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IMPRESSUM

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http://www.diw.de

ISSN electronic edition 1619-4535

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Entrepreneurial spillovers over space and time*

Frank M. Fossen† Thorsten Martin‡

November 3, 2016

Abstract:

Entrepreneurship is a local and dynamic phenomenon. We jointly investigate spatial spillovers and time persistence of regional new business formation. Using panel data from all 402 German counties for 1996-2011, we estimate dynamic spatial panel models of business creation in the high-tech and manufacturing industries. We consider regions of different sizes and systematically search for the most suitable spatial weighting matrices. We find substantial spatial spillovers as well as time persistence of start-up activity, especially in the high-tech industry. This indicates that entrepreneurship is deeply rooted in regions and underlines the importance of local entrepreneurship culture for new business formation.

JEL classification: L26, C23, R12, O30.

Keywords: Entrepreneurship, new business formation, spatial spillovers, path dependency, persistence, spatial panel.

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* **Acknowledgement**: We thank Ulf Slopek and participants at the 2015 World Congress of the Spatial Econometrics Association in Miami, FL, for valuable comments.

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1 Introduction

Entrepreneurship is a local and dynamic phenomenon. Regarding locality, entrepreneurship tends to prosper in certain regions, the Silicon Valley in the USA or the Rhine-Main-Neckar region in southwest Germany being famous examples. Researchers recognize the regional embeddedness of entrepreneurship, and policymakers are interested in developing locally tailored policies to stimulate entrepreneurship in regions (see Fritsch and Storey, 2014, for a review of the literature). Despite the high awareness of the importance of the regional context for entrepreneurship, very little is known about spatial spillovers of entrepreneurship, or more specifically, start-up activity, into neighboring regions. Klotz (2004) and Audretsch and Keilbach (2007) provide initial evidence for the significance of such spillovers, but based on cross-sectional data without consideration of the time dimension. Regarding the time dynamics, entrepreneurship capital, understood as the ability of regions to generate new business formation, seems to be very persistent within certain regions over time (e.g., Fritsch and Mueller, 2007; Andersson and Koster, 2011). Fritsch and Wyrwich (2014; forthcoming) report that regional differences in the levels of self-employment and new business formation in Germany persisted from 1925 to 2005 despite major disruptions such as World War II and forty years of a socialist regime in East Germany.

In this paper, we are the first to investigate the spatial and time dynamics of entrepreneurship jointly in a consistent spatial econometric framework. We analyze how start-up activity spreads over to neighboring regions and its persistency over time. We use the Mannheim Enterprise Panel for the years 1996-2011 to measure firm births and consider complete sets of German regions of different sizes: all 402 German counties (NUTS 3 level), 258 labor market regions, which are defined as commuting zones, and 96 larger spatial planning regions. Rosenthal and Strange (2003) emphasize the importance of considering the geographic scope of spillovers for firm births. We econometrically eliminate unobserved time and regional unit fixed effects, which would otherwise be likely to bias the estimations. This allows us to identify spatial interactions of *changes* in regional start-up activity as well as path dependency in start-up rates. We avoid an arbitrary choice of the spatial weighting matrix and instead apply a systematic grid search to find the parameterized matrix that best reflects regional interactions of start-up activity (cf. Gibbons and Overman, 2012; Elhorst and Vega, 2015).

Our data allow identifying firm formation in the high-tech industry (in the manufacturing and services sectors) and in the manufacturing sector (including low-tech and high-tech businesses). The high-tech industry is of particular importance for innovation and economic growth (cf. Audretsch and Keilbach, 2004; Audretsch et al., 2006; Shane, 2009). In addition, the manufacturing sector in Germany is of high interest because Germany is well-known for its small and medium-sized specialized manufacturing businesses that are often world leaders in their global niche markets, sometimes called "hidden champions" (Simon, 2009).

