 5, the cross-county spillover effects for median income and population density are higher in the SAR and SDM models compared to model (2). The increase in the spillover effects of median income and population density from the SLX to SAR model suggests that besides network externalities, pure interaction mechanisms also play a role in land value determination.

Taken the results of all models together, we conclude that cross-county dependencies in land values are driven not only by network spillovers but also by pure land value spillovers. However, the magnitude and form of the underlying spatial interaction vary between the three types of spillovers.

5.3.4. Diagnostics. For consistency, the QMLE estimation by Lee and Yu (2010a) assumes residuals to be independent and identically distributed with Normal zero mean and finite $(4+\zeta)$ th moment, where $\zeta > 0$. Hence, this section tests for the residual assumptions in the baseline specification.

To check for normality of the error terms, we use Pearson's Chi-squared goodness-of-fit test. The test cannot reject the null of normality of the error terms for all three spatial models (SLX, SAR, SDM) at the 5% significance level. The spatial autocorrelation among the residuals is measured by Moran's I statistics for each of the years 2014-2018. We conduct this statistics to check whether the models capture the spatial correlation structure of the data. The Moran's I for the first order contiguity matrix does not significantly differ from zero at a 5% significance level for all years in the three spatial models. This result indicates that the models entirely capture the spatial correlation structure. To check for autocorrelation among the residuals, we conduct a Durbin-Watson test for each of the three models. Again, the test cannot reject the null that there is no autocorrelation in each case for a 5% significance level. Finally, the Breusch-Pagan test and the White test are used to check for homoscedasticity. Both tests do not reject the null of constant variance. Hence, there is no evidence for heteroskedasticity in the spatial models' residuals.

Given the conducted residual diagnostics, we conclude that the assumptions for consistency mentioned above are fulfilled and that the models capture the spatial correlation structure within the data quite well.

5.3.5. City comparison and West-East disparities. This section discusses the Spatial Durbin Model's estimation results for 314 counties in the old Federal States, 64 counties in the new Federal States, and the Big 7 German cities, including their surrounding counties. We find three main results from Tables 6 and 7. First, we do not find significant spillover effects in land values (W*log(land value per m^2)), except for East German counties and Cologne/Düsseldorf as well as a negative spillover effect for Hamburg. Second, Table 7 shows that there are significant direct effects of median income and population density in all regions except for population density in Hamburg. These direct agglomeration effects are stronger in the old Federal States than the new federal states, at least for median income. The Top 7 agglomerations' results further support this result. The estimated coefficients on median income are higher (and positive) for agglomerations in former West Germany. No clear pattern is observed for population density for the Top 7 cities. Third, Table 7 also shows that there is some empirical support for network externalities and spatial spillovers in land values. While for West German counties, we find spillover effects in median income, we find a significant negative coefficient on the spatial lag of population density for East German counties. The positive income spillover effect is also present in 3 of 5 West German agglomerations considered and Leipzig. While there is evidence for negative spillover effects of population density for all East German counties. This effect is significantly positive for Berlin on the 10 percent significance level. This result is economically sensible as Berlin is the largest agglomeration in the former East German area.[23] The negative externality of a high population density county on neighboring counties' land prices may be explained by a lack of large agglomerations in former East German counties. A lower spatial correlation between land values and population density compared to median income is also reflected in Table 3.

5.3.6. Alternate Dependent Variable: log(HPI). One of the main research questions is to analyze whether land values, besides construction costs, are the driving component in house prices.[24] To address this question, the models from Section 4 are re-estimated with log(HPI) as the dependent variable (Tables 8 and 9) and including log(land value per m^2) as an explanatory variable (Tables 10 and 11). The estimation results support land values to be a major determinant in housing prices. The coefficients of interest in Tables 8 and 9 are much smaller compared to those in Tables 4 and 5. Additionally, controlling for log(land value per m^2) the coefficients further decrease in Tables 10 and 11 and the coefficient of log(land value per m^2) is positive and statistically significant on the 1 percent significance level in models (1)-(4). Controlling for the log(land value per m^2) in the estimation on house prices,

23. Berlin as the German capital is denoted as West German, although some parts of Berlin were located in East Germany before 1990.

24. Davis and Heathcote (2007); Davis and Palumbo (2008) and Braun and Lee (2021)

	West	East	Berlin	Munich	Hamburg	Cologne /Düsseldorf	Frankfurt	Leipzig	Stuttgart
log(Land value per m^2 (Braun,Lee (2021)))									
log(Median income)	3.46***	2.79***	1.78***	2.21***	2.02***	3.29***	2.93***	1.65***	3.19***
	(18.21)	(3.96)	(5.24)	(8.72)	(3.62)	(10.21)	(7.96)	(6.03)	(11.66)
log(Lag Population density (person per km^2))	2.01***	5.10***	3.31***	2.78***	1.33	1.08	2.74**	2.16***	0.35
	(6.17)	(3.95)	(4.98)	(5.12)	(0.88)	(1.51)	(3.97)	(3.44)	(1.13)
Green coverage	-1.25	-11.33***	5.55	2.17	2.48	-1.33	-33.59***	-1.85	-13.83
	(-1.06)	(-4.16)	(0.69)	(0.68)	(0.31)	(-0.69)	(-2.83)	(-1.54)	(-1.21)
log(Construction cost index)	-1.09***	-3.06***	-1.04***	-0.46***	-1.41***	-0.30*	-0.66***	-1.61***	-0.51***
	(-13.28)	(-6.49)	(-5.18)	(-3.93)	(-6.50)	(-1.91)	(-2.96)	(-8.31)	(-3.49)
log(arable land (sqkm) per capita)	-0.50***	-1.50**	-0.15	-0.38**	-1.50***	-0.05	-1.69*	-0.40	-1.45
	(-3.30)	(-2.38)	(-0.19)	(-2.37)	(-3.18)	(-0.18)	(-1.81)	(-0.57)	(-0.61)
log(Land area (km^2))	1.91*	15.32	20.42	-98.30**	6.48	8.40	38.62	-10.41	2.47
	(1.74)	(0.87)	(1.10)	(-2.11)	(0.86)	(0.67)	(1.02)	(-0.99)	(0.73)
F									
log(Mean income)	0.15***	0.04	-0.01	0.02	0.83***	-0.23**	0.18	0.07	0.02
	(3.30)	(0.30)	(-0.15)	(0.26)	(3.96)	(-2.51)	(1.27)	(1.23)	(0.88)
log(Population density (person per km^2))	0.05	-1.42**	0.54*	-0.03	-0.05	0.10	-0.06	0.08	-0.01
	(0.61)	(-2.44)	(1.83)	(-0.17)	(-0.12)	(0.45)	(-0.29)	(0.28)	(-0.10)
log(Land value per m^2 (Braun,Lee (2021)))	0.01	0.03*	0.02	0.04	-0.08**	0.08***	0.002	0.04	0.04
	(0.76)	(1.95)	(0.65)	(1.47)	(-2.34)	(4.25)	(0.08)	(1.24)	(1.02)
N	1570.00	320.00	105.00	95.00	95.00	140.00	110.00	90.00	75.00
R2	0.754	0.280	0.811	0.974	0.845	0.912	0.914	0.707	0.972
Log-Likelihood	2035.7	115.8	187.8	243.1	153.5	290.7	207.4	169.1	191.5

t statistics in parentheses
dependent variable: log(landvalue per m^2) Braun&Lee (2021)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 6. Spatial Durbin Model - Baseline estimation results for Top 7 cities as well as West and East Germany

	West	East	Berlin	Munich	Hamburg	Cologne/Dusseldorf	Frankfurt	Leipzig	Stuttgart
direct									
log(Median income)	3.45***	2.83***	1.81***	2.22***	1.80***	3.30***	2.94***	1.67***	3.22***
	(17.71)	(4.16)	(5.51)	(8.85)	(2.92)	(10.47)	(7.89)	(6.06)	(12.27)
log(Lag Population density (person per km^2))	2.02***	4.97**	3.40***	2.81***	1.33	1.20*	2.72***	2.20***	0.35*
	(6.27)	(3.81)	(5.26)	(5.25)	(0.81)	(1.66)	(3.91)	(3.38)	(1.14)
indirect									
log(Median income)	0.88***	0.69	0.10	0.64	2.28***	0.44	0.83*	0.64**	0.68**
	(4.62)	(1.15)	(0.25)	(1.56)	(3.08)	(0.86)	(1.67)	(2.13)	(2.18)
log(Lag Population density (person per km^2))	0.33	-6.63**	2.81*	0.48	-0.54	1.44	-0.20	0.83	0.03
	(0.78)	(-2.18)	(1.93)	(0.68)	(-0.32)	(1.13)	(-0.23)	(0.49)	(0.05)
Observations	1570	320	105	95	95	140	110	90	75

t statistics in parentheses
dependent variable: log(landvalue per m^2) Braun&Lee (2021)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 7. Spatial Durbin Model - Baseline estimation results for Top 7 cities as well as West and East Germany (direct and indirect effects)

the coefficient on green-coverage now has the expected positive sign and is either statistically significant on a 1 or 5% significance level in the spatial models (2)-(4).[25]

We complement this analysis by the Spatial Durbin Model estimation results for 314 counties in the old Federal States, 64 counties in the new federal states, and the Big 7 German cities including their surrounding counties (Tables 12 and 13). As for the total German sample, the coefficients are smaller than those with land value as a dependent variable. Compared to former East Germany, land prices have a higher impact on house prices in the old Federal States on the county of interest itself but not on neighboring counties. We only find positive statistically significant indirect spillover effects of land value on house prices for Berlin, Leipzig, and all new Federal States' counties. A county's land value has a statistically positive effect on the county's house price in all Top 7 agglomerations, ceteris paribus. However, controlling for land prices in this house price estimation, we only find occasional evidence for agglomeration spillover effects. We even find a negative agglomeration spillover effect of median income on house prices when controlling for log(land value per m^2) both among former East and West German counties. For population density, network effects are only significant for the old federal states, Berlin and Frankfurt on the 1% and for Leipzig on the 10% significance level. The next section discusses the robustness of the results using different explanatory variables and the inverse distance matrix.

