Land price diffusion across borders – The case of Germany

Aaron Grau, Martin Odening, and Matthias Ritter
Humboldt-Universität zu Berlin, Faculty of Life Sciences,
Department of Agricultural Economics,
Unter den Linden 6, 10099 Berlin, Germany
Aaron.grau@agrar.hu-berlin.de

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Land market regulations are often justified by the assumption that activities of foreign and non-agricultural investors drive up prices in domestic land markets. However, empirical knowledge about the dynamics of agricultural land prices across borders is sparse. Using the German reunification as a natural experiment, we study the effect of the former inner German border on the dynamics of agricultural land prices in East and West Germany. We apply a land price diffusion model with an error correction specification to analyze spatial agricultural land markets. A novel feature of our model is its ability to distinguish price diffusion within states and across state borders. We provide evidence for a persistent border effect given that the fraction of spatially integrated counties is larger within states than across the former border. Moreover, we observe non-significant error correction terms for many counties along the former border. From a policy perspective, it is striking to realize that even 25 years after German reunification, pronounced land price differences persist. It is quite likely that price diffusion through existing borders within the EU would take even more time given language barriers, different institutional frameworks, and information asymmetries between domestic and foreign market participants.

Keywords: Agricultural land markets; price diffusion; spatial dependence; border effect

JEL Code: Q13, Q15

1 Introduction

Recent surges in agricultural land prices and ongoing changes in land use due to urban sprawl, renewable energy production, and growing demands from non-agricultural investors have triggered debates on the effectiveness of existing land market regulations. Although boom and bust cycles are not new to land markets, current changes in the market are considered to result from a new constellation of driving forces. For instance, it is conjectured that the increased demand for land by financial investors has increased land rental and sales prices. These developments have led to demands for stricter regulations of land markets in many countries, including developed countries (cf. Kay et al., 2015). In 2010, the UK Government Office of Science stressed the need to balance competing pressures on land use and to roll out new land use policies (Government Office for Science, 2010). Four years later, Belgium laid the foundation for new land market instruments, such as a land observatory, land bank, and updated preemption rights. Belgium also tightened land market regulations, which had previously been liberal. Likewise, in Germany, the Federal Ministry and the State Ministries of Agriculture currently aim for a broad distribution of land ownership, the prevention of dominant land market positions on the supply and demand side, the capping of land rental and sales prices, prioritizing agricultural use of farmland, and establishing greater transparency for land markets (Bund-Länder-Arbeitsgruppe "Bodenmarktpolitik", 2015). Although these goals are fairly general, they fall in line with the trend toward stricter land market regulations. The proposed measures envision restricting market access for actors who treat land as an investment asset and do not have farming interests, while simultaneously prioritizing land purchases by farmers and facilitating farm succession and start-ups.

Remarkably, it is mainly the new EU Member States, which carry the legacy of weaker land market institutions from their socialist past, that opt for particularly strong regulations (cf. Swinnen et al., 2016). For example, new land market regulations aiming to restrict the purchase of agricultural land by foreigners and non-farmers was released in Slovakia (Lazíková and Bandlerová, 2015). In 2016, Poland passed the *Act on the Structuring of the Agricultural System*, which postponed exemptions from EU laws regarding the acquisition of land. The bill proposes to stop the sale of state-owned land for the next five years and includes very strict rules on who can sell and buy privately-owned land. The objective of the new law is to ensure that farmland remains in the hands of Polish farmers after the transition period. Bulgaria, Hungary, Latvia, and Lithuania followed suit with regulations directly or indirectly restricting the free movement of capital and freedom of establishment.

Most of the aforementioned attempts to regulate land markets have been motivated by the apprehension that in countries with low land price levels, farmers will encounter a drastic price surge unless land markets are protected against demand by foreign and non-agricultural investors. This assumption, however, lacks empirical evidence. Little is known about the spatio-temporal behavior of agricultural land prices and virtually no empirical study exists that investigates the diffusion of agricultural land prices across borders. In other words, we do not know if and how fast land prices in two neighboring countries with different price levels would converge if there were no restrictions on the acquisition of land. The main objective of this paper is to address this research gap. Our empirical analysis is conducted for West and East Germany, i.e., we study the effect of the former intra-German border on the dynamics of agricultural land prices. The German reunification constitutes a natural experiment on the establishment and evolution of land markets that allows us to study market integration. It is well-known that a gap exists between land prices in West and East Germany, but little is known about how this gap evolves over time and if the same land price dynamics prevail in both parts of Germany. After reunification, regions in Western Germany (especially near the former border between West and East Germany) lost their remoteness since they were suddenly situated in the center of Europe and thus became more attractive. On the other hand, the supply of cheaper land increased and redirected demand to regions in Eastern Germany, so that the effect of the reunification on land prices remains unclear.

To the best of our knowledge, there are only few studies that test for spatial market integration in the context of agricultural land.[1] Carmona and Roses (2012) investigate the spatial integration of Spanish land markets between 1904 and 1934 from a historical perspective. Their analysis is based on aggregated data and does not take into account heterogeneity of land characteristics and structural breaks in the price series that may bias the test results. More recently, Yang et al. (2017, 2019) explore the spatial pattern of land price development. Based on county-level data for the German state Lower Saxony, they employ stationarity tests and unit root tests to examine whether relative prices between counties converge. Using a sequential testing procedure allows Yang et al. (2017, 2019) to identify several distinct convergence clusters. The closest study to ours investigates the impact of a language border on spatio-temporal price diffusion of house prices in Belgium (Helgers and Buyst, 2016). Starting with a pairwise approach to provide insight into the degree of integration among housing prices, the study estimates a bivariate VAR model with error correcting coefficients. The results indicate

[1] There is, however, a rich literature on spatial price convergence in real estate markets, particularly in housing markets (cf. Hiebert and Roma (2010) for an overview).

that the fraction of pairs for which the regional house price differentials are stationary is higher within a linguistic area than between these areas. Although there are many structural similarities between house markets and land markets, which allow the transfer of methods across these two fields, one should also recognize the differences between these two markets. First, while agricultural land is mainly a production factor, houses have the character of a consumption good. This makes house prices more dependent on buyers' preferences and incomes. Second, potential buyers of houses are usually more mobile than farmers, making it more likely for house prices to converge. Finally, the supply of land follows a different mechanism than the supply of houses. Thus, one cannot readily adopt findings from real estate markets to agricultural land markets.

The remainder of this paper is organized as follows: The following section introduces the spatial price diffusion model and explains the logic of identifying a "border effect"; Section 3 provides some background information about the study region, the relevant land market environment after reunification, and the derivation of the data; Section 4 presents and discusses the empirical results; and Section 5 concludes.

2 A land price diffusion model with a border effect

At the heart of our research lies the question of whether land prices in Germany are integrated through time and space and converge in absence of barriers, such as the former German border. Consequently, the desired empirical application requires a model that allows for the incorporation of time and space. This can be achieved by a price diffusion model as proposed by Holly et al. (2011) and applied by Gong et al. (2016). In general, a price diffusion model is based on a Vector Error Correction Model (VECM) since cointegration is a necessity for price convergence in the long-run. The VECM accounts for this cointegration relationship by correcting the short-run responses of prices by deviations from a stable long-run equilibrium.

At first glance, to test the integration of land prices in a study area consisting of N regions would imply to test for $N(N-1)/2$ cointegration relationships. Nevertheless, one price of a cointegration vector can always be expressed by one other price or a combination of cointegrated prices (Holly et al., 2011). Thus, it is feasible to apply a neighbor approach that reduces the rank of the cointegration vector to unity and the number of equations to be estimated to N. In this parsimonious representation, the cointegration relationship is reduced to the price $p_{i,t}$ of region i and a weighted average price of region i's neighbors j, $\bar{p}_{i,t}^{\text{neighbor}} = \sum_{j=1}^{N} w_{ij} p_{j,t}$, with $\sum_{j=1}^{N} w_{ij} = 1$ if row-standardization is applied. The weights w_{ij} measure connectivity through proximity in geographic, economic, or social terms. Stacking all of the weights in a matrix with the diagonal elements equal to zero gives a spatial weight matrix W, which incorporates the dimension of space into the model. Another benefit of this approach is that no benchmark region has to be selected a priori in the cointegration system (Abbott and De Vita, 2013). The regional price diffusion model can be formulated into a VECM:

$$\Delta p_{i,t} = c_i + \phi_i ECT_{i,t-1} + \sum_{p=1}^{k} \gamma_{i,1,p} \Delta p_{i,t-p} + \sum_{p=1}^{m} \gamma_{i,2,p} \Delta \bar{p}_{i,t-p}^{\text{neighbor}} + \lambda_i z_t + \varepsilon_{it}, \tag{1}$$

where $p_{i,t}$ is the land price in region i at time t, $\bar{p}_{i,t}^{\text{neighbor}}$ is a weighted average land price in neighboring regions, z_t is a vector of exogenous common factors that affect all region prices, ε_{it} is an error term, and Δ is the difference operator. The term c_i is a region specific constant term to capture unobserved individual effects. The parameter vectors $\gamma_{i,1,p}$, $\gamma_{i,2,p}$, and λ_i capture the short-run responses of $\Delta p_{i,t}$ to k own price lags, m weighted neighbor price lags, and the common factors, respectively. ϕ_i measures the adjustment speed of corrections given that random deviations $ECT_{i,t-1}$ in the long-run equilibrium relationship between land prices occur. Error correction requires ϕ_i to be negative. A flexible form of the cointegration relationship that includes a constant and a trend is given by

$$ECT_{i,t-1} = p_{i,t-1} - \beta_{0i} - \beta_{1i} \bar{p}_{i,t-1}^{\text{neighbor}} - \beta_{2i} t_i, \tag{2}$$

where βs are parameters defining the cointegration relationship between price pairs. Note that the error correction term $ECT_{i,t-1}$ incorporates the spatial dimension in the long-run relationship through the neighboring prices. The error correction term incorporates the spatial lag of $p_{i,t}$ and equals the spatial autoregressive cointegration vector of a Spatial Error Correction Model (Beenstock and Felsenstein, 2010). While cointegration is sufficient to establish a long-run price relationship, further parameter restrictions have to be fulfilled to assert prices convergence among neighboring regions (Abbott and De Vita, 2013; Yang et al., 2017). If β_{1i} equals unity and the trend parameter β_{2i} and constant β_{0i} equal zero, prices of neighboring regions converge to the same level (absolute convergence). If β_{0i} is instead positive, prices converge toward a constant difference (relative convergence) (Waights, 2018).