The ability of regions to generate a high start-up rate of new businesses is sometimes termed entrepreneurship capital (e.g., Audretsch et al., 2008). Besides regional economic opportunities, the industry structure and human capital relevant for entrepreneurship, entrepreneurship capital includes formal and informal local institutions favorable toward entrepreneurship.[1] The strong time persistency of entrepreneurship capital suggests that regional entrepreneurship culture, which changes very slowly, is an important part of it. Entrepreneurship culture describes intangible components of entrepreneurship capital, such as regional cultural norms and values that shape attitudes toward entrepreneurship (e.g., Fritsch and Wyrwich, forthcoming), personality traits (Sutter, 2008; Caliendo et al., 2014; Stuetzer et al., 2016) and creativity (Lee et al., 2004) prevalent in the region. Entrepreneurship culture is considered the most enduring component of entrepreneurship capital, because it may persist

[1] For factors explaining regional entrepreneurship see, e.g., Glaeser et al. (2010), Ghani et al. (2014), Glaeser et al. (2015), and Minniti (2005) on the role of the social environment.

even if formal institutions and business opportunities are disrupted (Fritsch and Wyrwich, 2014).

Entrepreneurship capital manifests itself in the observed regional start-up rate. Thus, if we econometrically find spatial interaction in start-up rates, this indicates that entrepreneurship capital spills over to neighboring regions and suggests positive external effects. A time persistency in start-up rates confirms that entrepreneurship capital can build up and remain productive in a region for a long time, which is at the center of the concept of capital.

A better understanding of the time and spatial dynamics of entrepreneurship capital is important because the literature shows that entrepreneurship capital matters for regional growth. Audretsch and Keilbach (2004) and Pijnenburg and Kholodilin (2014) assess the returns to entrepreneurship capital by estimating production functions based on regional data for Germany. They operationalize entrepreneurship capital as start-up rates, as we do in this paper. Audretsch and Keilbach (2004) report that entrepreneurship capital increases regions' output in terms of GDP. Pijnenburg and Kholodilin (2014) focus on knowledge intensive industries and estimate a production function in a spatial econometric model, taking into account the effect of neighboring regions on local output. Their results suggest that not only more entrepreneurial regions, but also regions with more entrepreneurial neighbors perform better, although the spatial spillover effects are statistically insignificant in most of their specifications. Acs et al. (2009b) estimate spatial panel models of regional personal income growth and report that new high-tech venture creation has a positive influence. Carree and Thurik (2003) conclude from their literature review and own analysis that entrepreneurship has a positive impact on growth.

One way how start-up activity may spill over inter-temporally and inter-regionally is via spillovers of knowledge created in start-up companies. Thus, our analysis is also related to the literature on the knowledge spillover theory of entrepreneurship (Audretsch et al., 2006; Acs et al., 2009a) and extends the perspective by not only considering spillovers over time, but also over space. How much are spillovers bound to certain regions, and how far do relevant networks spread out geographically? Even in a globalized world where physical distances partially lose importance due to electronic communication and virtual work spaces, local proximity and face-to-face interactions still seem to be crucial for spillovers of tacit knowledge and entrepreneurship (cf. Leamer and Storper, 2001; Kaufmann et al., 2003; Scott, 2006). However, little is known about the critical distances for entrepreneurial interaction in space and time. This paper contributes to closing this knowledge gap. Based on our estimated models, we simulate impulse response functions showing that most of the response to a temporary and local impulse in the high-tech start-up rate takes place within a distance of about 200km from the place and a period of about two years after the time of the shock. Intertemporal and spatial spillovers are stronger in the high-tech than in the general manufacturing industry, which points to the importance of knowledge spillovers.

The remainder of this paper is structured as follows. Section 2 describes the panel data of German regions we use. In section 3, we discuss the dynamic spatial econometric model we estimate. The econometric results and impulse response simulations are presented in Section 4, and Section 5 concludes the analysis.

2 Spatial panel data

For our analysis we use panel data of three sets of German regions that differ in the sizes of the geographical units. Each set covers the complete area of Germany for the period of 1996-2011. The set with the smallest regional units, which we use in our main estimations, includes all 402 German counties. These are administrative units that cover a city or several municipalities and correspond to the Geocode standard NUTS 3 of the European Union.[2] The second set is comprised of all 258 German labor market regions. These combine several counties and are defined in a way that maximizes commuting within and minimizes commuting between the regions (cf. Kosfeld and Werner, 2012), so they may also be called commuting zones. The third set covers Germany's 96 spatial planning regions. These again combine several counties and are generally used for statistical reporting in Germany. Labor market regions and spatial planning regions do not have administrative functions.