5.4. Robustness Analysis

In this section, we focus on land values as the dependent variable and evaluate the robustness of the results in terms of two factors: different sets of explanatory variables and the inverse distance matrix as spatial weighting pattern. Moreover, we also discuss the results in light of different land value measurements for Germany. The results estimated using the land values estimated in Braun and Lee (2021) are compared with estimations using the land prices on vacant land sales of land ready for construction.

5.4.1. Control variables. We re-estimate the models (1)-(4) using different sets of explanatory variables. Tables 14 and 15 present the results for the SDM model, with the baseline specification in column (1).

In column (2), we remove the log(land area km^2). Column (3) repeats column (1) and includes the spatial lag of log(land area km^2). Column (4) additionally controls

25. While the log(construction cost index) coefficient in the land price estimation was negative by construction, it now is strongly statistically significant and positive. See Section 5.4.3 for more discussion.

	FE	SLX	SAR	SDM
main				
log(median income)	1.14***	1.06***	0.79***	1.11***
	(41.74)	(25.13)	(24.62)	(27.03)
log(Lag Population density (person per km^2))	2.40***	1.72***	1.98***	1.66***
	(42.47)	(23.80)	(34.11)	(23.62)
green coverage	0.002	-0.12	-0.16	-0.14
	(0.01)	(-0.63)	(-0.81)	(-0.77)
log(construction cost index)	0.27***	0.23***	0.21***	0.20***
	(12.87)	(12.05)	(10.16)	(10.48)
log(arable land (sqkm) per capita)	-0.15***	-0.16***	-0.16***	-0.14***
	(-4.26)	(-4.74)	(-4.63)	(-4.38)
log(land area (km^2))	1.77***	0.87***	1.20***	1.20***
	(5.88)	(3.08)	(4.09)	(4.33)
F				
log(median income)		0.01		-0.12***
		(0.79)		(-13.10)
log(Lag Population density (person per km^2))		0.25***		-0.04*
		(14.57)		(-1.91)
log(House price index)			0.05***	0.09***
			(20.68)	(19.92)
N	1890.00	1890.00	1890.00	1890.00
R2	0.916	0.928	0.926	0.930
Log-Likelihood	4631.7	4779.7	4866.03	4961.8

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8. House price estimation - Germany

	SLX	SAR	SDM
direct			
log(median income)	1.06***	0.80***	1.10***
	(25.13)	(26.00)	(27.36)
log(Lag Population density (person per km^2))	1.72***	2.01***	1.73***
	(23.80)	(34.15)	(24.96)
indirect			
log(median income)	0.01	0.28***	-0.25***
	(0.79)	(17.85)	(-4.12)
log(Lag Population density (person per km^2))	0.25***	0.71***	1.21***
	(14.57)	(15.23)	(8.42)
Observations	1890	1890	1890

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9. House price estimation - Germany (direct and indirect effects)

for the log(number of accommodation facilities in a county), the log(housing stock of single-/double family houses)) and unemployment rates.

We find most of the estimated coefficients of the baseline model (1) to be robust throughout the 4 specifications. But, the controls for tourism, housing stock and unemployment in a county have no significant impact on the dependent variable.

	FE	SLX	SAR	SDM
main				
log(Land value per m^2 (Braun,Lee (2021)))	0.10***	0.08***	0.08***	0.07***
	(24.03)	(21.01)	(18.82)	(18.09)
log(median income)	0.87***	0.86***	0.60***	0.92***
	(30.57)	(22.69)	(19.68)	(23.53)
log(Lag Population density (person per km^2))	1.97***	1.45***	1.70***	1.43***
	(37.44)	(22.71)	(31.27)	(21.76)
green coverage	0.70***	0.51***	0.42**	0.40**
	(3.86)	(3.03)	(2.33)	(2.35)
log(construction cost index)	0.38***	0.32***	0.30***	0.29***
	(20.06)	(18.37)	(15.91)	(16.04)
log(arable land (sqkm) per capita)	-0.09***	-0.09***	-0.11***	-0.10***
	(-2.93)	(-3.20)	(-3.53)	(-3.24)
log(land area (km^2))	1.38***	0.73***	0.98***	0.98***
	(5.22)	(2.97)	(3.70)	(3.87)
F				
log(Land value per m^2 (Braun,Lee (2021)))		0.01***		0.002
		(9.36)		(1.35)
log(median income)		-0.03***		-0.11***
		(-4.07)		(-12.62)
log(Lag Population density (person per km^2))		0.15***		-0.03
		(9.47)		(-1.42)
log(House price index)			0.04***	0.08***
			(18.80)	(15.26)
N	1890.00	1890.00	1890.00	1890.00
R2	0.936	0.946	0.943	0.948
Log-Likelihood	4884.5	5054.8	5063.3	5155.9

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10. House price estimation - Germany (including log(Land value per m^2))

	SLX	SAR	SDM
direct			
log(Land value per m^2 (Braun,Lee (2021)))	0.08***	0.08***	0.08***
	(21.01)	(19.65)	(19.18)
log(median income)	0.86***	0.60***	0.89***
	(22.69)	(20.48)	(24.01)
log(Lag Population density (person per km^2))	1.45***	1.72***	1.46***
	(22.71)	(31.74)	(23.36)
indirect			
log(Land value per m^2 (Braun,Lee (2021)))	0.01***	0.02***	0.07***
	(9.36)	(12.96)	(5.51)
log(median income)	-0.03***	0.17***	-0.40***
	(-4.07)	(15.24)	(-7.03)
log(Lag Population density (person per km^2))	0.15***	0.48***	0.71***
	(9.47)	(13.95)	(5.69)
Observations	1890	1890	1890

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 11. House price estimation - Germany (including log(Land value per m^2); direct and indirect effects)

	West	East	Berlin	Munich	Hamburg	Cologne /Düsseldorf	Frankfurt	Leipzig	Stuttgart
log(House price index)									
log(Land value per m^2 (Braun,Lee (2021)))	0.12***	0.02***	0.48***	0.53***	0.29***	0.30***	0.25***	0.20***	0.32***
	(18.64)	(4.82)	(21.91)	(21.52)	(12.63)	(11.02)	(9.85)	(9.07)	(6.15)
log(Median income)	0.97***	0.87***	-0.26***	0.07	0.08	0.45***	0.49***	0.40***	0.88***
	(20.85)	(15.19)	(-3.39)	(0.95)	(0.65)	(3.66)	(4.19)	(6.26)	(4.36)
log(Lag Population density (person per km^2))	1.33***	1.57***	-0.27*	0.49***	0.57*	1.26***	1.23***	0.58***	0.40***
	(18.40)	(14.95)	(-1.84)	(3.54)	(1.85)	(6.31)	(6.86)	(4.47)	(3.13)
Green coverage	0.23	0.26	1.01	1.97***	-1.61	-1.52***	-14.51***	-0.12	14.24***
	(0.93)	(1.17)	(0.65)	(2.86)	(-1.06)	(-2.68)	(-4.77)	(-0.51)	(2.99)
log(Construction cost index)	0.31***	0.12***	0.71***	0.31***	0.45***	0.37***	0.26***	0.34***	0.29***
	(16.11)	(3.02)	(16.00)	(11.40)	(8.56)	(8.11)	(4.68)	(6.60)	(4.40)
log(arable land (sqkm) per capita)	-0.15***	-0.01	0.0004	-0.24***	-0.13	-0.21**	-0.33	-0.28**	0.83
	(-4.55)	(-0.12)	(0.003)	(-6.48)	(-1.19)	(-2.36)	(-1.46)	(-2.09)	(0.85)
log(Land area (km^2))	1.03***	0.16	7.57**	34.99***	-4.10***	-1.45	20.52**	-2.50	-0.83
	(4.27)	(0.17)	(2.12)	(3.36)	(-2.80)	(-0.41)	(2.25)	(-1.22)	(-0.6)
F									
log(Land value per m^2 (Braun,Lee (2021)))	-0.005*	0.004*	0.02*	0.01	0.02*	-0.04***	-0.08***	0.01	-0.04*
	(-1.84)	(1.92)	(1.73)	(0.31)	(1.80)	(-3.00)	(-5.45)	(1.10)	(-1.71)
log(Median income)	-0.09***	-0.09***	-0.01	0.02	0.11*	-0.01	0.05	-0.02	-0.02
	(-6.51)	(-5.18)	(-0.43)	(0.64)	(1.69)	(-0.37)	(1.04)	(-0.89)	(-0.27)
log(Lag Population density (person per km^2))	-0.05**	-0.10*	0.19***	-0.08	0.05	-0.07	0.09	0.11	-0.07
	(-2.37)	(-1.86)	(3.40)	(-1.53)	(0.48)	(-1.05)	(1.30)	(1.36)	(-1.35)
log(House price index)	0.07***	0.08***	-0.01	0.02	-0.04	0.09***	0.11***	0.03	0.09***
	(11.37)	(5.33)	(-0.26)	(0.79)	(-1.28)	(5.03)	(6.81)	(1.04)	(3.39)
N	1570.00	320.00	105.00	95.00	95.00	140.00	110.00	90.00	75.00
R2	0.960	0.923	0.988	0.998	0.985	0.986	0.985	0.972	0.992
Log-Likelihood	4402.2	924.1	362.6	390.3	311.5	470.2	360.7	319.1	257.8

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 12. Spatial Durbin Model - House price estimation results for Top 7 cities as well as West and East Germany