To examine whether a predetermined barrier, such as a border, affects the diffusion of prices, we follow Helgers and Buyst (2016) by splitting neighboring prices into two groups. One group is the weighted price consisting of regions on the same side of the border, $\bar{p}_{i,t}^{\text{same}} = \sum_{j=1}^{N} w_{ij}^{\text{same}} p_{j,t}$, and the other group of regions on the opposite side of the border, $\bar{p}_{i,t}^{\text{opp}} =$

$\sum_{j=1}^{N} w_{ij}^{\text{opp}} p_{j,t}$. Therein weights are based on the individual elements w_{ij} of the original weighting matrix W with the difference that the individual elements of w_{ij}^{same} (w_{ij}^{opp}) are set to zero if region j lies on the opposite (same) side of the border as region i. Again, w_{ij}^{same} and w_{ij}^{opp} are row-standardized. In contrast to Helgers and Buyst (2016), we refrain from including a dominant region in the model since a dominant region is less likely to exist in agricultural land markets (Yang et al., 2019). With this regrouping, the price diffusion model (3) is transformed into:

$$\begin{aligned}\Delta p_{i,t} = c_i + \phi_{i,1} ECT_{i,1,t-1} + \phi_{i,2} ECT_{i,2,t-1} + \sum_{p=1}^{k} \gamma_{i,1,p} \Delta p_{i,t-p} + \sum_{p=1}^{m} \gamma_{i,2,p} \Delta \bar{p}_{i,t-p}^{\text{same}} \\ + \sum_{p=1}^{q} \gamma_{i,3,q} \Delta \bar{p}_{i,t-p}^{\text{opp}} + \lambda_i z_t + \varepsilon_{it}.\end{aligned} \tag{4}$$

Herein, $ECT_{i,1,t-1}$ captures deviations from the long-run relationship between region i's land price and the within state average neighbors' land price $\bar{p}_{i,t-1}^{\text{same}}$. Accordingly, $ECT_{i,2,t-1}$ corresponds to deviations from the across state neighbors' land price $\bar{p}_{i,t-1}^{\text{opp}}$. Equation (3) allows the empirical investigation of whether a border effect is present in land price diffusion. A border effect can exist under two different circumstances. The first is if deviations from the long-run equilibrium with the weighted average land price of neighboring regions are not corrected ($\phi_{i,2} \geq 0$). The second is if deviations from the average weighted land price of neighbors within the same state are corrected faster than the average weighted land price of neighboring regions across the border ($\phi_{i,1} < \phi_{i,2}$). This leads to the following hypotheses:

Hypothesis 1: The former border does not slow down the long-run price diffusion process of region i with neighbors across the border compared to neighbors within the state. Thus, deviations in the cointegration relationship with neighbors across the former border are corrected faster or at the same speed as with neighbors on the same side of the border ($\phi_{i,1} \geq \phi_{i,2}$).

Hypothesis 2: The former border prohibits any correction toward a long-run equilibrium between region i's land price and the land price of neighboring regions across the border ($\phi_{i,2} \geq 0$).

If hypothesis 1 is rejected, the former border still affects land price diffusion for region i with its neighboring land markets across the border. If hypothesis 2 is rejected, land price changes diffuse across the former border. Thus, we can deduce that if hypothesis 1 is not rejected and hypothesis 2 is rejected, land price diffusion to and from region i to its neighbors across the former border is not blocked or slowed down, i.e., there is evidence supporting no border effect. Vice versa, if hypothesis 1 is rejected or hypothesis 2 is not rejected, we can conclude that land price diffusion to and from region i to its neighbors across the former border is slowed down and possibly completely blocked, i.e., there is evidence supporting a border effect.

Assuming independence of the error terms, the N regional VECM equations (3) can be estimated with Ordinary Least Squares (OLS). The seemingly unrelated regression (SUR) allows for the estimation of an unrestricted covariance matrix E_t with possible contemporaneous correlation between the individual region equations, $\mathrm{Cov}(\varepsilon_{it}, \varepsilon_{jt}) \neq 0$ for $i \neq j$. We apply an iterative SUR, which allows updating the covariance matrix in each iteration and converges to maximum likelihood (Greene, 2002).

While the system of regional VECM equations is a parsimonious representation of N cointegration relationships and allows one to test whether the former German border still affects long-run land price diffusion, it cannot display the full complexity of the spatio-temporal land price diffusion process and restricts the analysis to regions adjacent to the former border. Regional land markets, however, can be linked over far distances and react to one another, even though no direct cointegration relationship exists due to short-run dynamics and temporal and spatial spillover effects. The price diffusion model in a VECM form is the basis for deriving impulse response function (IRF) specifications. Through impulse response analysis, it is possible to investigate the diffusion of shocks to one region in a regional system over time and space (Holly et al., 2011). To derive IRFs, the original system of N regional VECM equations with a border effect (3) is stacked and rewritten in matrix notation:

$$\Delta P_t = C + \Pi P_{t-1} + \sum_{p=1}^{l} \Gamma_p \Delta P_{t-p} + \Lambda Z_t + E_t \tag{5}$$

$$\text{with } C = \begin{bmatrix} c_1 + \phi_{1,1}\beta_{01,1} + \phi_{1,2}\beta_{01,2} \\ c_2 + \phi_{2,1}\beta_{02,1} + \phi_{2,2}\beta_{02,2} \\ \vdots \\ c_{N-1} + \phi_{N-1,1}\beta_{0N-1,1} + \phi_{N-1,2}\beta_{0N-1,2} \\ c_N + \phi_{N,1}\beta_{0N,1} + \phi_{N,2}\beta_{0N,2} \end{bmatrix},$$

$$\Pi = \begin{bmatrix} \phi_{1,1} + \phi_{1,2} & 0 & \cdots & 0 & 0 \\ 0 & \phi_{2,1} + \phi_{2,2} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \phi_{N-1,1} + \phi_{N-1,2} & 0 \\ 0 & 0 & \cdots & 0 & \phi_{N,1} + \phi_{N,2} \end{bmatrix} -$$

$$\begin{bmatrix} \phi_{1,1}\beta_{11,1}w_1^{\text{same}\prime} + \phi_{1,2}\beta_{11,2}w_1^{\text{opp}\prime} \\ \phi_{2,1}\beta_{12,1}w_2^{\text{same}\prime} + \phi_{2,2}\beta_{12,2}w_2^{\text{opp}\prime} \\ \vdots \\ \phi_{N-1,1}\beta_{1N-1,1}w_{N-1}^{\text{same}\prime} + \phi_{N-1,2}\beta_{1N-1,2}w_{N-1}^{\text{opp}\ \prime} \\ \phi_{N,1}\beta_{1N,1}w_N^{\text{same}\prime} + \phi_{N,2}\beta_{1N,2}w_N^{\text{opp}\prime} \end{bmatrix}, \text{ and}$$

$$\Gamma_p = \begin{bmatrix} \gamma_{1,1p} & 0 & \cdots & 0 & 0 \\ 0 & \gamma_{2,1p} & \cdots & 0 & 0 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \cdots & \gamma_{N-1,1p} & 0 \\ 0 & 0 & \cdots & 0 & \gamma_{N,1p} \end{bmatrix} + \begin{bmatrix} \gamma_{1,2p}w_1^{\text{same}\prime} + \gamma_{1,3p}w_1^{\text{opp}\prime} \\ \gamma_{2,2p}w_2^{\text{same}\prime} + \gamma_{2,3p}w_2^{\text{opp}\prime} \\ \vdots \\ \gamma_{N-1,2p}w_{N-1}^{\text{same}\prime} + \gamma_{N-1,3p}w_{N-1}^{\text{opp}\ \prime} \\ \gamma_{N,2p}w_N^{\text{same}\prime} + \gamma_{N,3p}w_N^{\text{opp}\prime} \end{bmatrix}.$$

The price vector $P_t = (p_{1,t}, p_{2,t}, \dots, p_{N,t})'$ comprises all N regions' land prices and thus all endogenous time series. Π is the $N \times N$ cointegration matrix to parameterize the long-run spatial relationship in P_t, while the $p \times N$ matrix Γ_p captures the short-run responses to p past changes in P_t.[2] The spatial weight vectors $w_i^{\text{same}\prime} = (w_1^{\text{same}\prime}, w_2^{\text{same}\prime}, \dots, w_{N-1}^{\text{same}\prime}, w_N^{\text{same}\prime})$ and $w_i^{\text{opp}\prime} = \left(w_1^{\text{opp}\prime}, w_2^{\text{opp}\prime}, \dots, w_{N-1}^{\text{opp}\ \prime}, w_N^{\text{opp}\prime}\right)$ are the N rows of the corresponding spatial weight matrices W^{same} and W^{opp}.

The vector autoregression (VAR) representation of (4) is

$$P_t = C + \Phi_1 P_{t-1} + \Phi_2 P_{t-2} + \cdots + \Phi_p P_{t-p} + \Phi_{p+1} P_{t-(p+1)} + \Lambda Z_t + E_t, \tag{6}$$

where the parameter matrices $\Phi_1 = I_N + \Pi + \Gamma_1$, $\Phi_p = \Gamma_p - \Gamma_{p-1}$, and $\Phi_{p+1} = -\Gamma_p$ are compounds of the VECM coefficient matrices.