For the three sets of regions, we obtain annual characteristics such as the regional gross value added and demographics (population size, age structure, and employees' education structure) from the Regional Statistical Data Catalogue for our 16-years period.[3] In supplementary estimations, we use the shorter period of 2001-2011, which allows us to include the industry structure, the unemployment rate and the average wage in the region as additional control variables.

We obtain annual regional start-up rates for our regions and time period from the Mannheim Enterprise Panel (MUP by its German initials) provided by the Centre for European Economic Research (ZEW) in Mannheim (Bersch et al., 2014). The MUP is constructed from data provided by Creditreform, Germany's largest credit rating agency. Therefore, it covers companies with sufficient economic activity to be noticed and registered by Creditreform and mostly excludes micro and sideline businesses (Bersch et al., 2014) or letterbox companies. The start-up rates we measure using the MUP therefore reflect substantial entrepreneurship better than administrative business registration rates (Fritsch et al., 2002). The overall start-up rate based on the MUP is smaller than the official firm

[2] We take into account county reforms, in particular in Saxony-Anhalt in 2007, Saxony in 2008, and Mecklenburg-West Pomerania in 2011. To construct a consistent spatial panel, we use the final 2011 map of counties in all observation years. To do so, we sum up the variables of counties that are amalgamated in the observation years before amalgamation, and we split up variables according to the population size in the observation years before counties separate (which happened very rarely).

[3] The Regional Statistical Data Catalogue is provided by the Federal Statistical Office and the statistical offices of the Federal States of Germany.

registration rate for the reasons mentioned above, but the time trends are similar (Fossen and König, 2015). Our start-up data is very complete and accurate because we focus on high-tech and manufacturing businesses that usually have non-negligible initial credit requirements and therefore quickly enter the database of Creditreform (cf. Audretsch and Keilbach, 2004, who use similar data).[4]

Using the MUP, we measure the start-up rate as the number of newly founded businesses in a given region and year per 10,000 inhabitants at working age (18-65 years of age). Similarly, Audretsch and Keilbach (2004; 2007) and Pijnenburg and Kholodilin (2014) also use the number of new firms relative to the region's population as their measure of entrepreneurship capital. We distinguish between start-ups in the high-tech and manufacturing industries. The high-tech industry is comprised of R&D-intensive manufacturing and technology-oriented services (including the software industry). The high-tech and manufacturing industries partially overlap because R&D-intensive manufacturing belongs to both sectors. The manufacturing industry also includes low-tech manufacturing businesses.

Table 1 provides descriptive statistics of our county data, and Table A 1 in Appendix A shows mean characteristics of the labor market regions and spatial planning regions. During our period of analysis, the annual start-up rate in the high-tech industry was 2.9 per 10,000 working-age inhabitants in the average county and year. The respective rate in the manufacturing sector was 2.2. The average population is 204,000 in counties, 319,000 in labor market regions and 856,000 in spatial planning regions. About 7% of the employees have a university degree, ranging from 1.95% to 27.14% in the most extreme counties.

[4] We abstain from analyzing the start-up rate over all industries because businesses in the low-tech services industry such as retail stores or catering firms often enter the MUP with a time lag, which would result in a less precise analysis.