	West	East	Berlin	Munich	Hamburg	Cologne /Düsseldorf	Frankfurt	Leipzig	Stuttgart
direct									
log(Land value per m^2 (Braun,Lee (2021)))	0.12***	0.03***	0.48***	0.53***	0.29***	0.29***	0.21***	0.21***	0.32***
	(18.14)	(5.38)	(21.46)	(21.65)	(12.57)	(10.82)	(6.77)	(8.95)	(5.59)
log(Median income)	0.96***	0.86***	-0.26***	0.07	0.06	0.47***	0.58***	0.39***	0.91***
	(20.55)	(15.66)	(-3.36)	(0.95)	(0.46)	(3.81)	(4.38)	(5.92)	(4.24)
log(Lag Population density (person per km^2))	1.35***	1.59***	-0.27*	0.48***	0.57*	1.28***	1.42***	0.59***	0.38***
	(19.22)	(15.36)	(-1.79)	(3.67)	(1.81)	(6.47)	(7.52)	(4.52)	(2.91)
indirect									
log(Land value per m^2 (Braun,Lee (2021)))	0.03	0.04***	0.08**	0.06	0.05	-0.13	-0.51***	0.07*	-0.11
	(1.32)	(2.75)	(2.39)	(1.19)	(1.07)	(-1.14)	(-2.67)	(1.74)	(-0.60)
log(Median income)	-0.23**	-0.13**	-0.04	0.09	0.40*	0.21	1.15**	-0.06	0.44
	(-2.46)	(-2.28)	(-0.39)	(0.67)	(1.74)	(0.67)	(2.19)	(-0.69)	(0.73)
log(Lag Population density (person per km^2))	0.30**	0.15	0.79***	-0.32	0.09	0.35	2.54***	0.55*	-0.22
	(2.24)	(0.50)	(3.40)	(-1.40)	(0.25)	(0.63)	(3.26)	(1.73)	(-0.63)
Observations	1570	320	105	95	95	140	110	90	75

t statistics in parentheses
dependent variable: log(house price index)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 13. Spatial Durbin Model - House price estimation results for Top 7 cities as well as West and East Germany (direct and indirect effects)

	(1)	(2)	(3)	(4)
log(Land value per m^2 (Braun,Lee (2021)))				
log(median income)	2.56***	2.59***	2.55***	2.54***
	(10.76)	(10.94)	(10.74)	(9.33)
log(Lag Population density (person per km^2))	3.38***	3.27***	3.43***	3.39***
	(8.28)	(8.12)	(8.39)	(8.18)
green coverage	-7.18***	-7.22***	-7.28***	-7.14***
	(-6.68)	(-6.72)	(-6.78)	(-6.63)
log(construction cost index)	-1.20***	-1.20***	-1.21***	-1.20***
	(-10.90)	(-10.88)	(-10.95)	(-10.89)
log(arable land (sqkm) per capita)	-0.59***	-0.55***	-0.60***	-0.58***
	(-3.12)	(-2.96)	(-3.18)	(-3.05)
log(land area (km^2))	2.51		2.69*	2.54
	(1.57)		(1.67)	(1.58)
log(open accomodation facilities)				-0.03
				(-0.56)
log (housing stock (single/double family houses))				0.09
				(0.66)
unemployment rate				-0.0001
				(-0.01)
F				
log(median income)	0.01	0.01	0.02	0.01
	(0.26)	(0.33)	(0.51)	(0.23)
log(Lag Population density (person per km^2))	0.15	0.18*	0.16	0.14
	(1.47)	(1.91)	(1.57)	(1.35)
log(Land value per m^2 (Braun,Lee (2021)))	0.04***	0.04***	0.04***	0.04***
	(7.21)	(6.63)	(6.81)	(7.20)
log(land area (km^2))			-0.90*	
			(-1.65)	
N	1890.00	1890.00	1890.00	1890.00
R2	0.524	0.525	0.526	0.524
Log-Likelihood	1682.3	1680.8	1684.0	1682.8

t statistics in parentheses
dependent variable: log(landvalue per m^2) Braun&Lee (2021)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

TABLE 14. SDM estimation results for different sets of controls variables - Germany

Thus, they are excluded from the benchmark model. Moreover, Table 15 shows no evidence for network effects of the size of a county on land values. Due to this fact and given that explanatory power does not increase significantly from columns 1 and 2, we also exclude the spatial lag of land area.

5.4.2. Inverse distance matrix. As outlined in Section 5.3.1, we further re-estimate models (FE)-(SDM) using an inverse distance matrix to measure spatial dependence between counties and also account for spatial dependence between counties that are geographically further apart. The weight between two counties i and j is calculated as

$$w_{ij} = 1/d_{ij} \tag{9}$$

	(1)	(2)	(3)	(4)
direct				
log(median income)	2.60***	2.64***	2.58***	2.56***
	(11.31)	(11.63)	(11.53)	(9.62)
log(Lag Population density (person per km^2))	3.45***	3.34***	3.51***	3.46***
	(8.58)	(8.56)	(8.43)	(8.50)
log(land area (km^2))			2.49	
			(1.54)	
indirect				
log(median income)	0.84***	0.78***	0.87***	0.83***
	(3.52)	(3.39)	(3.74)	(352)
log(Lag Population density (person per km^2))	2.04***	2.20***	2.01***	1.96***
	(3.60)	(3.88)	(3.45)	(3.18)
log(land area (km^2))			-5.18	
			(-1.48)	
Observations	1890	1890	1890	1890

t statistics in parentheses
dependent variable: log(landvalue per m^2) Braun&Lee (2021)
spatial weight matrix: first order contiguity
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 15. SDM estimation results for different sets of controls variables - Germany (direct and indirect effects)

and diminishes with distance d. Results are presented in Tables 16 and 17.

Overall, the results are more or less robust to the specification of the spatial weight matrix with the first-order contiguity. The estimated coefficients for the explanatory variables do not change dramatically in terms of significance and size. Except for log(median income) coefficients are significantly smaller but still significant at the one percent significance level compared to the baseline specification. However, given that spatial dependence is now also allowed between counties of higher neighbor-order, the spatial interaction effects increase in size (See Table 17). The fact that the indirect spillover effects of median income and population density increase substantially from the SLX to SAR model suggests that besides network externalities, pure interaction mechanisms also play an important role in land value determination. However, with the inverse distance weight matrix specification, there is no evidence for agglomeration spillovers between counties regarding population density. We even find a negative effect that is significant on the 10% significance level. This result is not surprising as it coincides with the Moran's I cross-correlation measure for population density and land values in Table 3 that drastically decreases with distance.

5.4.3. Vacant land prices (ready for construction). In the land price estimation literature, there are several popular approaches to measuring land prices. Based on the underlying data and methods to estimate land prices, one can argue that each of the resulting land price indices represents different purposes. In this section, using the SDM, we compare the spatial analysis for the land values from Braun and Lee (2021), the house price index from vdpResearch, and the land values based on vacant

	FE	SLX	SAR	SDM
main				
log(median income)	3.08***	0.73***	1.46***	1.01***
	(23.42)	(3.59)	(9.76)	(4.43)
log(Lag Population density (person per km^2))	4.30***	3.20***	2.65***	3.09***
	(15.74)	(10.07)	(8.56)	(8.80)
green coverage	-6.98***	-8.01***	-7.82***	-8.12***
	(-7.04)	(-8.49)	(-7.51)	(-7.79)
log(construction cost index)	-1.09***	-1.37***	-1.31***	-1.35***
	(-10.78)	(-13.98)	(-12.30)	(-12.46)
log(arable land (sqkm) per capita)	-0.61**	-0.43***	-0.41**	-0.41**
	(-3.49)	(-2.59)	(-2.21)	(-2.25)
log(land area (km^2))	3.90***	3.39**	2.69*	3.29**
	(2.68)	(2.43)	(1.75)	(2.14)
inv				
log(median income)		3.75***		1.55***
		(12.53)		(3.73)
log(Lag Population density (person per km^2))		-1.54*		-2.80***
		(-1.89)		(-2.91)
log(Land value per m^2 (Braun,Lee (2021)))			0.82***	0.68***
			(25.55)	(8.43)
N	1890.00	1890.00	1890.00	1890.00
R2	0.516	0.565	0.446	0.551
Log-Likelihood	1654.2	1775.0	1738.4	1748.2

t statistics in parentheses
dependent variable: log(landvalue per m^2) Braun&Lee (2021)
spatial weight matrix: inverse distance
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 16. Estimation results - Germany - Inverse distance matrix

	SLX	SAR	SDM
direct			
log(median income)	0.75***	1.47***	1.03***
	(3.59)	(9.74)	(4.60)
log(Lag Population density (person per km^2))	3.20***	2.71***	3.09***
	(10.07)	(8.84)	(8.73)
indirect			
log(median income)	3.75***	6.34***	7.00***
	(12.53)	(4.67)	(3.27)
log(Lag Population density (person per km^2))	-1.54*	11.61***	-2.23
	(-1.89)	(4.86)	(-0.76)
Observations	1890	1890	1890

t statistics in parentheses
dependent variable: log(landvalue per m^2) Braun&Lee (2021)
spatial weight matrix: inverse distance
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 17. Estimation results - Germany - Inverse distance matrix (direct and indirect effects)

land sales of land ready for construction from the Statistical Offices of the Federal

Government and the German States.[26] Results for the SDM are displayed in Tables 18 and 19.

The main methodological difference between the residential and vacant land prices is the following. While Braun and Lee (2021) estimate the price of residential land with a two-step residual approach using listings data from the ImmobilienScout24 website on single-/double-family housing, the vacant land price statistic calculates a per m^2 price of the transaction prices of vacant land sales ready for construction (Statistisches Bundesamt, 2012).