The generalized impulse response function (GIRF) g_i for a one unit (one standard error) shock originating in region i at h time step intervals ahead can be calculated after Pesaran and Shin (1998) by

2 *p* is the maximum of the lag numbers *k*, *q*, and *m* of the lagged own and neighbors' price differences suggested by Schwarz Criterion (BIC).

$$g_i(h) = \frac{\Psi_h \Sigma e_i}{\sqrt{\sigma_{ii}}} \text{ for } h = 0,1,\dots,H\,, \tag{7}$$

where Σ is the covariance matrix, e_i is a $N \times 1$ vector of zeros with exclusion of its i^{th} element set to unity, and σ_{ii} are the diagonal elements of the covariance matrix. The Ψs are calculated recursively with the help of the VAR coefficients by

$$\Psi_h = \Phi_1 \Psi_{h-1} + \Phi_2 \Psi_{h-2} + \cdots + \Phi_p \Psi_{h-p} + \Phi_{p+1} \Psi_{h-(p+1)}, \tag{8}$$

with $\Psi_0 = I_N$ and $\Psi_h = 0$ for all $h < 0$ (Pesaran and Shin, 1998). The GIRF approach is a better representation of dynamic spatial integration since a shock originating in region i will eventually progress to the non-neighboring region j via spatial linkage through other regions (Abbott and De Vita, 2013).

3 Study Region and Data

3.1 The border region of Lower Saxony and Saxony-Anhalt

During the division of Germany from 1945 to 1990, the two sides divided by the inner German border were exposed to different political and economic systems. This difference also applied to agricultural land markets. Whereas a free land market was established in West Germany, East Germany was characterized by expropriation and collectivization of land. In 1989, East German agriculture consisted of 464 state-owned farms called *Volkseigene Güter* (VEGs, People-Owned Properties) and 3,844 collective farms called *Landwirtschaftliche Produktionsgenossenschaften* (LPGs, Agricultural Production Cooperatives) (Jochimsen, 2010). After reunification in 1990, the property rights in East Germany had to be clarified and former owners were indemnified according to the *Entschädigungs- und Ausgleichsleistungs-gesetz* (Indemnification and Compensation Act). The *Landwirtschaftsanpassungsgesetz* (Law on the Adjustment of Agriculture) regulated the decollectivization process and transformation of LPGs toward other legal forms. State-owned land was privatized through the *Treuhandanstalt* (1990–1992) and the *Bodenverwertungs- und -verwaltungs GmbH* (BVVG, since 1992). After 1990, many farmers from West Germany or other Western European countries bought or rented land in former East Germany at prices that were considerably lower than in former West Germany (Koester, 2000). This privatization process was recently prolonged to 2030 since the BVVG still holds 136,700 ha of agricultural land in East Germany (BMWi, 2017).

Almost 30 years after the reunification, it could be expected that the open border led to an equalization of conditions on both sides. In this study, we focus on the border region between the state of Lower Saxony (in former West Germany) and the state of Saxony-Anhalt (in former East Germany). After a reform of the counties in Saxony-Anhalt in 2007 (*Kreisreform*), the border region between Saxony-Anhalt and Lower Saxony now consists of four counties on the former east side and six counties on the former west side. With around 415 km, almost one-third of the former inner German border is covered in this analysis.

Table 1 shows similarities and differences between the counties in east and west: The number of farms per county is comparable on both sides of the border (approximately 500 per county), but farms, on average, are more than two times larger in Saxony-Anhalt. This is a result of the history of LPGs: Nowadays, farms in former East Germany are often still organized as cooperatives. In fact, in the former East German border counties, 24% to 47% of the agricultural area is operated by legal persons, whereas this percentage is almost zero in former West German border counties. Joint ownership leads to information asymmetries and could prevent Western farmers from buying land on the Eastern side of the former border due to higher transaction costs. At the same time, however, access to information is facilitated for land sold by the BVVG since it uses public auctions. The BVVG is an important player on the East German land market: It has sold between 21% and 58% of the total transacted agricultural land in the Eastern border counties after reunification.

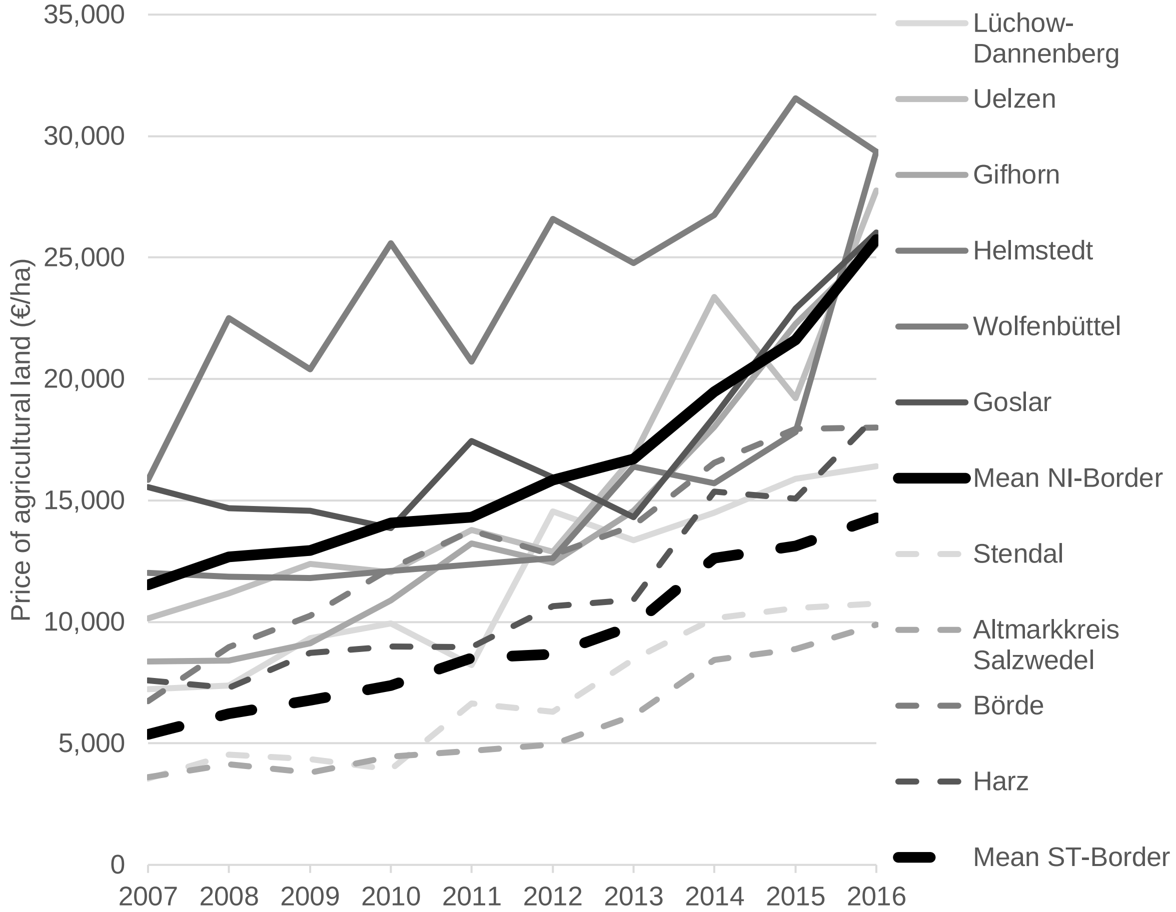
Similar production structures on both sides of the border could also lead to an assimilation of prices. For example, wheat production is quite strong in the south of both border regions where 50% of the available arable land is used for wheat growing. Moreover, there is a cross-border potato cluster in Lüchow-Dannenberg and Uelzen on the western side and in Altmarkkreis Salzwedel and Börde on the eastern side. Livestock densities are, in general, higher on the eastern side and decrease from north to south.

Table 1: Descriptive statistics for the border counties (sorted from north to south)

	Border length (km)	Number of farms	Avg. farm size (ha)	Share of arable land	Area hold by juridical person	Share BVVG (% of transacted agricultural land sold by BVVG)	Wheat area (ha) (% of arab. land)	Potato area (ha) (% of arab. land)	Livestock density (livestock units/ha arab. land)	Price 2016 (€/ha)	Price growth 2007–2016
Lower Saxony											
Lüchow-Dannenberg	107	587	103	80%	n/a	–	8,045 *(17%)*	5,559 *(11.5%)*	0.37	16,409	127%
Uelzen	15	693	108	90%	n/a	–	14,454 *(21%)*	13,239 *(19.6%)*	0.29	27,761	174%
Gifhorn	71	817	95	83%	n/a	–	9,585 *(15%)*	7,553 *(11.7%)*	0.30	25,519	205%
Helmstedt	122	359	115	91%	n/a	–	16,924 *(45%)*	153 *(0.4%)*	0.09	29,360	144%
Wolfenbüttel	32	403	126	96%	n/a	–	26,603 *(54%)*	60 *(0.1%)*	0.05	29,355	85%
Goslar	69	289	95	87%	n/a	–	12,511 *(53%)*	23 *(0.1%)*	0.20	26,032	67%
Saxony-Anhalt											
Stendal	21	579	269	70%	39%	58%	27,958 *(25%)*	482 *(0.4%)*	0.39	10,755	203%
Altmarkkreis Salzwedel	161	491	256	75%	47%	33%	13,069 *(14%)*	2,008 *(2.1%)*	0.43	9,886	174%
Börde	114	546	277	89%	24%	21%	50,814 *(38%)*	4,569 *(3.4%)*	0.36	18,001	167%
Harz	120	341	303	87%	42%	35%	44,511 *(49%)*	742 *(0.8%)*	0.23	18,494	144%

Data sources: The data for the number and size of farms, the share of arable land, the area held by a juridical person, the wheat and potato growing areas, the livestock density, and the prices for agricultural land in 2007 and 2016 are from the Statistical Office of Lower Saxony and the Statistical Office of Saxony-Anhalt. The area held by a juridical person is not provided by the Statistical Office of Lower Saxony due to the low number of cases and the resulting confidentiality of the information. The border length and share of BVVG in the counties of Saxony-Anhalt are based on own calculations.