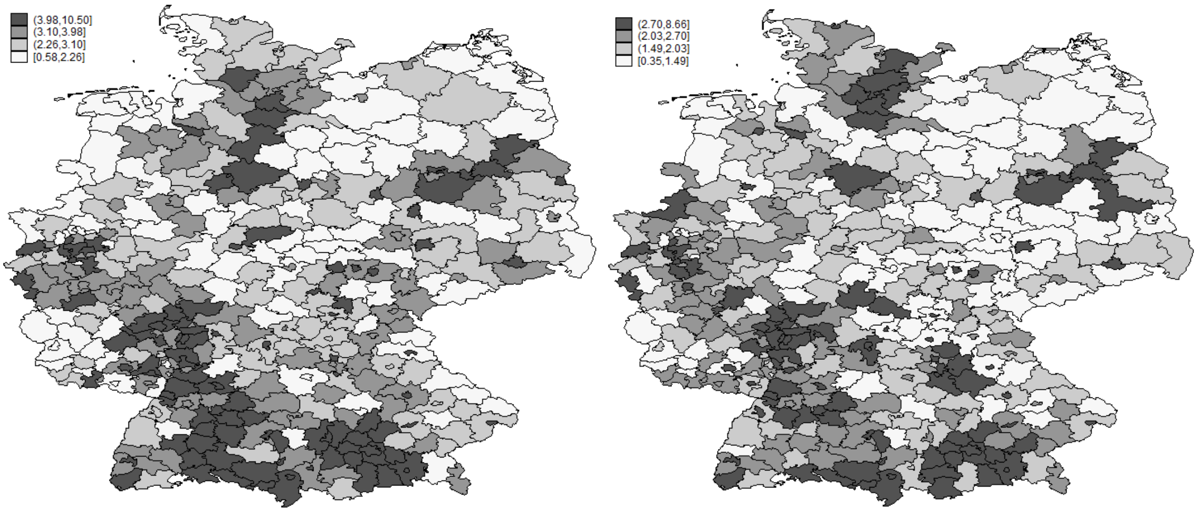
Table 1: Descriptive statistics for Germany's counties

	Mean	Std dev.	Min.	Max.
Period 1996-2011:				
Annual start-ups in high-tech per 10,000 inhabitants at working age	2.91	1.34	0.22	13.43
Annual start-ups in manufacturing per 10,000 inh. at working age	2.22	0.85	0.00	7.53
Population in 10,000	20.44	22.81	3.38	350.19
Share population at working age in total population (in %)	63.23	2.12	57.35	70.81
Share employees without apprenticeship (in %)	17.00	5.03	3.31	35.33
Share employees with apprenticeship (in %)	64.03	5.44	26.21	80.55
Share employees with university degree (in %)	7.20	3.61	1.95	27.14
Gross value added in real thousand euro per employee	63.66	15.26	23.31	140.50
Period 2001-2011:				
Share workers in the manufacturing sector (in %)	28.78	8.93	6.17	59.98
Share workers in the services sector (in %)	68.71	9.67	35.48	93.59
Share unemployed in the working age population (in %)	7.21	3.56	1.22	20.32
Average wage per employee in 1,000 real euro	32.21	5.14	10.31	49.07

Notes: The descriptive statistics are based on all 402 counties in Germany (NUTS 3 level) and not weighted. Thus, we have 6432 annual observations in the period 1996-2011 and 4422 in 2001-2011. Working age refers to ages 18-65. Real euro are in prices of 2010. Concerning the education structure of the employees, the omitted base category is the share of employees without information on education. Concerning the industry structure, the omitted base category is the agricultural and mining sector.
Sources: Own calculations based on regional data from the Federal Statistical Office and the Mannheim Enterprise Panel, 1996-2011.