One can see two noteable results from Tables 18 and 19. First, direct and indirect spillover effects are larger and more statistically significant for residential land prices compared to vacant land price estimation results (Table 19). For example, in the results on the SDM model, if median income increases by one percent, the land price changes by 2.88 percent or 1.06 percent, respectively, ceteris paribus. We do not find indirect spatial effects for median income in all specifications in the smaller sample. However, the spatial spillover effects for population density are also much more significant using the residential land prices estimates and even insignificant in the SDM model for the price of vacant land. If population density in a county increases by 1 percent. In that case, land prices in neighboring counties increase by 2.24 percent, ceteris paribus, for the SDM using residential land prices. At the same time, there is no significant indirect effect on vacant land prices. From my perspective, this result is because the residential land prices denote everything except for the structure's replacement cost to the land component in the housing bundle. Hence, the residential land prices more likely reflect the presence of agglomeration economies/amenities. On the other hand, we argue that vacant land transactions are more likely to occur in new development areas that often are located on the outskirts of towns and cities. Second, by construction, the construction cost index should significantly negatively impact the residential land prices resulting from the residual approach. However, as expected, the construction costs have a significant positive effect on the vacant land prices and house prices.

6. Concluding Remarks

In this paper, we analyze spatial spillover patterns in German land and house prices. We estimate the SLX, SAR, and SDM model for the total of 378 counties, 314 counties in the old Federal States, 64 counties in the new Federal States, and the

26. As there is no vacant land sales data for some county-year observations, the sample size reduces to 1520 from 1890. To maintain a balanced panel, we have to remove observations of 74 counties that have one or more missing county-year observations.

	log(landvalue per m^2) Braun&Lee (2021) SDM	log(landvalue per m^2) (vacant land sales) SDM	log(house price index) SDM
main			
log(median income)	2.87***	1.08***	1.19***
	(11.53)	(2.72)	(27.68)
log(Lag Population density (person per km^2))	3.45***	2.10***	1.63***
	(7.95)	(3.05)	(21.90)
green coverage	-7.39***	-0.80	-0.18
	(-6.57)	(-0.45)	(-0.93)
log(construction cost index)	-1.11***	0.59***	0.21***
	(-8.93)	(2.98)	(10.00)
log(arable land (sqkm) per capita)	-0.64***	-1.01***	-0.17***
	(-2.95)	(-2.93)	(-4.43)
log(land area (km^2))	2.81*	0.62	1.42***
	(1.77)	(0.25)	(5.18)
F_LPI_RS			
log(median income)	-0.11**	-0.12	-0.15***
	(-2.32)	(-1.64)	(-14.86)
log(Lag Population density (person per km^2))	0.16	0.07	-0.04
	(1.40)	(0.44)	(-1.55)
log(dependent variable)	0.06***	0.04***	0.10***
	(8.15)	(5.83)	(19.01)
N	1520.00	1520.00	1520.00
R2	0.51	0.23	0.93
Log-Likelihood	1374.5	675.2	4020.5

t statistics in parentheses
spatial weight matrix: first order contiguity
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 18. Estimation results - Germany - Vacant vs. residential land values

	log(landvalue per m^2) Braun&Lee (2021) SDM	log(landvalue per m^2) (vacant land sales) SDM	log(house price index) SDM
direct			
log(median income)	2.88***	1.06***	1.16***
	(11.96)	(2.61)	(27.59)
log(Lag Population density (person per km^2))	3.58***	2.16***	1.71***
	(8.54)	(3.22)	(24.12)
indirect			
log(median income)	0.36	-0.43	-0.34***
	(1.53)	(0.95)	(-5.98)
log(Lag Population density (person per km^2))	2.24***	0.95	1.21***
	(3.81)	(1.05)	(8.37)
Observations	1520	1520	1520

t statistics in parentheses
spatial weight matrix: first order contiguity
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

TABLE 19. Estimation results - Germany - Vacant vs. residential land values (direct and indirect effects)

Big 7 German cities including their surrounding counties using a panel data set for 378 German counties from 2014-2018. Besides local housing market determinants, we find evidence for the importance of both exogenous and endogenous spatial interaction patterns between housing and land markets.

The results are summarized as follows. First, we find that cross-county spillovers can explain variation in land values for Germany. While these spillovers are relatively weak in a smaller dataset on a more local level for new and old Federal States and 7 Big German cities and their surrounding counties, we find agglomeration effects to be more substantial in the West than East German counties, at least for median income. This result is also similar for the Top 7 German agglomerations but to a lesser degree. Consequently, we show, unlike Gyourko et al. (2013), that the Big 7 German cities do not exhibit the characteristics of the so-called Superstar Cities. Second, while still significant, we show that the spatial effects are smaller when using house prices as the dependent variable. Third, when including the land price in house price estimation, the spillover effects in house prices further decrease. Moreover, the significantly positive coefficient on land value per m^2 both for direct and indirect spatial effects supports the theory that clustering patterns in house prices can be attributed to spatial variations in land prices. Lastly, we explore these patterns in two different land price measurements for Germany. The direct and indirect spillover effects can explain more variation in residential land values than in vacant land prices of land ready for construction from the Statistical Offices of the Federal Government and the German States.

These results suggest that changes in agglomeration variables such as median income (productivity) and population density cannot completely explain disparate local land and house prices. Consequently, the results support the theory that house and land prices, indeed are a local phenomenon and that land prices are a major determinant for the development of house prices. The fact that we find spillover effects in land prices raises the question whether more rural counties may be better off in investing in public goods and services to increase attractiveness and strengthen local externality (spillover) effects.

Focusing more on the urban-peripheral inequalities would be an interesting extension for future research. Moreover, one could pay more attention to the impact of climate conditions and other environmental and natural amenities on land prices. For example, do German's value the spatial proximity to the mountainside or the sea? A longer time series would also be a great extension to focus more on the spatio-temporal dimension.

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Appendix: Appendix

A.1. *Tables*

Dependent Variable	Availability	Source	Regional Level
House Price Index	2012-2018	vdpResearch	County
Land value per m^2	2014-2018	Braun and Lee (2021)	County
Land value m^2 (vacant land sales)	1995-2019	Statistical Offices of the Federal Government and the German States (Statistic 61511-01-03-4)	County
Control Variable			
Land area km^2	2008-2019	Statistical Offices of the Federal Government and the German States (Statistic 11111-01-01-4)	County
Income	2014-2019	Federal Employment Agency	County
Population	1995-2019	Federal Statistical Office (Statistic 12411-0015)	County
Unemployment Rate	2008-2018	Federal Employment Agency	County
Construction Cost Index	1958-2020	Federal Statistical Office (Statistic 61261-0001)	National
Regional Construction Cost Factors	2012-2019	BKI	County
Amount of accomodation facilities	1995-2019	Statistical Offices of the Federal Government and the German States (Statistic 45412-01-02-4)	County
Green coverage	1995-2019	Statistical Offices of the Federal Government and the German States (Statistic 33111-01-02-4 and 33111-01-01-4)	County
Housing Stock measures	1995-2019	Statistical Offices of the Federal Government and the German States (Statistic 31231-02-01-4)	County

Table A.1. Dependent and explanatory variables

House price index data	
GER,FRA,UK,DNK,AUT	Internatioal House Price Database - Federal Reserve Bank of Dallas
US	Davis and Heathcote (2007)
Construction cost index data	
GER	Destatis statistic 61261-0014: Construction cost indices for residential buildings: Germany, quarters, type of construction costs
FRA	Institut national de la statistique et des études économiques Identifier 000008630: Cost-of-Construction Index (CCI)
DNK	Statistics Denmark BYG42: Construction cost index for residential buildings
UK	1975-2012: BCIS Series Numbers 7504/7505 "Output price index for All Work (New Construction and Repair& Maintenance)" 2013-2020: Office for National Statistics "All construction output prices"
AUT	Australian Bureau of Statistics. 2020. Australian National Accounts 5206005: National Income, Expenditure and Product. Table 5. Expenditure on Gross Domestic Product (GDP), Implicit price deflators
US	Davis and Heathcote (2007)