Figure 1: Price development of agricultural land in border counties in Lower Saxony (NI, solid) and Saxony-Anhalt (ST, broken line)



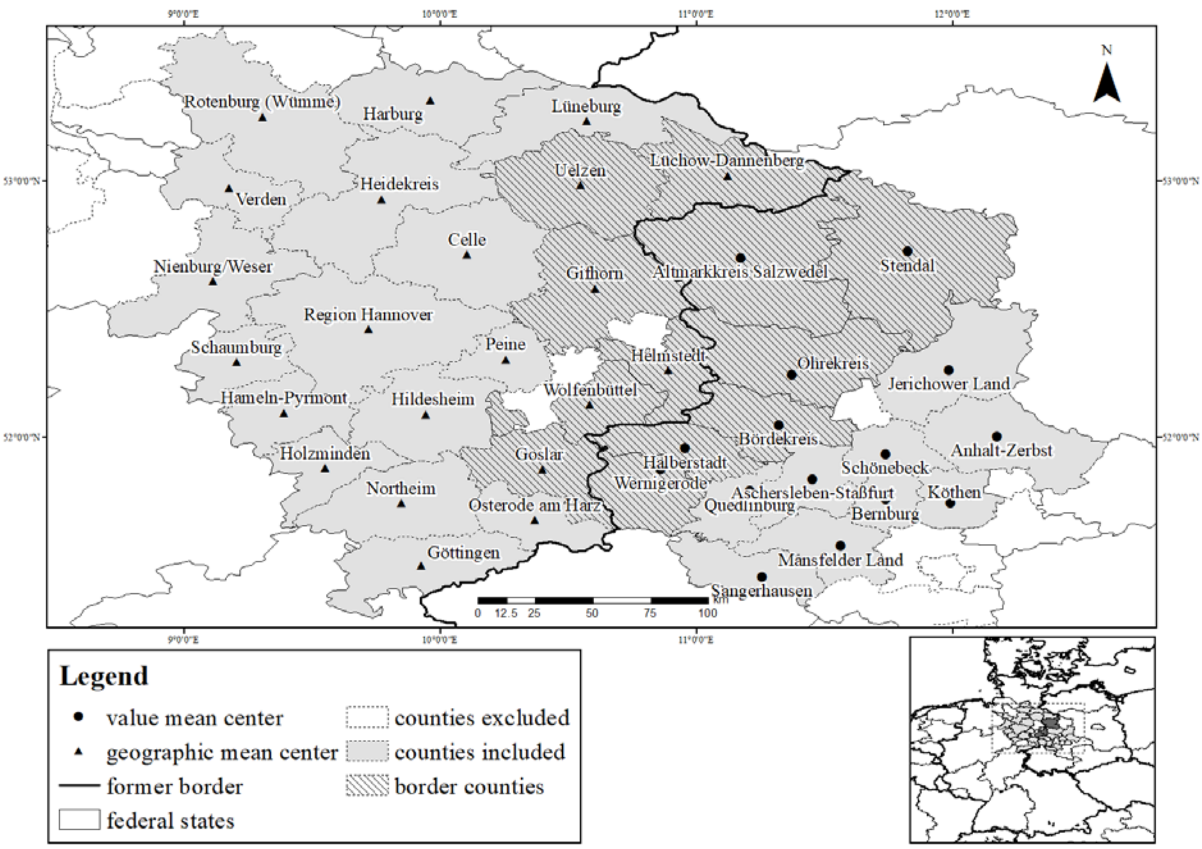
Source: authors' presentation based on data from the Statistical Office of Lower Saxony and the Statistical Office of Saxony-Anhalt.

Agricultural land prices in 2016, however, strongly differ with around 25,000 €/ha in Lower Saxony and 15,000 €/ha in Saxony-Anhalt. The percentage increase from 2007 to 2016 is, in general, slightly larger in Saxony-Anhalt. Figure 1 shows that the absolute gap between prices in former East and West Germany rises, so that a tendency of eastern counties to catch up to their western neighbors cannot be observed. The figure also shows that there is only a small overlap of the time series for eastern and western counties and a rather homogenous price development, especially for the eastern counties. These numbers provide a mixed picture. While production structures show similarities across the border, prices seem to evolve differently. In our empirical analysis, we will scrutinize whether the border still influences price development and if there are regional differences between counties in former East and West Germany.

3.2 Data

The empirical analysis is based on a comprehensive dataset of sale transactions of arable land between 1994 and 2015 in Lower Saxony and Saxony-Anhalt provided by Oberer Gutachterausschuss für Grundstückswerte in Niedersachsen and Gutachterausschuss für Grundstückswerte in Sachsen-Anhalt. It includes information on the price, size, soil quality, and location of sold plots. To conduct the analysis, these data have to be converted into a balanced panel.

Figure 2: Counties included and excluded as well as the geographic location of value and geographic mean centers; the shape of the counties corresponds to the situation before 2007.



Source: authors' presentation.

Using transaction data has two advantages compared to county averages provided by statistical offices. First, we can derive quarterly instead of yearly average prices and hence obtain a larger panel. Second, the reform of the counties in Saxony-Anhalt in 2007 led to a fusion and reshaping of counties.[3] Through the transaction data, we can create consistent time series for the counties in the pre-reform shape and hence also increase the regional dimension of the panel.

The focus of the study is to evaluate a possible effect of the former German border on land price diffusion. Consequently, to keep the number of regional units at a manageable level, counties in Saxony-Anhalt and Lower Saxony more distant than the 2nd neighbors of border regions are excluded (see Figure 2).[4]

Land price transaction data cannot simply be aggregated to county level cross-section data since land is a heterogeneous factor (Yang et al. 2017). To homogenize the transaction data, we apply the following hedonic regression to all transactions ($k = 1, \ldots, 82\,672$):

$$\ln p_k = \delta_{0i} + \delta_{1i} t_i + \delta_2 \text{quality}_k + \delta_3 \text{size}_k + \eta_k, \tag{9}$$

which accounts for soil quality and the size of the transferred plot.[5] The regression also includes a county-specific constant δ_{0i} and time trend t_i to account for county-individual effects that otherwise could bias the estimated effects of size and quality. The hedonic regression is estimated via OLS. Then, the 5% observations with the largest and smallest residuals $\hat{\eta}_k$ are removed and (8) is re-estimated. As expected, soil quality and the size of the transferred land have a positive effect on the price of arable land ($\hat{\delta}_2 = 0.012$, $\hat{\delta}_3 = 0.003$). With these coefficients at hand, log land prices are adjusted to average soil quality and average size:

$$\ln p_k^* = \ln p_k - \hat{\delta}_2\left(\text{quality}_k - \overline{\text{quality}}\right) - \hat{\delta}_3\left(\text{size}_k - \overline{\text{size}}\right) \tag{10}$$

where $\overline{\text{quality}}$ and $\overline{\text{size}}$ denote the sample means of soil quality and plot size, respectively. The adjusted transaction prices p_k^* are then averaged to quarterly county-level data. The resulting time series are smoothed to eliminate outliers, which can occur due to infrequent transactions for some counties and time periods. A standard exponential moving average of up to four time periods before t are applied in form of $p_{it} = \frac{p_{it} + \sum_{n=1}^{p}(1-\alpha)^n\, p_{it-n}}{1 + \sum_{n=1}^{p}(1-\alpha)^n}$ with $\alpha = \frac{1}{p+1}$. The resulting panel dataset with average prices in 37 counties from the first quarter of 1994 to the fourth quarter of 2015 ($37 \times 88 = 3{,}256$ observations) is used to estimate the price diffusion model.

3 The reform of the counties in 2007 had the following consequences for the border region: Bördekreis and Ohrekreis merged into Börde; Halberstadt, Quedlinburg, Wernigerode, and a small part of Aschersleben-Staßfurt became one county called Harz; and Altmarkkreis Salzwedel and Stendal remained the same.

4 It could be argued that the empirical application should be confined to border regions. This would, however, prevent the analysis of spillover and spatial effects.

5 Soil quality is measured by *'Ackerzahl'*, a German evaluation scheme for the quality of agricultural land based on criteria such as soil type, climate, and topography. It has a value that ranges from one ('very poor') to 120 ('very good').

Equation (3) allows the incorporation of common factors that might influence the development of land prices across the study region. We follow Helgers and Buyst (2016) and add the change in real GDP growth for the same time period as a possible explanatory variable for the price development at county-level within the entire study region.

To get a tentative idea of whether there is spatial integration of land markets among the 37 counties, we run unit root tests for log land price pairs ($p_{i,t} - p_{j,t}$) including a constant term to allow for relative convergence. Descriptive statistics of the Augmented Dickey-Fuller test results at a significance level of 5% are presented in Table 2. The results show that 61.1% of all price pairs are stationary and converge in the long-run, at least in relative terms. However, the share of stationary pairs is higher within states, with about 67% for both Lower Saxony and Saxony-Anhalt. In contrast, market integration across state borders is notably lower with only 54.8%. This finding suggests that the former German border still manifests itself as a barrier to land price diffusion.

Table 2: Augmented Dickey-Fuller test results for counties' land price pairs ($\boldsymbol{p_{i,t} - p_{j,t}}$) including a constant with p-value ≤ 0.05

	Stationary		Non-stationary		Total
	#	%	#	%	
All counties	407	61.1	259	38.9	666
Saxony-Anhalt	71	67.6	34	32.4	105
Lower Saxony	155	67.1	76	32.9	231
Within states	226	67.3	110	32.7	336
Across the border	181	54.8	149	45.2	330

Source: Authors' calculations

Since the spatio-temporal price diffusion model (3) is based on cointegration, we have to establish that the prices of county i are in fact cointegrated with the weighted neighboring prices. To this end we apply a Johansen trace test (Johansen, 1991) with a cointegration constant and unrestricted β_{1i}. Table 3 shows that prices in all counties are cointegrated with their neighbors' prices in the same state with the exception of Peine. Moreover, land prices in Uelzen, one of the border neighboring counties, are not cointegrated with prices across the former border. Note that only significant cointegration relationships (at the 10% significance level) enter the price diffusion model via $ECT_{i,1,t-1}$ or $ECT_{i,2,t-1}$. Furthermore, we test whether land prices converge in the long-run by testing the hypothesis $H_0: \beta_{1i} = -1$. The hypothesis of (relative) convergence is rejected in 48 out of 49 cointegration relationships at the 10% significance level. Thus, price convergence is very rare, a finding which is also reported in other studies (Yang et al. 2019).