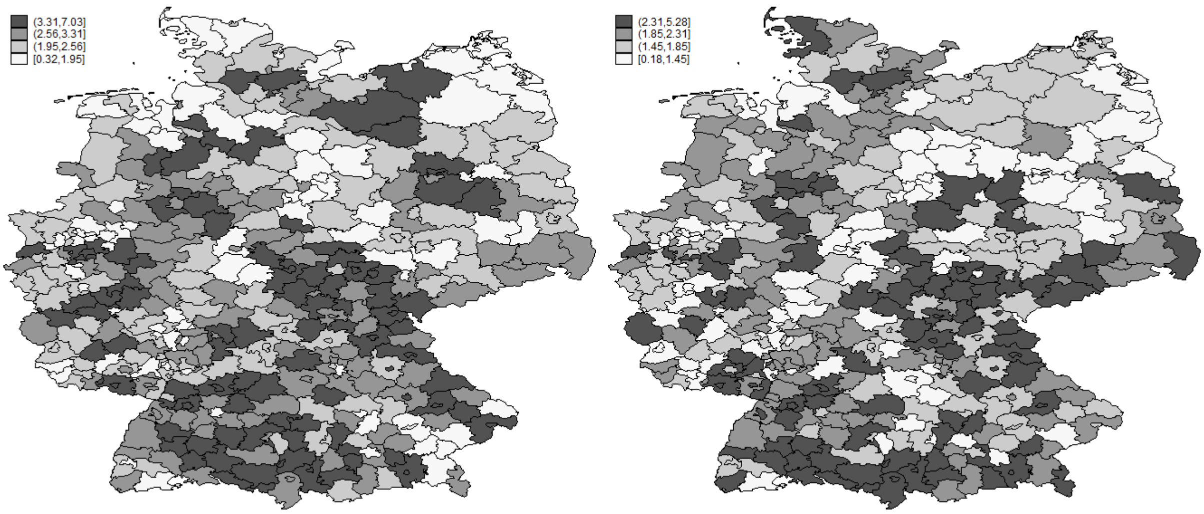
Figures 1 and 2 show the start-up rates in the high-tech industry and the manufacturing industry, respectively, in the first and last years covered by our data, 1996 (left) and 2011 (right). Spatial clustering is clearly visible, perhaps even more so in the high-tech industry than in the manufacturing industry. In the high-tech sector (Figure 1), the largest cluster is in the southwest in the greater region Rhine-Main-Neckar spreading parts of the Federal States of Baden-Wuerttemberg, Hesse and Rhineland-Palatinate, and other clusters are found around the cities Munich, Hamburg-Hannover and Berlin and in the region Rhine-Rhur-Wupper within North-Rhine Westfalia. Interestingly, these clusters largely persist over the time span of 15 years, although some clusters become weaker and others emerge, notably around Nuremberg in Bavaria. In the manufacturing sector (Figure 2), spatial clustering as well as time persistency in start-up rates can also be observed. The clusters are different from the high-tech clusters to a large extent, with an important cluster spreading parts of Thuringia and northern Bavaria. Between 1996 and 2011, this cluster spreads further east into Saxony, suggesting a spatial spillover.[5]

Figure 1: Start-up rates in the *high-tech* industry, German counties 1996 and 2011



Notes: Start-ups in the high-tech industry per 10,000 inhabitants in 1996 (left panel) and 2011 (right panel). The regions are counties (NUTS 3 level). Note the different scales: Start-up rates were generally higher in 1996 than in 2011.
Source: Own illustration based on the Mannheim Enterprise Panel, 1996 and 2011.

Figure 2: Start-up rates in the *manufacturing* industry, German counties 1996 and 2011



Notes: Start-ups in the manufacturing industry per 10,000 inhabitants in 1996 (left panel) and 2011 (right panel). The regions are counties (NUTS 3 level).
Source: Own illustration based on the Mannheim Enterprise Panel, 1996 and 2011.

[5] Figure B 1 in Appendix B depicts the development of spatial autocorrelation in start-up rates in German counties from 1996-2011 as measured by Moran's I, using a binary contiguity matrix as a starting point (Elhorst, 2010a). Spatial autocorrelation is larger in the high-tech industry than in the manufacturing industry, although the difference vanishes at the end of the observation period.

In sum, the figures strongly suggests the importance of both, spatial clustering and time persistence. The limitation of the extant literature is that neither cross-sectional spatial econometrics (Klotz, 2004; Audretsch and Keilbach, 2007) nor dynamic panel econometrics without consideration of spatial spillovers (Andersson and Koster, 2011) can fully capture the dynamics of firm formation. Therefore, this paper provides the first analysis of start-up activity jointly taking into account the spatial and the time dimension in a consistent dynamic spatial panel estimation.[6]

Which size of regional units is most appropriate to analyze the spatial distribution of start-up rates? Figures B2 and B3 in Appendix B show start-up rates in the high-tech and manufacturing industries in 2011, based on labor market regions and spatial planning regions, respectively. The comparison with the maps based on counties (Figures 1 and 2) suggests that the larger regions hide important heterogeneity, for example, between cities and surrounding counties, which sometimes have very different start-up rates. Therefore, we base our main analysis on county data and provide estimations for the larger regions for comparison.