Table A.2. Sources - Figure 1

City/Tier	County	City/Tier	County	City/Tier	County	City/Tier	County	City/Tier	County	County
Berlin			LK Freising		LK Cuxhaven		SK Oberhausen		LK Halle(Saale)	LK Heilbronn
Tier 1			LK Fürstenfeldbruck		LK Lüneburg		LK Wesel		LK Saalekreis	SK Heilbronn
	SK Berlin		LK Miesbach		LK Rotenburg (Wümme)	Frankfurt am Main			LK Burgenlandkreis	LK Enzkreis
Tier 2			LK Landberg am Lech		LK Heidekreis	Tier 1			LK Nordsachsen	SK Pforzheim
	SK Potsdam		LK Starnberg	Cologne/Düsseldorf			SK Frankfurt am Main	Tier 3		LK Calw
	LK Barnim	Tier 3		Tier 1		Tier 2			LK Mandfeld-Südharz	LK Tübingen
	LK Dahme-Spreewald		LK Weilheim-Schongau		SK Köln		LK Offenbach		LK Salzlandkreis	LK Reutlingen
	LK Havelland		LK Mühldorf am Inn		SK Düsseldorf		LK Groß-Gerau		SK Dessau-Roßlau	
	LK Märkisch-Oderland		LK Neuburg-Schrobenhausen	Tier 2			SK Offenbach am Main		LK Anhalt-Bitterfeld	
	LK Oberhavel		LK Pfaffenhofen a.d. Ilm		LK Mettmann		LK Main-Minzig-Kreis		LK Wittenberg	
	LK Oder-Spree		LK Rosenheim		LK Rhein-Kreis Neuss		LK Wetteraukreis		LK Elbe-Elster	
	LK Potsdam-Mittelmark		LK Landshut		SK Bonn		LK Hochtaunuskreis		LK Meißen	
	LK Teltow-Fläming		SK Landshut		SK Leverkusen		LK Main-Taunus-Kreis		Mittelsachsen	
Tier 3			LK Aichach-Friedberg		LK Rhein-Erft-Kreis	Tier 3			LK Altenburger Land	
	LK Uckermark	Hamburg			LK Rheinisch-Bergischer Kreis		SK Aschaffenburg		SK Gera	
	LK Ostprignitz-Ruppin	Tier 1			LK Rhein-Sieg-Kreis		LK Aschaffenburg		LK Greiz	
	SK Cottbus		SK Hamburg		SK Krefeld		SK Mainz		LK Saale-Holzland-Kreis	
	LK Elbe-Elster	Tier 2			SK Mülheim an der Ruhr		LK Mainz-Bingen		SK Jena	
	LK Ostspreewald-Lausitz		LK Herzogtum Lauenburg		SK Duisburg		SK Darmstadt		LK Weimarer Land	
	LK Prignitz		LK Pinneberg	Tier 3			SK Wiesbaden		SK Weimar	
	LK Spree-Neiße		LK Segeberg		LK Ahrweiler		LK Darmstadt-Dieburg		LK Sömmerda	
	LK Anhalt-Bitterfeld		LK Stormarn		LK Altenkirchen (Westerwald)		LK Rheingau-Taunus-Kreis		LK Kyffhäuserkreis	
	LK Jerichower Land		LK Harburg		LK Neuwied		LK Gießen	Stuttgart		
	LK Stendal		LK Stade		SK Essen		LK Lahn-Dill-Kreis	Tier 1		
	LK Wittenberg	Tier 3			SK Mönchengladbach		LK Limburg-Weilburg		SK Stuttgart	
Munich			LK Schwerin		SK Remscheid		LK Vogelbergkreis	Tier 2		
Tier 1			LK Nordwestmeck-lenburg		SK Solingen		LK Fulda		LK Böblingen	
	SK München		LK Ludwigslust-Parchim		SK Wuppertal		LK Main-Spessart		LK Esslingen	
Tier 2			SK Lübeck		LK Viersen		LK Bad Kissingen		LK Ludwigsburg	
	LK München		SK Neumünster		LK Düren	Leipzig			LK Rems-Murr-Kreis	
	LK Bad Tölz-Wolfratshausen		LK Ostholstein		LK Einkirchen	Tier 1		Tier 3		
	LK Dachau		LK Plön		LK Heinsberg		SK Leipzig		LK Göppingen	
	LK Ebersberg		LK Rendsburg-Eckernförde		LK Oberbergischer Kreis	Tier 2			LK Ostalbkreis	
	LK Erding		LK Steinburg		LK Ennepe-Ruhr-Kreis		LK Leipzig		LK Schwäbisch Hall	

TABLE A.3. German Big 7 cities and surrounding counties (Tier 1-3)

City	Tier	Kreis	Landvalue/sqm			
			2015	2016	2017	2018
Berlin	1	SK Berlin	0.04	0.21	0.21	0.12
		Average Tier 2	0.02	0.05	0.10	0.12
Berlin	2	SK Potsdam	0.05	0.14	0.14	0.15
Berlin	2	LK Barnim	-0.01	0.02	0.07	0.11
Berlin	2	LK Dahme-Spreewald	0.04	0.03	0.05	0.07
Berlin	2	LK Havelland	0.01	0.06	0.08	0.16
Berlin	2	LK Märkisch-Oderland	0.02	0.09	0.09	0.10
Berlin	2	LK Oberhavel	0.02	0.05	0.05	0.10
Berlin	2	LK Oder-Spree	0.00	-0.02	0.16	0.11
Berlin	2	LK Potsdam-Mittelmark	0.02	0.04	0.11	0.10
Berlin	2	LK Teltow-Fläming	0.03	0.03	0.15	0.15
		Average Tier 3	0.02	0.03	0.04	0.02
Berlin	3	LK Uckermark	0.00	0.00	0.02	0.04
Berlin	3	LK Ostprignitz-Ruppin	0.06	0.05	0.05	0.02
Berlin	3	SK Cottbus	0.00	0.07	0.07	-0.01
Berlin	3	LK Elbe-Elster	0.05	-0.13	0.15	-0.02
Berlin	3	LK Ostspreewald-Lausitz	-0.02	-0.03	0.05	0.13
Berlin	3	LK Prignitz	0.01	0.11	0.10	0.08
Berlin	3	LK Spree-Neiße	0.14	0.10	-0.12	-0.02
Berlin	3	LK Anhalt-Bitterfeld	0.06	0.06	0.09	0.03
Berlin	3	LK Jerichower Land	-0.05	0.08	0.05	-0.02
Berlin	3	LK Stendal	0.01	0.01	-0.01	0.01
Berlin	3	LK Wittenberg	0.00	0.05	0.00	-0.04
Munich	1	SK München	0.11	0.12	0.13	0.05
		Average Tier 2	0.07	0.10	0.09	0.08
Munich	2	LK München	0.07	0.12	0.08	0.08
Munich	2	LK Bad Tölz-Wolfratshausen	0.07	0.08	0.08	0.10
Munich	2	LK Dachau	0.08	0.09	0.12	0.06
Munich	2	LK Ebersberg	0.05	0.11	0.05	0.10
Munich	2	LK Erding	0.13	0.12	0.05	0.11
Munich	2	LK Freising	0.04	0.13	0.10	0.10
Munich	2	LK Fürstenfeldbruck	0.05	0.08	0.09	0.07
Munich	2	LK Miesbach	0.08	0.09	0.07	0.08
Munich	2	LK Landberg am Lech	0.05	0.10	0.13	0.06
Munich	2	LK Starnberg	0.05	0.05	0.08	0.07
		Average Tier 3	0.04	0.08	0.09	0.09
Munich	3	LK Weilheim-Schongau	0.06	0.07	0.06	0.12
Munich	3	LK Mühldorf am Inn	0.03	0.06	0.06	0.10
Munich	3	LK Neuburg-Schrobenhausen	0.08	0.10	0.07	0.08
Munich	3	LK Pfaffenhofen a.d. Ilm	0.03	0.06	0.11	0.10
Munich	3	LK Rosenheim	0.06	0.08	0.08	0.12
Munich	3	LK Landshut	0.03	0.11	0.09	0.07
Munich	3	SK Landshut	0.03	0.08	0.12	0.08
Munich	3	LK Aichach-Friedberg	0.03	0.09	0.13	0.08
Hamburg	1	SK Hamburg	0.06	0.07	0.12	0.04
		Average Tier 2	0.04	0.09	0.06	0.12
Hamburg	2	LK Herzogtum Lauenburg	0.04	0.05	0.00	0.16
Hamburg	2	LK Pinneberg	0.06	0.04	0.10	0.15
Hamburg	2	LK Segeberg	0.03	0.11	0.04	0.08
Hamburg	2	LK Stormarn	0.02	0.05	0.04	0.09
Hamburg	2	LK Harburg	0.01	0.11	0.12	0.14
Hamburg	2	LK Stade	0.08	0.15	0.08	0.10
		Average Tier 3	0.04	0.05	0.06	0.08

Hamburg	3	LK Nordwestmecklenburg	-0.04	0.17	0.20	0.32
Hamburg	3	LK Ludwigslust-Parchim	0.07	-0.03	-0.01	-0.07
Hamburg	3	SK Lübeck	0.06	0.05	0.07	0.08
Hamburg	3	SK Neumünster	0.05	0.14	0.11	0.21
Hamburg	3	LK Ostholstein	0.08	0.05	0.03	0.06
Hamburg	3	LK Plön	0.08	0.12	0.03	0.10
Hamburg	3	LK Rendsburg-Eckernförde	0.03	0.04	0.05	0.04
Hamburg	3	LK Steinburg	0.00	0.16	0.00	0.20
Hamburg	3	LK Cuxhaven	0.15	0.19	0.18	0.01
Hamburg	3	LK Lüneburg	0.08	0.12	0.20	0.13
Hamburg	3	LK Rotenburg (Wümme)	0.02	0.10	0.05	0.06
Hamburg	3	LK Heidekreis	-0.02	0.08	0.12	0.07
Düsseldorf/Köln	1	SK Köln	0.06	0.07	0.06	0.07
Düsseldorf/Köln	1	SK Düsseldorf	0.07	0.10	0.09	0.06
		Average Tier 2	0.04	0.09	0.07	0.08
Düsseldorf/Köln	2	LK Mettmann	0.03	0.09	0.09	0.07
Düsseldorf/Köln	2	LK Rhein-Kreis Neuss	0.01	0.12	0.08	0.10
Düsseldorf/Köln	2	SK Bonn	0.04	0.10	0.06	0.07
Düsseldorf/Köln	2	SK Leverkusen	0.04	0.09	0.07	0.08
Düsseldorf/Köln	2	LK Rhein-Erft-Kreis	0.09	0.10	0.06	0.08
Düsseldorf/Köln	2	LK Rheinisch-Bergischer Kreis	0.07	0.08	0.06	0.08
Düsseldorf/Köln	2	LK Rhein-Sieg-Kreis	0.03	0.11	0.11	0.09
Düsseldorf/Köln	2	SK Krefeld	0.02	0.11	0.01	0.11
Düsseldorf/Köln	2	SK Mülheim an der Ruhr	0.02	0.05	0.05	0.09
Düsseldorf/Köln	2	SK Duisburg	0.04	0.06	0.10	0.01
		Average Tier 3	0.03	0.09	0.09	0.09
Düsseldorf/Köln	3	LK Ahrweiler	-0.01	0.12	0.11	0.04
Düsseldorf/Köln	3	LK Altenkirchen (Westerwald)	0.01	0.10	0.15	0.22
Düsseldorf/Köln	3	LK Neuwied	0.11	0.02	0.17	0.05
Düsseldorf/Köln	3	SK Essen	0.01	0.09	0.09	0.05
Düsseldorf/Köln	3	SK Mönchengladbach	0.04	0.13	0.02	0.11
Düsseldorf/Köln	3	SK Remscheid	0.04	0.02	0.06	0.07
Düsseldorf/Köln	3	SK Solingen	0.04	0.06	0.05	0.08
Düsseldorf/Köln	3	SK Wuppertal	0.00	0.06	0.08	0.10
Düsseldorf/Köln	3	LK Viersen	-0.01	0.15	0.11	0.14
Düsseldorf/Köln	3	LK Düren	0.04	0.17	0.06	0.12
Düsseldorf/Köln	3	LK Einkirchen	0.05	0.10	0.10	0.14
Düsseldorf/Köln	3	LK Heinsberg	0.11	0.07	0.12	0.06
Düsseldorf/Köln	3	LK Oberbergischer Kreis	0.07	0.11	0.04	0.11
Düsseldorf/Köln	3	LK Ennepe-Ruhr-Kreis	0.00	0.06	0.08	0.09
Düsseldorf/Köln	3	SK Oberhausen	0.00	0.08	0.12	0.08
Düsseldorf/Köln	3	LK Wesel	0.02	0.06	0.08	0.06
Frankfurt am Main	1	SK Frankfurt am Main	0.06	0.07	0.11	0.10
		Average Tier 2	0.07	0.10	0.08	0.10
Frankfurt am Main	2	LK Offenbach	0.03	0.09	0.10	0.09
Frankfurt am Main	2	LK Groß-Gerau	0.06	0.08	0.08	0.10
Frankfurt am Main	2	SK Offenbach am Main	0.11	0.10	0.06	0.14
Frankfurt am Main	2	LK Main-Minzig-Kreis	0.09	0.09	0.05	0.12
Frankfurt am Main	2	LK Wetteraukreis	0.10	0.10	0.08	0.10
Frankfurt am Main	2	LK Hochtaunuskreis	0.06	0.11	0.09	0.08
Frankfurt am Main	2	LK Main-Taunus-Kreis	0.07	0.10	0.10	0.08
		Average Tier 3	0.05	0.12	0.08	0.10
Frankfurt am Main	3	LK Aschaffenburg	0.07	0.06	0.05	0.14
Frankfurt am Main	3	SK Mainz	0.04	0.07	0.10	0.09
Frankfurt am Main	3	LK Mainz-Bingen	0.04	0.10	0.03	0.11
Frankfurt am Main	3	SK Darmstadt	0.02	0.08	0.07	0.08
Frankfurt am Main	3	SK Wiesbaden	0.10	0.11	0.10	0.11
Frankfurt am Main	3	LK Darmstadt-Dieburg	0.07	0.11	0.06	0.15
Frankfurt am Main	3	LK Rheingau-Taunus-Kreis	0.12	0.15	0.13	0.06