Table 3: Johansen cointegration test with constant (trace statistic) and test for restrictions on cointegration vector

County	Trace statistic $\bar{p}_{i,t}^{\text{same}}$ $H_0: r = 0$	p-value $H_0: \beta_1^{\text{same}} = -1$	Trace statistic $\bar{p}_{i,t}^{\text{opp}}$ $H_0: r = 0$	p-value $H_0: \beta_1^{\text{same}} = -1$
Lower Saxony				
Gifhorn	24.95	<0.01	22.25	0.01
Göttingen	24.47	0.04		
Goslar	24.10	<0.01	22.14	<0.01
Helmstedt	21.46	<0.01	31.24	0.02
Northeim	27.87	<0.01		
Osterode am Harz	21.55	<0.01		
Peine	13.84	0.06		
Wolfenbüttel	21.66	<0.01	29.46	<0.01
Hameln-Pyrmont	20.99	<0.01		
Hildesheim	19.35	0.01		
Holzminden	24.22	<0.01		
Nienburg/Weser	33.23	<0.01		
Schaumburg	33.32	<0.01		
Region Hannover	30.30	0.02		
Celle	29.10	0.01		
Harburg	31.32	<0.01		
Lüchow-Dannenberg	35.56	0.03	22.52	0.01
Lüneburg	44.83	0.01		
Rotenburg (Wümme)	36.78	<0.01		
Heidekreis	37.56	<0.01		
Uelzen	37.87	0.03	16.57	0.05
Verden	45.43	<0.01		
Anhalt-Zerbst	49.75	<0.01		
Bernburg	43.47	<0.01		
Köthen	35.95	0.03		
Mansfelder Land	33.82	<0.01		
Sangerhausen	25.85	0.26		
Saxony-Anhalt				
Aschersleben-Straßfurt	55.05	<0.01		
Bördekreis	30.73	0.02	25.73	0.05
Halberstadt	28.13	<0.01	21.95	0.01
Jerichower Land	50.14	<0.01		
Ohrekreis	32.15	<0.01	22.92	0.04
Stendal	27.14	0.08	25.92	0.02
Quedlinburg	35.99	<0.01		
Schönebeck	45.62	<0.01		
Wernigerode	31.50	<0.01	18.02	<0.01
Altmarkkreis Salzwedel	31.92	0.02	25.98	0.05

Source: Authors' calculations. The critical values for 10%, 5%, 1% level of significance are: 17.85, 19.96, 24.6.

4 Empirical application

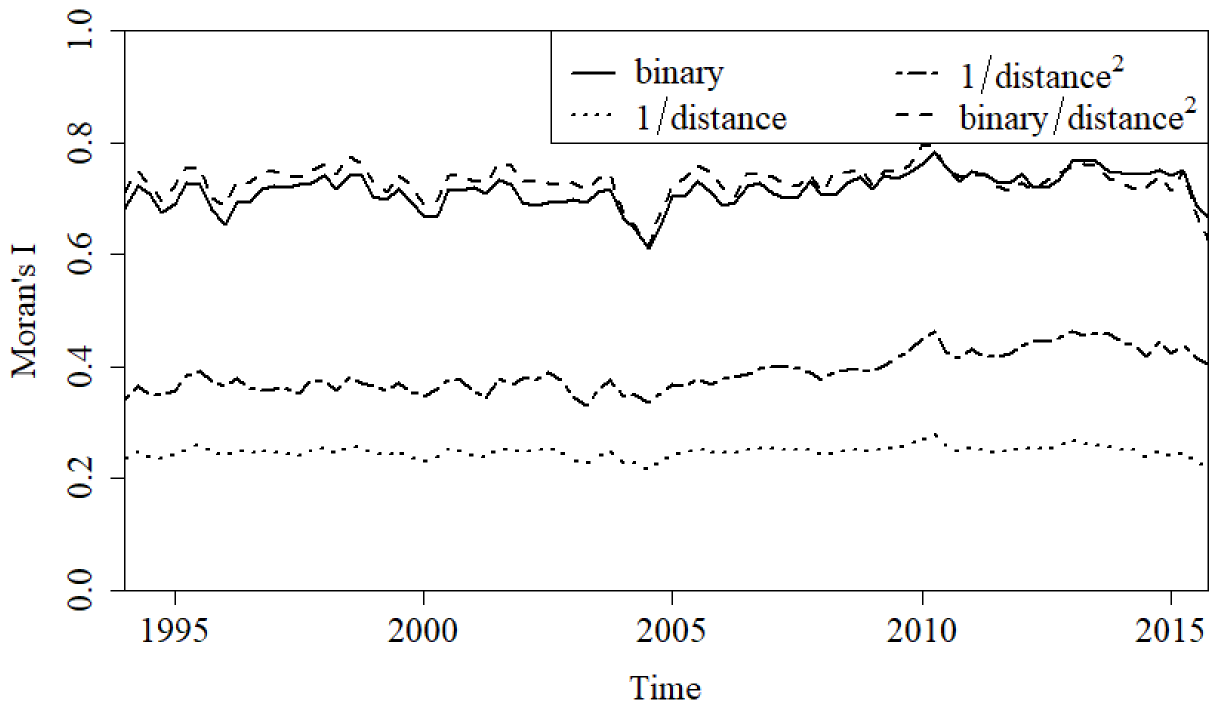
4.1 Model specification

To model the spatial relationship between the counties and to estimate the VAR of price pairs, a spatial weighting matrix representing spatial dependencies has to be chosen *a priori*. Although its specification is arbitrary, it is influential for the results of the price diffusion model (Meen, 1996). Hence, we apply several widely used weighting matrices in our empirical application. Most spatial weight matrices rely either on neighborhood expressed in binary terms, namely, $w_{ij} = 1$ for a (direct) bordering county and zero otherwise, or in the distance measured from a selected point which is frequently the main market in the county. Since it is usually assumed that spatial market integration increases with proximity, inverse distance weighting is alternatively used to measure the connectivity of counties: $w_{ij} = \left(\frac{1}{\text{distance between } i \text{ and } j}\right)^n$. More specifically, we consider four different candidates of spatial weight matrices. Two inverse distance matrices with $n = 1$ and $n = 2$, respectively, a simple binary neighborhood matrix ('binary'), and a so-called 'binary/distance^2' matrix, which is the product of the 'binary' and '1/distance^2' matrix. The latter matrix extends on the simple binary relationship, but limits the influence to first neighbors. Distance is measured between value mean centres of the land transactions for Saxony-Anhalt where geographic coordinates for all transactions are available. For Lower Saxony, where no coordinates are available, the geographic mean of a county is used as its centre.

To select the weight matrix among the four candidates, we apply Moran's I, which is a measure of spatial autocorrelation. The higher Moran's I is, the higher spatial autocorrelation is within the data. Figure 3 displays the results of Moran's I for all four spatial weight matrices over the observation period. Apparently, the inverse distance and distance decay matrices show lower Moran's I values than the binary based ones, which almost coincide for all time periods. While the pure binary matrix achieves the highest values for all time intervals until about 2010, the mixed binary-distance matrix slightly surpasses the binary's value afterwards. We proceed with both binary configurations of the spatial weight matrix for the model selection procedure. Note that Moran's I values are rather stable over time irrespective of the spatial weight matrix. This is a first indication that the underlying price diffusion process does not exhibit drastic changes during the sample period.

Apart from the choice of a spatial weight matrix, restrictions set in the long-run relationship (2) will also affect the estimation results. Three model variants are estimated: the case of absolute convergence ($\beta_{1i} = -1$ and $\beta_{0i} = 0$), relative convergence ($\beta_{1i} = -1$ and $\beta_{0i} \neq 0$), and non-convergence ($\beta_{1i} \neq -1$). Moreover, we compare models with and without inclusion of common factors. Finally, we estimate model variants with a border effect (3) and without a border effect (11) to address our main research question. This differentiation leads to $2 * 3 * 2 * 2 = 24$ model specifications. To choose the model that best represents the data generating process among these specifications, Akaike Information Criterion (AIC) values were calculated.

Figure 3: Moran's I



Source: Authors' calculations.

Table 4 reports the ΔAIC and weighted AIC (ωAIC) values for each of the 24 specifications. ΔAIC and ωAIC are defined as $\Delta\text{AIC}_i = \text{AIC}_i - \min_i \text{AIC}_i$ for the i^{th} model specification and $\omega\text{AIC}_i = \exp(-\text{AIC}_i/2)/\sum_{i=1}^{k} \exp(-\text{AIC}_i/2)$. All models were estimated with iterative seemingly unrelated regression (SUR), since the Breusch-Pagan Lagrange test rejected the null hypothesis of no correlation between the error terms. While ΔAIC ranks the model specifications, ωAIC states the probability of a specification being the best model for the data relative to alternative specifications (Burnham and Anderson, 2004).

Table 4 shows that models distinguishing between prices within states and across states are superior according to the model selection criteria. This is a further indication that the former border still influences the diffusion of land prices in Germany. The probability of being the best model among the candidates is almost 1 for the top ranked model. This specification uses the 'binary/distance^2' spatial weight matrix, does not restrict county prices to converge, incorporates a common factor, and separates neighboring prices into two groups, thus representing the border effect.

Table 4: AIC results for different model specifications

Spatial weight matrix	Border effect	Common factor	$\beta_{1i} = -1$	$\beta_{0i} \neq 0$	ΔAIC	ωAIC
binary/distance^2	yes	yes	no	yes	0.00	100.0%
binary/distance^2	yes	yes	yes	yes	18.50	0.0%
binary	yes	yes	no	yes	26.49	0.0%
binary	no	yes	no	yes	53.00	0.0%
binary	yes	yes	yes	yes	55.01	0.0%
binary	yes	no	no	yes	56.32	0.0%
binary/distance^2	no	yes	no	yes	58.32	0.0%
binary/distance^2	no	yes	yes	yes	59.29	0.0%
binary	no	no	no	yes	76.98	0.0%
binary/distance^2	yes	no	no	yes	77.58	0.0%
binary	yes	no	yes	yes	77.83	0.0%
binary	no	yes	yes	yes	83.66	0.0%
binary/distance^2	yes	no	yes	yes	90.69	0.0%
binary	no	no	yes	yes	106.31	0.0%
binary	yes	no	yes	no	116.32	0.0%
binary	no	no	yes	no	119.23	0.0%
binary/distance^2	no	no	no	yes	122.65	0.0%
binary/distance^2	no	no	yes	yes	123.83	0.0%
binary	yes	yes	yes	no	128.09	0.0%
binary	no	yes	yes	no	140.54	0.0%
binary/distance^2	yes	no	yes	no	227.05	0.0%
binary/distance^2	yes	yes	yes	no	230.73	0.0%
binary/distance^2	no	no	yes	no	291.88	0.0%
binary/distance^2	no	yes	yes	no	316.72	0.0%

Source: Authors' calculations.