3 Dynamic spatial panel model

In order to investigate intertemporal and spatial spillovers of regional start-up activity, we estimate dynamic Spatial Durbin Models:[7]

$$y_{it} = \tau y_{i,t-1} + \rho \sum_{j=1}^{N} w_{ij} y_{jt} + \boldsymbol{x}_{it}\boldsymbol{\beta} + \sum_{j=1}^{N} w_{ij}\boldsymbol{x}_{jt}\boldsymbol{\theta} + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

The endogenous variable y_{it} is the log start-up rate in region i and year t, or more precisely, the log of the number of newly founded businesses per 10,000 inhabitants (see Section 2). We include the time lag $y_{i,t-1}$ with the intertemporal autoregressive coefficient τ, which captures

[6] Fritsch and Mueller (2007) estimate time dynamics using panel data of German spatial planning regions and also include the mean value of the residuals in the adjacent regions as a control variable, but without further discussion of the spatial dimension.

[7] Because of its generality and flexibility, the Spatial Durbin Model produces unbiased coefficient estimates for a broad range of data-generation processes (Elhorst, 2010a).

path dependency of start-up activity within the geographical region. Potential spillovers from other regions are modeled by including spatial lags $\sum_{j=1}^{N} w_{ij} y_{jt}$, where N is the total number of regions in Germany and w_{it} is the spatial weight. It represents element (i,j) of a nonnegative $N \times N$ spatial weighting matrix W, which defines the neighboring regions. We discuss the precise definition of W further below. The spatial autoregressive coefficient ρ to be estimated indicates the strength of spatial spillovers of regional start-up activity. Hence, τ represents spillovers of start-up activity from within the geographical region over time, whereas ρ represents spillovers from neighboring regions. The $1 \times K$ vector $\boldsymbol{x}_{it}$ includes the control variables and the $K \times 1$ vectors $\boldsymbol{\beta}$ and $\boldsymbol{\theta}$ the coefficients that reflect the influences of these variables on the same region and on the neighboring regions of the focal region. The model includes unobserved region fixed effects μ_i and year fixed effects δ_t, and ε_{it} is the remaining error term.

As control variables in $\boldsymbol{x}$, in the main estimations spanning 1996-2011, we use regional real gross value added per employee, the population size, and variables describing the age structure of the population and the education structure of the employees. In additional estimations using the period of 2001-2011, when more variables are available, we also include the industry structure, unemployment rate, and the average wage per employee in the region.[8] All variables enter the model in logarithmic form, so the coefficients reflect elasticities; for comparison we also provide results for level equations. Because we account for region fixed effects, we control any time-invariant factors such as geographical conditions, climate, natural resources, and long-term infrastructure. Since the region fixed effect also captures the area size of a region, by including the population size we also account for the population density. By additionally including the spatial lags of all control variables in the model, we are able to separate influences of neighboring regions on a focal region's start-up rate through the

[8] See Table 1 for a more detailed description of the variables.

neighbors' characteristics such as their population size from direct spillovers of neighboring start-up activity.

We estimate the model using the Quasi Maximum Likelihood (QML) estimator for dynamic spatial panels developed by Lee and Yu (2010a; 2010b).[9] Simply including region and time dummy variables would lead to the incidental parameter problem and inconsistent estimates. Therefore, the estimator we use eliminates the region and time fixed effects by a double data transformation procedure and corrects the bias that would otherwise occur.[10] For our purposes, we adapt an implementation in Matlab provided by Elhorst (2012).[11]

Regions are assigned as neighbors ex-ante via the definition of a spatial weighting matrix W. Usually regions that are at a closer geographical distance to a given region receive a higher weight, indicating that the regions are neighbors. As Gibbons and Overman (2012) point out, the consistency of the QML estimator rests on the assumption that the true connectivity matrix W is known. They criticize that most applied papers using QML only examine a single matrix or an arbitrary set of pre-defined matrices. To take this remark into account, we follow the idea of Elhorst and Vega (2015) and apply a systematic grid-search procedure to find the weighting matrix that best describes the data.