Frankfurt am Main	3	LK Gießen	0.08	0.17	0.08	0.09
Frankfurt am Main	3	LK Lahn-Dill-Kreis	0.03	0.12	0.06	-0.01
Frankfurt am Main	3	LK Limburg-Weilburg	-0.02	0.13	0.10	0.07
Frankfurt am Main	3	LK Vogelbergkreis	0.06	0.13	0.01	0.16
Frankfurt am Main	3	LK Fulda	0.06	0.19	-0.03	0.24
Frankfurt am Main	3	LK Main-Spessart	0.03	0.05	0.11	0.08
Frankfurt am Main	3	LK Bad Kissingen	0.07	0.15	0.28	-0.05
Leipzig	1	SK Leipzig	0.01	0.06	0.13	0.16
		Average Tier 2	-0.03	0.00	0.09	0.05
Leipzig	2	LK Leipzig	0.00	-0.03	0.14	0.06
Leipzig	2	LK Halle(Saale)	-0.02	0.04	0.12	0.05
Leipzig	2	LK Saalekreis	-0.09	0.06	0.06	-0.06
Leipzig	2	LK Burgenlandkreis	0.05	0.04	0.06	0.03
Leipzig	2	LK Nordsachsen	-0.07	-0.09	0.09	0.16
		Average Tier 3	0.05	-0.04	0.04	0.02
Leipzig	3	LK Mandfeld-Südharz	0.09	-0.04	0.08	0.02
Leipzig	3	LK Salzlandkreis	-0.03	0.05	-0.07	0.11
Leipzig	3	LK Anhalt-Bitterfeld	0.06	0.06	0.09	0.03
Leipzig	3	LK Wittenberg	0.00	0.05	0.00	-0.04
Leipzig	3	LK Elbe-Elster	0.05	-0.13	0.15	-0.02
Leipzig	3	LK Meißen	0.00	-0.02	0.07	0.05
Leipzig	3	Mittelsachsen	0.24	-0.21	0.04	0.10
Leipzig	3	LK Greiz	0.15	-0.18	-0.07	-0.03
Leipzig	3	LK Saale-Holzland-Kreis	-0.03	-0.02	0.05	-0.01
Leipzig	3	LK Weimarer Land	-0.01	0.00	0.01	0.09
Leipzig	3	LK Sömmerda	0.01	-0.04	0.07	0.06
Leipzig	3	LK Kyffhäuserkreis	0.07	0.04	0.10	-0.11
Stuttgart	1	SK Stuttgart	0.03	0.08	0.11	0.08
		Average Tier 2	0.05	0.07	0.09	0.11
Stuttgart	2	LK Böblingen	0.07	0.06	0.12	0.09
Stuttgart	2	LK Esslingen	0.04	0.07	0.08	0.11
Stuttgart	2	LK Ludwigsburg	0.06	0.08	0.07	0.12
Stuttgart	2	LK Rems-Murr-Kreis	0.02	0.08	0.09	0.12
		Average Tier 3	0.06	0.08	0.09	0.10
Stuttgart	3	LK Göppingen	0.07	0.13	0.03	0.10
Stuttgart	3	LK Ostalbkreis	0.07	0.05	0.20	0.10
Stuttgart	3	LK Schwäbisch Hall	0.04	0.08	0.09	0.08
Stuttgart	3	LK Heilbronn	0.06	0.08	0.08	0.14
Stuttgart	3	SK Heilbronn	0.04	0.06	0.07	0.09
Stuttgart	3	LK Enzkreis	0.04	0.04	0.09	0.11
Stuttgart	3	SK Pforzheim	0.04	0.11	0.12	0.08
Stuttgart	3	LK Calw	0.08	0.08	0.09	0.11
Stuttgart	3	LK Tübingen	0.07	0.08	0.05	0.15
Stuttgart	3	LK Reutlingen	0.06	0.09	0.10	0.06

Table A.4. Percentage changes in land value per m^2 - Top 7 agglomerations and surrounding tiers

City	Tier	Kreis	HPI 2015	2016	2017	2018
Berlin	1	SK Berlin	0.04	0.17	0.14	0.12
		Average Tier 2	0.03	0.04	0.07	0.08
Berlin	2	SK Potsdam	0.06	0.07	0.11	0.11
Berlin	2	LK Barnim	0.01	0.03	0.05	0.09
Berlin	2	LK Dahme-Spreewald	0.03	0.04	0.05	0.08
Berlin	2	LK Havelland	0.03	0.04	0.06	0.08
Berlin	2	LK Märkisch-Oderland	0.04	0.05	0.07	0.08
Berlin	2	LK Oberhavel	0.03	0.04	0.05	0.08
Berlin	2	LK Oder-Spree	0.02	0.03	0.06	0.07
Berlin	2	LK Potsdam-Mittelmark	0.03	0.04	0.07	0.08
Berlin	2	LK Teltow-Fläming	0.03	0.04	0.07	0.08
		Average Tier 3	0.01	0.02	0.03	0.04
Berlin	3	LK Uckermark	0.02	0.03	0.04	0.05
Berlin	3	LK Ostprignitz-Ruppin	0.02	0.03	0.04	0.05
Berlin	3	SK Cottbus	0.02	0.03	0.04	0.05
Berlin	3	LK Elbe-Elster	0.00	0.01	0.04	0.02
Berlin	3	LK Ostspreewald-Lausitz	0.02	0.02	0.04	0.07
Berlin	3	LK Prignitz	0.02	0.03	0.04	0.05
Berlin	3	LK Spree-Neiße	0.01	0.02	0.02	0.05
Berlin	3	LK Anhalt-Bitterfeld	0.01	0.02	0.02	0.02
Berlin	3	LK Jerichower Land	0.01	0.02	0.02	0.01
Berlin	3	LK Stendal	0.01	0.01	0.02	0.02
Berlin	3	LK Wittenberg	0.01	0.01	0.03	0.02
Munich	1	SK München	0.08	0.10	0.10	0.06
		Average Tier 2	0.06	0.08	0.07	0.08
Munich	2	LK München	0.07	0.09	0.07	0.08
Munich	2	LK Bad Tölz-Wolfratshausen	0.05	0.08	0.08	0.08
Munich	2	LK Dachau	0.05	0.08	0.08	0.07
Munich	2	LK Ebersberg	0.06	0.08	0.06	0.09
Munich	2	LK Erding	0.07	0.08	0.06	0.08
Munich	2	LK Freising	0.05	0.07	0.08	0.09
Munich	2	LK Fürstenfeldbruck	0.05	0.08	0.07	0.07
Munich	2	LK Miesbach	0.06	0.08	0.07	0.08
Munich	2	LK Landberg am Lech	0.05	0.07	0.07	0.07
Munich	2	LK Starnberg	0.04	0.06	0.09	0.07
		Average Tier 3	0.05	0.07	0.07	0.08
Munich	3	LK Weilheim-Schongau	0.05	0.07	0.06	0.08
Munich	3	LK Mühldorf am Inn	0.05	0.06	0.05	0.08
Munich	3	LK Neuburg-Schrobenhausen	0.05	0.06	0.06	0.07
Munich	3	LK Pfaffenhofen a.d. Ilm	0.04	0.06	0.08	0.07
Munich	3	LK Rosenheim	0.05	0.07	0.07	0.08
Munich	3	LK Landshut	0.04	0.06	0.07	0.07
Munich	3	SK Landshut	0.05	0.07	0.07	0.09
Munich	3	LK Aichach-Friedberg	0.04	0.06	0.07	0.07
Hamburg	1	SK Hamburg	0.05	0.06	0.09	0.05
		Average Tier 2	0.04	0.06	0.06	0.08
Hamburg	2	LK Herzogtum Lauenburg	0.04	0.05	0.05	0.09
Hamburg	2	LK Pinneberg	0.04	0.06	0.06	0.09
Hamburg	2	LK Segeberg	0.03	0.06	0.06	0.08
Hamburg	2	LK Stormarn	0.04	0.06	0.06	0.08
Hamburg	2	LK Harburg	0.04	0.07	0.08	0.08
Hamburg	2	LK Stade	0.04	0.06	0.05	0.07
		Average Tier 3	0.01	0.01	0.01	0.01