4.2 Estimation results

Table 5 reports the shares of significant parameters for the N price diffusion equations for the iterative SUR estimation results. In line with the previous unit root and Johansen trace tests, we observe a large share of significant adjustment coefficients (75.0% and 72.7% respectively) pointing at a long-run equilibrium of land prices with their neighbor counties' prices. In only six cases neither $\phi_{i,1}$ nor $\phi_{i,2}$ are statistically different from zero at the 5% level. The average speed of adjustment for all is rather slow (-0.23). This value is comparable to other studies in the real estate market (e.g., Helgers and Buyst, 2016; Holly et al., 2011). As a robustness check, Table 5 also reports the shares of significant parameters for another model specification using a binary spatial matrix as well as the results of an OLS estimation. The choice of the spatial weight matrix influences the estimation results considerably. For a binary spatial weight matrix, a lower share of significant parameter estimates is found at the 5%-level, in particular for the adjustment speed of average prices in regions across the former border. Thus, this specification would result in a stronger border effect. Likewise, an estimation with OLS results in a lower share of significant model parameters (see Table 5).

Table 5: Share of significant parameters for the *N* price diffusion equations (p-value smaller or equal to 0.05)

	$\boldsymbol{\phi_{i,1}}$	$\boldsymbol{\phi_{i,2}}$	$\boldsymbol{\gamma_{i,1}}$	$\boldsymbol{\gamma_{i,2}}$	$\boldsymbol{\gamma_{i,3}}$	$\boldsymbol{\lambda_i}$
Presented Model (No. 1 by ΔAIC)	75.0%	72.7%	65.1%	59.2%	20.0%	40.5%
Alternative Model with binary spatial weight matrix	80.8%	25.0%	58.1%	44.2%	13.3%	45.9%
Presented Model estimated with OLS	63.9%	36.4%	34.9%	8.2%	6.7%	29.7%

Source: Authors' calculations.

Details of the iterative SUR-estimation results of the price diffusion equations (3) for 12 border counties as well as the average results for the remaining counties' equations of each state are presented in Table 6. Apart from the estimates of the adjustment speeds ϕ_i, the effect of short-run deviations in the price time series γ_i, the effect of the common factor λ, and the number of time lags based on the suggestions of the Schwarz criterion k, m, and q for $\Delta p_{i,t}$, $\Delta \bar{p}_{i,t}^{\text{same}}$, and $\Delta \bar{p}_{i,t}^{\text{opp}}$, respectively, are depicted. In case of higher order lags, the table reports the parameter of the first lagged variable only.

Inspection of Table 6 reveals regional differences in land price diffusion. In most cases (8 out of 11), $\phi_{i,1}$ is larger (in absolute terms) than its counterpart $\phi_{i,2}$, i.e., border counties' prices adjust faster to a long-run equilibrium with neighbors in the same state compared to neighbors across the former border. Moreover, non-border counties show a higher level of land market integration than border counties in terms of their adjustment speed parameters. A possible explanation is that former border counties were located in the periphery of West and East

Germany. This remoteness led to a decoupling from the economic development of the rest of the country (Lehn and Bahrs, 2018; Redding and Sturm, 2008).

Short-run dynamics from the regional price diffusion equations are captured by lagged variables based on differences in the own price and neighbors' average price within the state and across the former border. The coefficient of the changes in the lagged own price is significant in almost all border county equations (10 out of 12) and has a negative sign. The spatial pattern of short-run dynamics is more heterogeneous compared to long-run estimates, but differences between the two groups of neighbors exist. The parameter estimates for changes in the lagged land price for within state neighbors $\gamma_{i,2}$ are of a greater magnitude (0.12), on average, for the former border counties compared to the parameters $\gamma_{i,3}$ for across border lagged land price differences (0.04). The overall effect of these rather heterogeneous parameters is captured by the GIRFs, which are presented below. Shocks in (real) GDP growth are included in the model as a common factor for all regional price equations. The corresponding parameters λ are statistically significant for more than 40% of the estimated equations. However, sign and size of λ estimates vary considerably among counties. A similar finding is reported by Helgers and Buyst (2016).

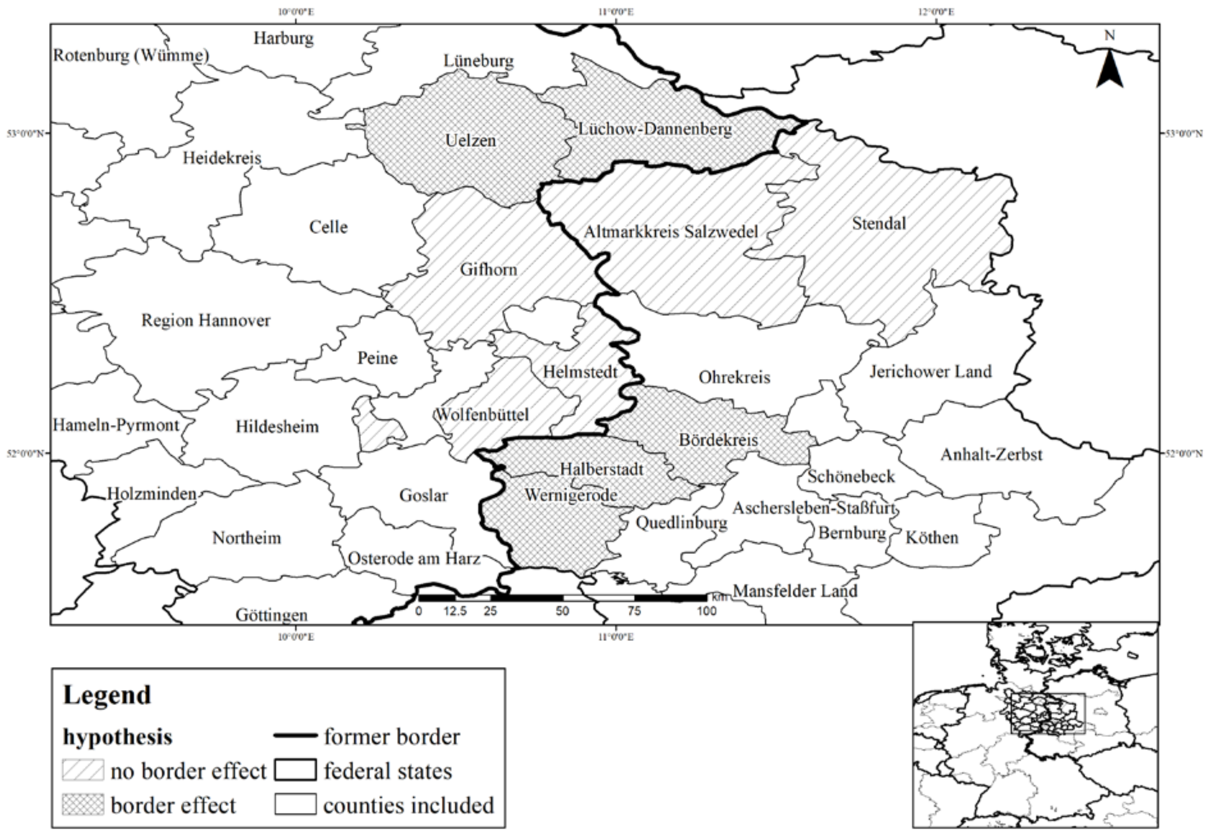
To examine the presence of a border effect more explicitly, we empirically test the two hypotheses from Section 2. This test procedure leads to the following classification: counties with a border effect (reject hypothesis 1 or fail to reject hypothesis 2), counties with no border effect (fail to reject hypothesis 1 and reject hypothesis 2), and counties that cannot be assigned to one of the former groups (fail to reject both hypothesis). The spatial distribution of these categories is displayed in Figure 4.

Table 6: Estimation results and hypotheses test statistics of border counties' price diffusion equations (3) with a binary/distance^2 spatial matrix (standard errors in brackets) and no convergence