The literature outlined in the introduction predicts that geographically closer regions will have a stronger influence on a region in terms of start-up activity than more distant regions, but theory does not give guidance on how quickly the influence diminishes when distance increases. This is an empirical question that we approach in this paper. Therefore, we use an inverse distance matrix, where all regions are assigned as neighbors, but closer neighbors receive a larger weight. We parameterize the spatial weighting matrix to allow for a flexible

[9] Unlike the estimator discussed in Lee and Yu (2010b), we do not include an additional spatial lag of the time lag of the dependent variable. Our data do not allow a precise separate identification of the spatial lag, the time lag and the spatial time lag of y because of the high correlation of these terms.
[10] Borck et al. (2015) use a similar model and estimator to analyze spatial interaction and time dynamics in local government debt.
[11] The QML estimator is consistent even without the assumption of a normally distributed error term if the number of neighbors with an influence does not become too large (Lee, 2004).

distance decay and to implement a systematic approach to finding the most appropriate matrix. Let d_{ij} denote the geographical distance between the centroids of two regions i and j (in km). Similarly to Elhorst and Vega (2015), we use a power inverse distance matrix and compute the spatial weights w_{ij} using the formula $w_{ij} = \frac{1}{d_{ij}{}^{\gamma}}$, where the exponent γ is a positive distance decay parameter to be determined. When γ=1, we obtain the standard form of an inverse distance matrix. When γ increases, the influence of neighboring regions decreases more quickly with their distance, as illustrated in Figure B 4 in Appendix B. We normalize the spatial weighting matrix with its largest eigenvalue to maintain the economic interpretation of the distance.

We employ a systematic search for the distance decay parameter γ that best describes the data. We re-estimate model (1) fifty times with different values of γ, starting with γ =0.1 and then gradually increasing γ in steps of 0.1 until it reaches 5.[12] This allows us to compare the estimated coefficients and the log-likelihood values over a wide range from highly localized to very distant spatial interactions. Based on the highest log-likelihood, we select the best feasible γ (Elhorst, 2010b).[13] Analogously, we also systematically explore the introduction of different cutoff distances beyond which neighbors are assumed to have no influence at all (zero weights). By finding an optimal spatial weighting between close and distant neighbors, this systematic approach delivers a good approximation of the underlying inter-regional connectivity of start-up activity. Furthermore, this procedure allows us to inspect the sensitivity of the estimated coefficients with respect to different weighting matrices.

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[12] We experiment with values of γ up to 10, but the estimation results almost do not change anymore when γ exceeds 5.

[13] We do not use the same routine as Elhorst and Vega (2015) to find γ because unlike the simpler SLX model they use, we include the spatial lag of the dependent variable, which leads to the "perfect solution problem" (Elhorst and Vega, 2015, 11-12).