Hamburg	3	LK Nordwestmecklenburg	0.02	0.03	0.06	0.04
Hamburg	3	LK Ludwigslust-Parchim	0.02	0.02	0.04	0.03
Hamburg	3	SK Lübeck	0.03	0.05	0.07	0.08
Hamburg	3	SK Neumünster	0.03	0.05	0.07	0.06
Hamburg	3	LK Ostholstein	0.03	0.05	0.04	0.07
Hamburg	3	LK Plön	0.03	0.06	0.05	0.05
Hamburg	3	LK Rendsburg-Eckernförde	0.03	0.05	0.05	0.05
Hamburg	3	LK Steinburg	0.03	0.04	0.05	0.07
Hamburg	3	LK Cuxhaven	0.04	0.05	0.07	0.05
Hamburg	3	LK Lüneburg	0.06	0.07	0.07	0.09
Hamburg	3	LK Rotenburg (Wümme)	0.03	0.04	0.06	0.05
Hamburg	3	LK Heidekreis	0.03	0.03	0.05	0.04
Düsseldorf/Köln	1	SK Köln	0.05	0.07	0.07	0.06
Düsseldorf/Köln	1	SK Düsseldorf	0.06	0.09	0.09	0.06
		Average Tier 2	0.04	0.06	0.06	0.06
Düsseldorf/Köln	2	LK Mettmann	0.04	0.07	0.07	0.07
Düsseldorf/Köln	2	LK Rhein-Kreis Neuss	0.04	0.06	0.06	0.07
Düsseldorf/Köln	2	SK Bonn	0.05	0.07	0.07	0.07
Düsseldorf/Köln	2	SK Leverkusen	0.03	0.06	0.07	0.05
Düsseldorf/Köln	2	LK Rhein-Erft-Kreis	0.04	0.06	0.05	0.06
Düsseldorf/Köln	2	LK Rheinisch-Bergischer Kreis	0.04	0.05	0.06	0.08
Düsseldorf/Köln	2	LK Rhein-Sieg-Kreis	0.04	0.06	0.07	0.07
Düsseldorf/Köln	2	SK Krefeld	0.04	0.06	0.03	0.07
Düsseldorf/Köln	2	SK Mülheim an der Ruhr	0.03	0.05	0.05	0.06
Düsseldorf/Köln	2	SK Duisburg	0.02	0.04	0.07	0.04
		Average Tier 3	0.03	0.05	0.05	0.06
Düsseldorf/Köln	3	LK Ahrweiler	0.03	0.05	0.04	0.07
Düsseldorf/Köln	3	LK Altenkirchen (Westerwald)	0.03	0.06	0.05	0.05
Düsseldorf/Köln	3	LK Neuwied	0.02	0.04	0.06	0.05
Düsseldorf/Köln	3	SK Essen	0.03	0.05	0.08	0.06
Düsseldorf/Köln	3	SK Mönchengladbach	0.04	0.06	0.06	0.07
Düsseldorf/Köln	3	SK Remscheid	0.02	0.04	0.04	0.04
Düsseldorf/Köln	3	SK Solingen	0.03	0.05	0.05	0.06
Düsseldorf/Köln	3	SK Wuppertal	0.02	0.04	0.06	0.08
Düsseldorf/Köln	3	LK Viersen	0.04	0.06	0.05	0.07
Düsseldorf/Köln	3	LK Düren	0.04	0.05	0.05	0.06
Düsseldorf/Köln	3	LK Einkirchen	0.04	0.06	0.06	0.07
Düsseldorf/Köln	3	LK Heinsberg	0.02	0.04	0.06	0.06
Düsseldorf/Köln	3	LK Oberbergischer Kreis	0.03	0.05	0.05	0.06
Düsseldorf/Köln	3	LK Ennepe-Ruhr-Kreis	0.02	0.03	0.06	0.06
Düsseldorf/Köln	3	SK Oberhausen	0.02	0.04	0.07	0.06
Düsseldorf/Köln	3	LK Wesel	0.03	0.05	0.04	0.05
Frankfurt am Main	1	SK Frankfurt am Main	0.05	0.06	0.10	0.09
		Average Tier 2	0.05	0.07	0.07	0.07
Frankfurt am Main	2	LK Offenbach	0.04	0.06	0.07	0.07
Frankfurt am Main	2	LK Groß-Gerau	0.04	0.06	0.07	0.07
Frankfurt am Main	2	SK Offenbach am Main	0.05	0.07	0.07	0.09
Frankfurt am Main	2	LK Main-Minzig-Kreis	0.05	0.06	0.05	0.07
Frankfurt am Main	2	LK Wetteraukreis	0.04	0.06	0.07	0.07
Frankfurt am Main	2	LK Hochtaunuskreis	0.05	0.07	0.06	0.06
Frankfurt am Main	2	LK Main-Taunus-Kreis	0.06	0.08	0.08	0.07
		Average Tier 3	0.04	0.05	0.05	0.06
Frankfurt am Main	3	LK Aschaffenburg	0.04	0.06	0.03	0.08
Frankfurt am Main	3	SK Mainz	0.04	0.07	0.08	0.09
Frankfurt am Main	3	LK Mainz-Bingen	0.04	0.06	0.04	0.07
Frankfurt am Main	3	SK Darmstadt	0.03	0.05	0.08	0.07
Frankfurt am Main	3	SK Wiesbaden	0.05	0.08	0.07	0.09
Frankfurt am Main	3	LK Darmstadt-Dieburg	0.05	0.06	0.06	0.09
Frankfurt am Main	3	LK Rheingau-Taunus-Kreis	0.05	0.07	0.06	0.07

Frankfurt am Main	3	LK Gießen	0.04	0.06	0.06	0.06
Frankfurt am Main	3	LK Lahn-Dill-Kreis	0.02	0.04	0.05	0.04
Frankfurt am Main	3	LK Limburg-Weilburg	0.03	0.04	0.06	0.04
Frankfurt am Main	3	LK Vogelbergkreis	0.02	0.03	0.04	0.04
Frankfurt am Main	3	LK Fulda	0.03	0.04	0.03	0.07
Frankfurt am Main	3	LK Main-Spessart	0.03	0.04	0.04	0.06
Frankfurt am Main	3	LK Bad Kissingen	0.04	0.05	0.05	0.04
Leipzig	1	SK Leipzig	0.02	0.04	0.08	0.08
		Average Tier 2	0.01	0.02	0.04	0.05
Leipzig	2	LK Leipzig	0.02	0.03	0.06	0.05
Leipzig	2	LK Halle(Saale)	0.02	0.03	0.06	0.05
Leipzig	2	LK Saalekreis	0.00	0.01	0.02	0.04
Leipzig	2	LK Burgenlandkreis	0.02	0.01	0.04	0.02
Leipzig	2	LK Nordsachsen	0.01	0.01	0.03	0.08
		Average Tier 3	0.02	0.02	0.03	0.03
Leipzig	3	LK Mandfeld-Südharz	0.02	0.02	0.02	0.03
Leipzig	3	LK Salzlandkreis	0.01	0.02	0.02	0.03
Leipzig	3	LK Anhalt-Bitterfeld	0.01	0.02	0.02	0.02
Leipzig	3	LK Wittenberg	0.01	0.01	0.03	0.02
Leipzig	3	LK Elbe-Elster	0.00	0.01	0.04	0.02
Leipzig	3	LK Meißen	0.02	0.01	0.04	0.05
Leipzig	3	Mittelsachsen	0.02	0.02	0.03	0.03
Leipzig	3	LK Greiz	0.01	0.01	0.00	0.03
Leipzig	3	LK Saale-Holzland-Kreis	0.02	0.03	0.01	0.03
Leipzig	3	LK Weimarer Land	0.02	0.03	0.03	0.06
Leipzig	3	LK Sömmerda	0.01	0.02	0.03	0.03
Leipzig	3	LK Kyffhäuserkreis	0.02	0.01	0.02	0.02
Stuttgart	1	SK Stuttgart	0.05	0.07	0.11	0.08
		Average Tier 2	0.05	0.07	0.08	0.08
Stuttgart	2	LK Böblingen	0.05	0.06	0.10	0.08
Stuttgart	2	LK Esslingen	0.05	0.07	0.07	0.08
Stuttgart	2	LK Ludwigsburg	0.05	0.07	0.06	0.09
Stuttgart	2	LK Rems-Murr-Kreis	0.05	0.06	0.07	0.08
		Average Tier 3	0.04	0.06	0.06	0.08
Stuttgart	3	LK Göppingen	0.05	0.06	0.05	0.07
Stuttgart	3	LK Ostalbkreis	0.04	0.05	0.07	0.07
Stuttgart	3	LK Schwäbisch Hall	0.04	0.05	0.06	0.06
Stuttgart	3	LK Heilbronn	0.05	0.06	0.06	0.08
Stuttgart	3	SK Heilbronn	0.05	0.06	0.08	0.08
Stuttgart	3	LK Enzkreis	0.04	0.05	0.06	0.08
Stuttgart	3	SK Pforzheim	0.05	0.06	0.06	0.09
Stuttgart	3	LK Calw	0.04	0.05	0.04	0.08
Stuttgart	3	LK Tübingen	0.05	0.07	0.05	0.08
Stuttgart	3	LK Reutlingen	0.05	0.06	0.05	0.07