	$\phi_{i,1}$	p-value	$\phi_{i,2}$	p-value	$\gamma_{i,1}$	p-value	$\gamma_{i,2}$	p-value	$\gamma_{i,3}$	p-value	λ	p-value	$k/m/q$	$\phi_{i,1} \geq \phi_{i,2}$	$0 \leq \phi_{i,2}$
Saxony Anhalt															
Bördekreis	-0.15	<0.01	-0.05	0.01	-0.30	<0.01	0.12	0.24	0.03	0.51	0.31	<0.01	1/1/1	-2.80	-2.65
	(-0.03)		(-0.02)		(-0.07)		(-0.10)		(-0.04)		(-0.06)				
Halberstadt	-0.25	<0.01	0.05	0.11	-0.15	0.10	-0.27	0.01	0.01	0.94	0.12	0.09	1/1/1	-4.77	1.59
	(-0.06)		(-0.03)		(-0.09)		(-0.11)		(-0.10)		(-0.07)				
Ohrekreis	-0.08	0.11	-0.08	0.11	-0.05	0.62	-0.10	0.55	-0.24	0.02	0.03	0.75	1/4/1	0.11	-1.59
	(-0.05)		(-0.06)		(-0.09)		(-0.17)		(-0.10)		(-0.10)				
Stendal	0.02	0.19	-0.09	<0.01	-0.04	0.59	0.23	<0.01	0.05	0.06	0.04	0.37	1/1/1	4.10	-4.09
	(-0.02)		(-0.02)		(-0.07)		(-0.08)		(-0.03)		(-0.05)				
Wernigerode	-0.18	0.01	0.02	0.01	-0.28	<0.01	0.33	<0.01	-0.10	0.01	0.05	0.52	2/1/1	-2.83	2.50
	(-0.07)		(-0.01)		(-0.08)		(-0.10)		(-0.04)		(-0.08)				
Altmarkreis-Salzwedel	-0.07	0.01	-0.08	<0.01	0.15	0.03	-0.51	<0.01	0.00	0.97	-0.44	<0.01	1/1/1	0.26	-5.20
	(-0.03)		(-0.02)		(-0.07)		(-0.09)		(-0.07)		(-0.13)				
Rest of Saxony-Anhalt	-0.25				-0.10		0.22				0.26				
Lower Saxony															
Gifhorn	0.03	0.66	-0.35	<0.01	-0.10	0.21	0.42	<0.01	-0.07	0.61	0.54	<0.01	1/1/1	3.86	-4.96
	(-0.07)		(-0.07)		(-0.08)		(-0.15)		(-0.14)		(-0.11)				
Goslar	-0.13	0.78	-0.20	0.67	-0.21	0.02	0.82	0.02	-0.42	0.07	0.05	0.80	1/1/1	0.11	-0.44
	(-0.44)		(-0.44)		(-0.09)		(-0.34)		(-0.23)		(-0.17)				
Helmstedt	-0.03	0.78	-0.45	<0.01	-0.20	0.03	0.10	0.46	-0.06	0.71	-0.22	0.01	1/1/4	2.58	-3.49
	(-0.10)		(-0.13)		(-0.09)		(-0.13)		(-0.16)		(-0.09)				
Wolfenbüttel	0.09	0.15	-0.33	<0.01	-0.06	0.32	-0.20	<0.01	-0.03	0.55	-0.01	0.85	1/1/1	4.26	-4.43
	(-0.06)		(-0.07)		(-0.06)		(-0.06)		(-0.05)		(-0.07)				
Lüchow-Dannenberg	-0.46	<0.01	-0.14	0.04	-0.57	<0.01	0.25	<0.01	-0.17	0.32	0.51	<0.01	1/1/1	-3.44	-2.03
	(-0.06)		(-0.07)		(-0.07)		(-0.09)		(-0.17)		(-0.13)				
Uelzen	-0.43	<0.01			-0.32	<0.01	0.15	0.19	0.48	<0.01	0.04	0.77	1/1/1		
	(-0.09)				(-0.08)		(-0.11)		(-0.12)		(-0.13)				
Rest of Lower Saxony	-0.37				-0.31		0.21				0.07				

Source: Authors' calculation. Note: The last two columns provide the tests statistics for the testing of the two hypotheses (H_0: $\boldsymbol{\phi_{i,1}} \geq \boldsymbol{\phi_{i,2}}$ & H_0: $\mathbf{0} \leq \boldsymbol{\phi_{i,2}}$), the critical value for alpha = 0.05 is -1.64.

Figure 4: County groups based on iterative SUR estimation results and hypotheses testing



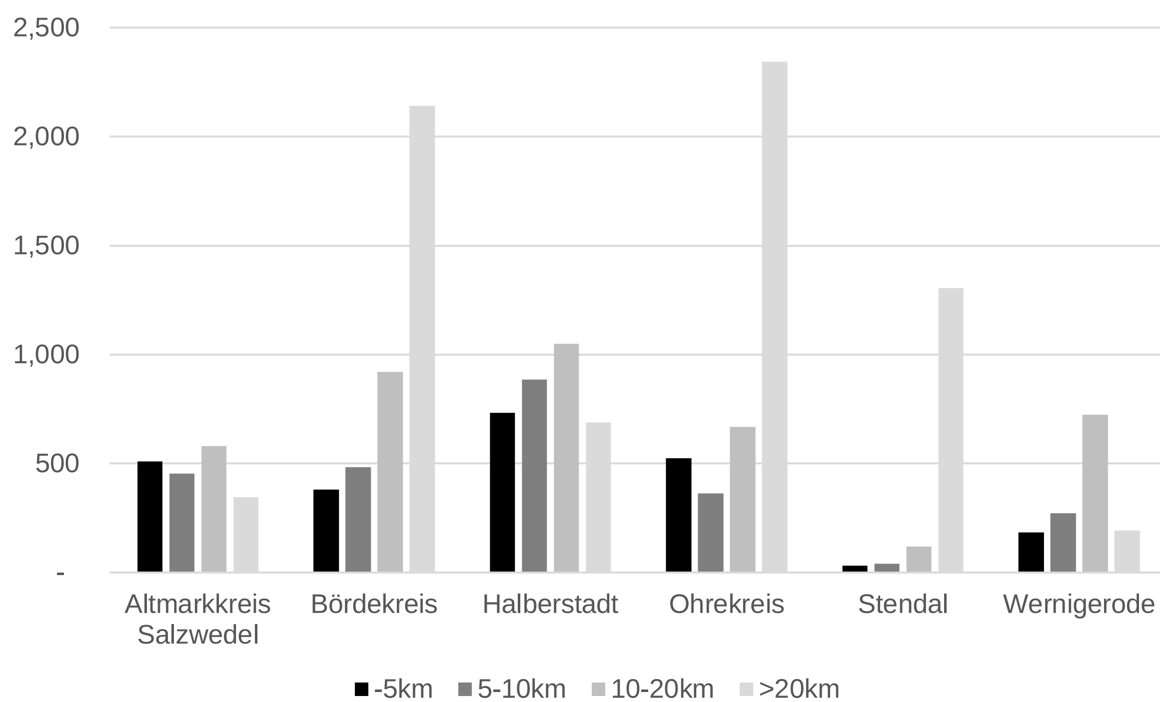
Source: Authors' presentation.

Land prices in counties that belong to the 'border effect' group do not have a long-run relationship with land prices from neighboring counties across the former border or they react more slowly to deviations for the cointegration relationship compared to within state neighbors. This group comprises Bördekreis, Halberstadt, Lüchow-Dannenberg, Uelzen, and Wernigerode. Most of these counties are located in Saxony-Anhalt and form a regional cluster at the southern intersection of both states. This finding may be traced back to the relative low share of BVVG administrated transactions in these counties, which, in turn, may lead to larger information asymmetries and higher transaction costs for West German buyers (see Table 1). Furthermore, in the East German counties of this group, a high share of land transactions took place more than 10 kilometers away from the former border (see Figure 5). It is unlikely that these land plots were attractive to farmers from Lower Saxony since it is unprofitable to operate them due to high transportation costs.

Another peculiarity of this group is that Lüchow-Dannenberg and Uelzen are characterized by high levels of potato production, while counties across the former border focus on wheat production.

The hypothesis of a border effect is rejected for five counties located in the northern part of Saxony-Anhalt (Altmarkkreis-Salzwedel, Stendal) and in Lower Saxony (Gifhorn, Helmstedt, and Wolfenbüttel). Counties in this group show a relatively high share of BVVG administrated transactions and transactions are located close to the border, lowering transaction and economic costs for farmers operating across the border (see Table 1 and Figure 5). Only for two counties, Goslar and Ohrekreis, neither hypothesis can be rejected.

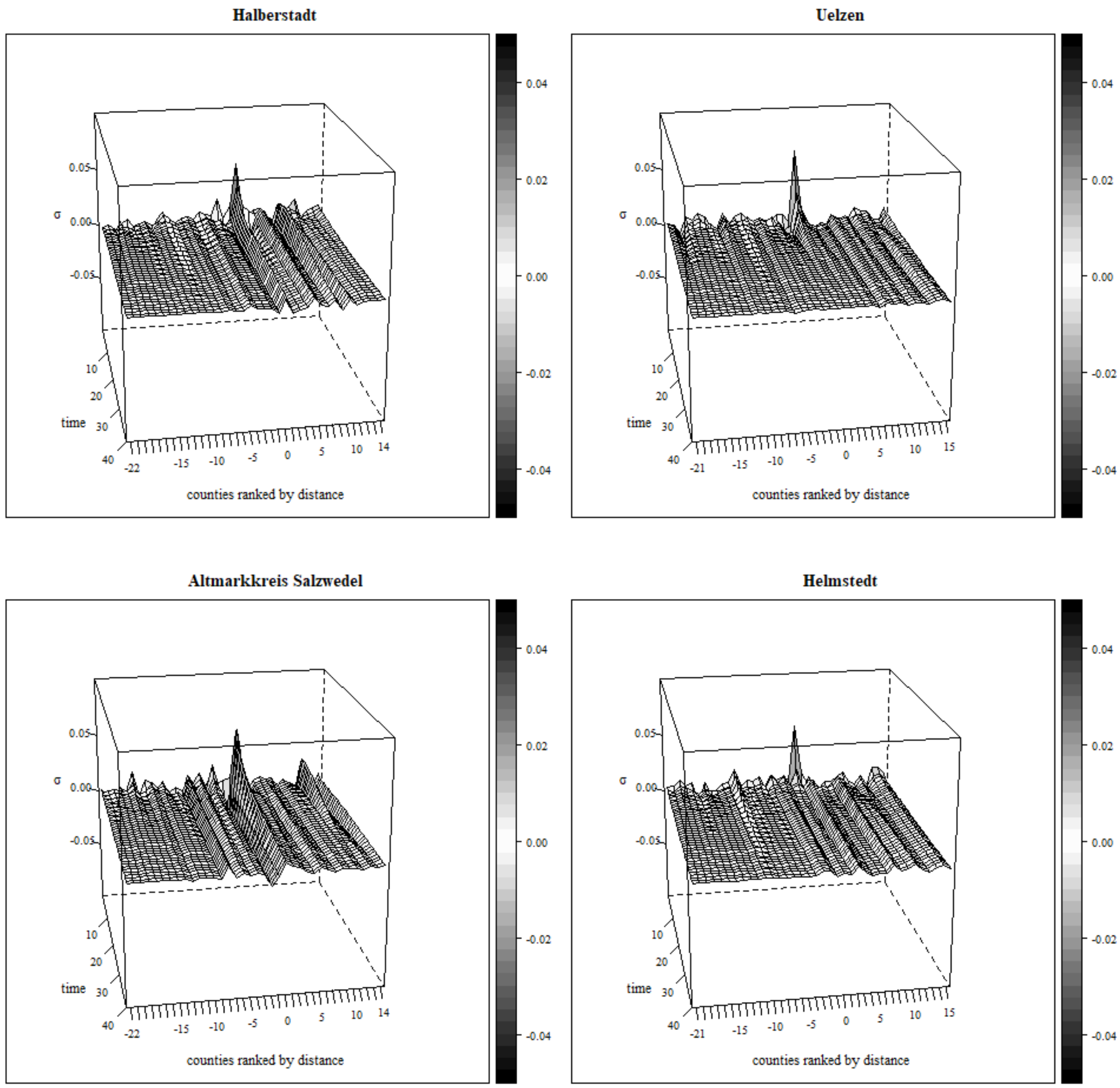
Figure 5: Number of transactions in border counties in Saxony-Anhalt from 1994 to 2016 sorted by distance from the former border



Source: Authors' presentation.

Figure 6 displays the reaction of a shock (one standard deviation) in county i across the study region over ten years. The origin of the price shock in county i shows a value of unity at $t = 1$. The other counties are ordered by distance from the origin of the shock county. Counties to the left (with a negative value) are located in Lower Saxony (the Western state) while counties to the right (with a positive value) are located in Saxony-Anhalt (the Eastern state).

Figure 6: GIRFs for selected border counties with shocks of one standard deviation σ



Source: Authors' calculations.0

The graphs at the top of Figure 6 show shocks originating in counties in which land prices are affected by the former border, Halberstadt (left) and Uelzen (right). The price diffusion model revealed that Halberstadt's land price interacts only with neighbors' prices in the same state and not with neighbors across border. Hence, we see that a shock to Halberstadt causes a permanent positive increase in its own price and prices for most of its neighboring counties in Saxony-Anhalt, while there is only little response in Lower Saxony caused by the short-run dynamics of the VECM.

A shock to the land price in Uelzen causes only a temporary deviation from the pre-shock level in Lower Saxony and is completely absorbed within the considered time horizon. In contrast, prices across the border do not return to their pre-shock level. The two graphs at the bottom of Figure 6 show cases of the ‘no border group’ on both sides of the former border (Altmarkkreis-Salzwedel and Helmstedt). In both cases, the prices do not return to their pre-shock level. These permanent increases are transmitted through the long-run spatial market integration to neighbors’ prices on both sides of the border.

The GIRFs confirm the results of the price diffusion model with a border effect (3). The former German border still affects land price diffusion in Germany, not just in counties’ land markets located directly at the former border. While most counties in the southern part of the study region are only integrated with within state land markets, a number of counties, particularly those in the northern study region with similar production structures, have a cointegration relationship with across neighbors’ prices and are sometimes separated from their own states’ overall land price diffusion process.

5 Conclusions

This article examines whether there is a diffusion of agricultural land prices across the former border separating East and West Germany. The research question was motivated by concerns among policymakers in several EU countries that in unregulated land markets, the activities of foreign investors may cause high prices to spill over into neighboring countries that initially have lower land price levels. On the other hand, the European Commission recently appealed to EU Member States to adjust their land market regulations according to European Law, which requires the free movement of capital within the EU (European Commission, 2016). To shed some light on this controversial discussion, we consider the German reunification as a case study on land price development in two different states after the border was removed. We apply a land price diffusion model with an error correction specification that estimates to what extent agricultural land markets are spatially integrated. A novel feature of our model is its ability to distinguish price diffusion within states and across state borders. We find that local agricultural land markets in Germany are spatially integrated, i.e., prices in one county are linked with prices in neighboring counties by a long-run equilibrium relationship. Spatial market integration, however, does not hold among all counties in our study area. In line with earlier studies, there is evidence for convergence clubs, which differ in their land price dynamics.

With regard to our main research question, we find evidence for a persistent border effect given that the fraction of spatially integrated counties is larger within states than across the former border. Moreover, for many counties along the former border, we observe non-significant error correction terms for prices of neighboring counties across the former border. It is noteworthy that the former border does not act as a strict barrier for price alignment between former East and West Germany. In fact, it is permeable at several locations. In some cases, it even happens that counties share similar land price dynamics with neighbors across the border, but not with neighbors within the same state. By virtue of its reduced form character, our model cannot provide a clear answer on what is behind this border effect and why it appears to be local. We conjecture that differences in farm size structures, long-lasting rental contracts, local market power, non-transparency of sellable land plots and information asymmetries regarding the property status of land may explain non-integration and stickiness of land prices in parts of East and West Germany. Providing empirical evidence for the role of these economic factors is a promising direction for further research.

Our results are not only interesting from a historical perspective, but they are also relevant for a better understanding of the functioning of agricultural markets. From a policy perspective, it is striking to realize that even 25 years after German reunification, pronounced land price differences persist. Even if regional land markets across the former border are integrated, land prices react rather slowly and only in relative terms, i.e., land prices do not reach the same level. It is quite likely that price diffusion through existing borders within the EU would take even more time given language barriers, different administrative procedures for land acquisitions, different tax systems, and more pronounced information asymmetries between domestic and foreign market participants. Therefore, proposals for stricter land market regulations aiming at the protection of local farmers and capping of land prices through the discrimination of foreign buyers appear questionable.

References

Abbott, A., Vita, G. de, 2013. Testing for long-run convergence across regional house prices in the UK: A pairwise approach. Applied Economics, 45(10), 1227–1238.

Beenstock, M., Felsenstein, D., 2010. Spatial error correction and cointegration in nonstationary panel data: Regional house prices in Israel. Journal of Geographical Systems, 12(2), 189–206.

Bundesministerium für Wirtschaft und Energie (BMWi), 2017. Jahresbericht der Bundesregierung zum Stand der Deutschen Einheit 2017. Accessed June 2018, available at https://www.bmwi.de/Redaktion/DE/Publikationen/Neue-Laender/jahresbericht-zum-stand-der-deutschen-einheit-2017.pdf?__blob=publicationFile&v=27.

Bund-Länder-Arbeitsgruppe „Bodenmarktpolitik", 2015. Landwirtschaftliche Bodenmarktpolitik: Allgemeine Situation und Handlungsoptionen. Accessed June 2018, available at https://www.bmel.de/SharedDocs/Downloads/Landwirtschaft/LaendlicheRaeume/Bodenmarkt-Abschlussbericht-Bund-Laender-Arbeitsgruppe.pdf?__blob=publicationFile.

Burnham, K. P., Anderson, D. R., 2016. Multimodel Inference: Understanding AIC and BIC in Model Selection. Sociological Methods & Research, 33(2), 261–304.

Carmona, J., Roses, J. R., 2012. Land markets and agrarian backwardness (Spain, 1904-1934). European Review of Economic History, 16(1), 74–96.

European Commission, 2016. Agricultural Land Prices and Rents data for the European Unio. Accessed June 2018, available at http://ec.europa.eu/eurostat/cache/metadata/en/apri_lpr_esms.htm.

Gong, Y., Hu, J., Boelhouwen, P.J., 2016: Spatial interrelations of Chinese housing markets: Spatial causality, convergence and diffusion. Regional Science and Urban Economics, 59, 103–117.

Greene, W. H., 2002. Econometric analysis. Prentice Hall, Upper Saddle River, NJ.

Helgers, R., Buyst, E., 2015. Spatial and Temporal Diffusion of Housing Prices in the Presence of a Linguistic Border: Evidence from Belgium. Spatial Economic Analysis, 11(1), 92–122.

Hiebert, P., Roma, M., 2010. Relative House Price Dynamics Across Euro Area and US Cities: Convergence or Divergence. ECB Working Paper 1206.

Holly, S., Hashem Pesaran, M., Yamagata, T., 2011. The spatial and temporal diffusion of house prices in the UK. Journal of Urban Economics, 69(1), 2–23.

Jochimsen, H., 2010. 20 Jahre Grüner Aufbau Ost. Berichte über Landwirtschaft, 88(2), 203–246.

Johansen, S., 1991. Estimation and Hypothesis Testing of Cointegration Vectors in Gaussian Vector Autoregressive Models. Econometrica, 59(6), 1551–1580.

Kay, S., Peuch, J., and Franco, J., 2015. Extent of Farmland Grabbing in the EU. Study on behalf of the European Parliament's Committee on Agriculture and Development PE 540.369.

Koester, U., 2000. Market Integration: How it Works, in A. Burrell and A. J. Oskam, eds. Agricultural policy and enlargement of the European Union. Wageningen Pers, Wageningen, 21–34.

Lazíková, J., Bandlerová, A., 2015. New Rules for Acquisition of Agricultural Land – Case of Slovakia. EU agrarian Law, 4(1).

Lehn, F., Bahrs, E., 2018. Analysis of factors influencing standard farmland values with regard to stronger interventions in the German farmland market. Land Use Policy, 73, 138–146.

Meen, G., 2007. Spatial aggregation, spatial dependence and predictability in the UK housing market. Housing Studies, 11(3), 345–372.

Pesaran, H.H., Shin, Y., 1998. Generalized impulse response analysis in linear multivariate models. Economics Letters, 58(1), 17–29.

Redding, S. J., Sturm, D. M., 2008. The Costs of Remoteness: Evidence from German Division and Reunification. American Economic Review, 98(5), 1766–1797.

Swinnen, J., van Herck, K., Vranken, L., 2016. The Diversity of Land Markets and Regulations in Europe, and (some of) its Causes. The Journal of Development Studies, 52(2), 186–205.

The Government Office for Science, 2010. Land Use Futures: Making the most of land in the 21st century. Accessed June 2018, available at https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/288843/10-631-land-use-futures.pdf.

Waights, S., 2018. Does the law of one price hold for hedonic prices? Urban Studies, 86(5).

Yang, X., Odening, M., Ritter, M., 2019. The Spatial and Temporal Diffusion of Agricultural Land Prices. Land Economics, 95(1), 108–123.

Yang, X., Ritter, M., Odening, M., 2017. Testing for regional convergence of agricultural land prices. Land Use Policy, 64, 64–75.