Table A.5. Percentage changes in house price index - Top 7 agglomerations and surrounding tiers

	OLS	OLS	FE	RE
log(Median income)	2.05***	2.09***	3.18***	3.14***
	(13.46)	(13.63)	(21.37)	(22.72)
log(Lag Population density (person per km^2))	0.88***	0.88***	3.06***	0.52***
	(13.53)	(13.59)	(7.74)	(4.07)
log(Land area (km^2))	0.22***	0.22***	5.01***	0.29***
	(8.00)	(8.04)	(3.01)	(4.80)
log(arable land (sqkm) per capita)	0.23***	0.25***	-0.81***	-0.15
	(4.46)	(4.69)	(-4.12)	(-1.47)
Green coverage	-4.36***	-3.81***	-7.90***	-9.32***
	(-3.24)	(-2.78)	(-7.06)	(-9.11)
log(Construction cost index)	1.74***	1.87***	-0.99***	-0.44***
	(9.45)	(9.66)	(-8.68)	(-4.16)
year=2015		-0.04		
		(-0.85)		
year=2016		-0.06		
		(-1.15)		
year=2017		-0.08		
		(-1.47)		
year=2018		-0.12**		
		(-2.21)		
Constant	-24.02***	-24.87***	-70.26***	-23.58***
	(-22.02)	(-21.45)	(-6.36)	(-24.66)
N	1890.00	1890.00	1890.00	1890.00
R^2	0.54	0.54	0.50	.
F(4, 1879)		1.28		
Prob > F		0.27		
chi2(6)				153.31
Prob > chi2				0.00

t statistics in parentheses
dependent variable: Land value per m^2 (Braun&Lee (2021))
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6. Non-spatial estimation results, tests

A.2. Figures

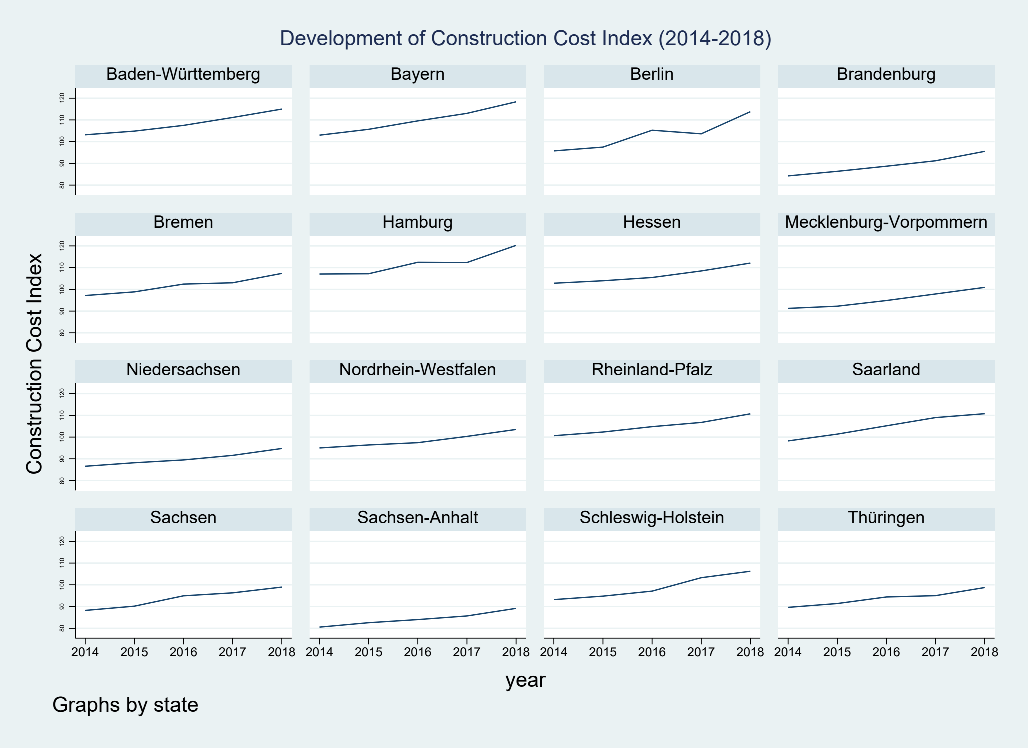

Figure A.1. Construction cost by state, 2014-2018

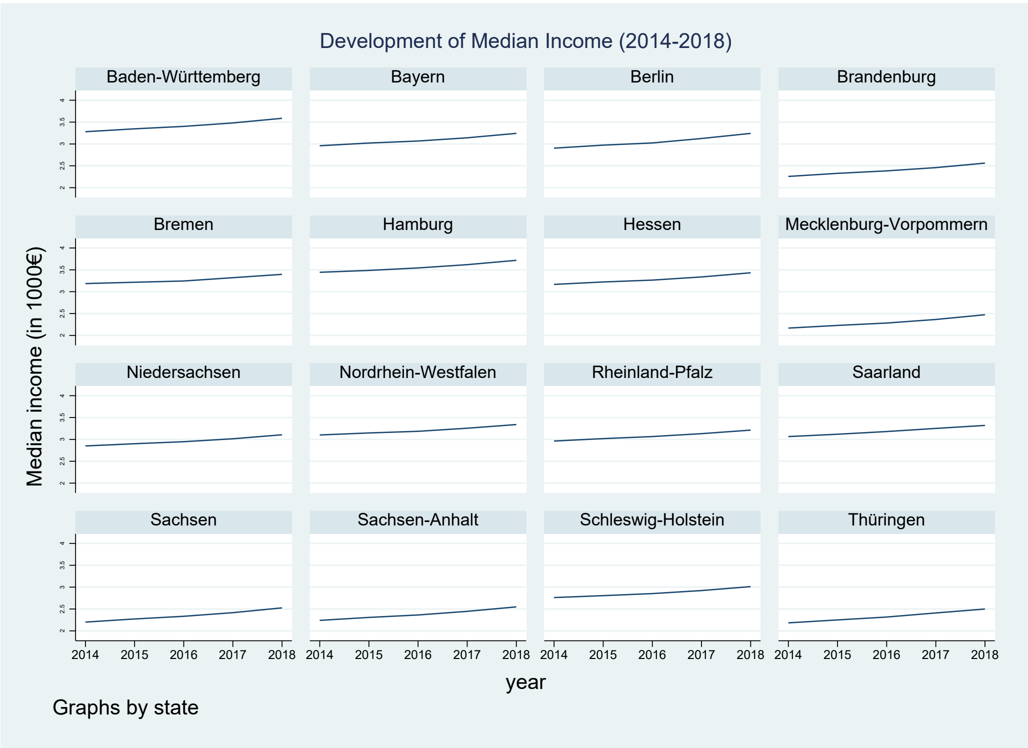

Figure A.2. Median income by state, 2014-2018

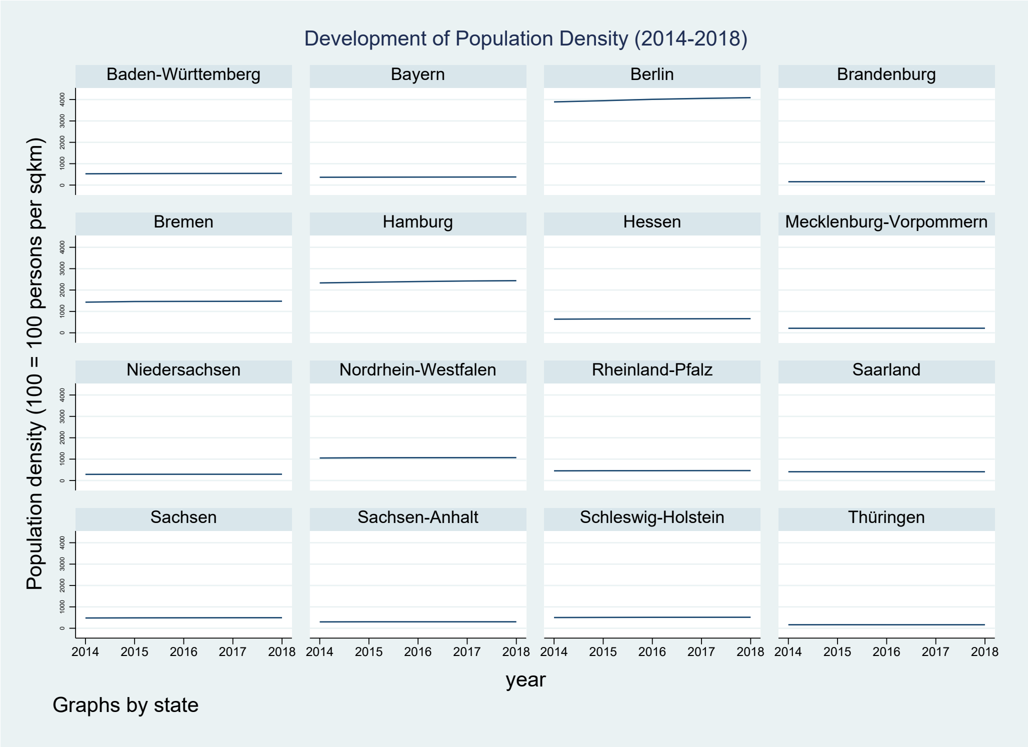

Figure A.3. Population density by state, 2014-2018