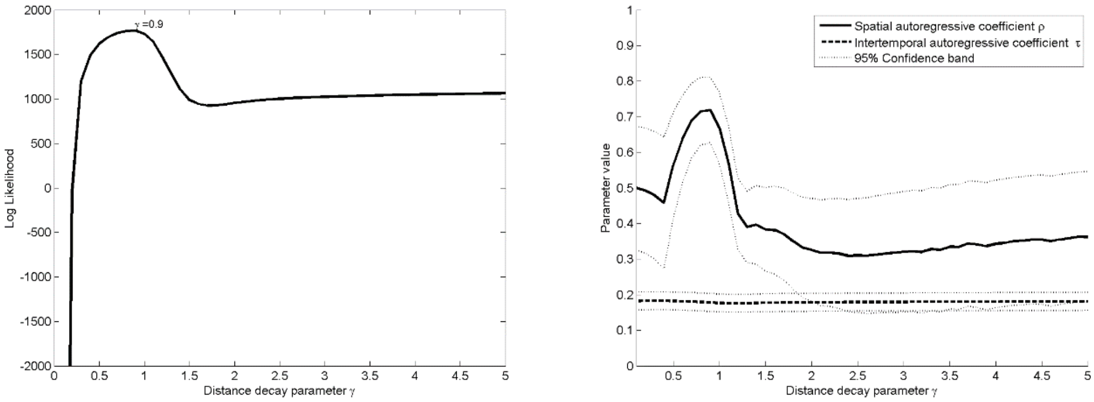
4 Econometric results

4.1 Model estimation and robustness

We start with exploring the impact of distance on spillovers of local start-up activity. To do so, we estimate model (1) on the county level with different distance decay parameters γ. Figure 3 displays the results for the high-tech industry and Figure 4 for the manufacturing industry. The left panels show the log-likelihood values and the right panels the estimates of the intertemporal autoregressive coefficient τ and the spatial autoregressive coefficient ρ. For both industries, a similar choice of γ leads to the highest log-likelihood values. A distance decay parameter of $\gamma = 0.9$ best describes spatial interaction of regional start-up activity in the high-tech industry, and the respective parameter for the manufacturing industry is $\gamma = 1.0$, which corresponds to the standard inverse distance matrix. For both industries, we also observe that the estimate of τ is almost completely insensitive to the choice of γ. Thus, even in cases where the spatial matrix is misspecified, a dynamic spatial econometric model is able to identify the intertemporal autoregressive coefficient in this context. In both industries, the spatial autoregressive parameter ρ is always positive and significantly different from zero regardless of the choice of γ, which robustly indicates that spatial spillovers of start-up activity exist. However, the point estimate of ρ is sensitive to the choice of γ. This confirms that it is important to search systematically for the distance decay parameter γ that best describes the data.[14]

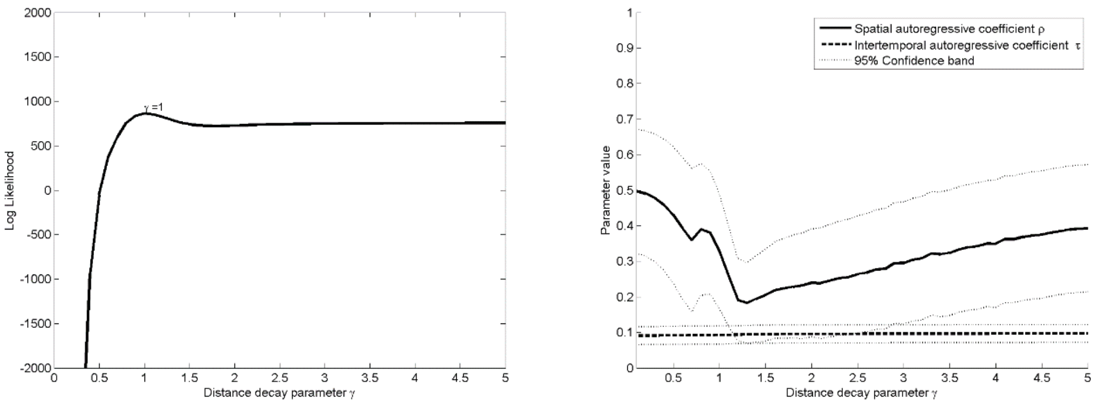
[14] When using labor market regions (spatial planning regions) instead of counties, the highest log-likelihood is reached when γ=1.0 (γ=0.6, respectively) in the high-tech industry. In manufacturing, γ=1.2 (γ=1.0) maximizes the log-likelihood. Again, the estimate of τ is insensitive to γ whereas ρ is more sensitive, exhibiting generally similar patterns as the ones we observe based on county data. The corresponding figures are available from the authors on request.

Figure 3: Influence of γ on the log-likelihood and autoregressive coefficients for *high-tech*



Notes: The figures show how the log-likelihood value (left panel) and the intertemporal and spatial autoregressive coefficients (right panel) change in the model of high-tech start-ups when increasing the distance decay parameter γ in the weighting matrix. We re-estimate model (1) fifty times with different values of γ, starting with γ =0.1 and then gradually increasing γ in steps of 0.1 until it reaches 5. For the high-tech industry, the highest log-likelihood is reached when γ=0.9.
Sources: Own estimations based on county level data from the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

Figure 4: Influence of γ on the log-likelihood and autoregressive coefficients for *manufacturing*



Notes: The figures show how the log-likelihood value (left panel) and the intertemporal and spatial autoregressive coefficients (right panel) change in the model of manufacturing start-ups when increasing the distance decay parameter γ in the weighting matrix. We re-estimate model (1) fifty times with different values of γ, starting with γ =0.1 and then gradually increasing γ in steps of 0.1 until it reaches 5. For the manufacturing industry, the highest log-likelihood is reached when γ=1.0.
Sources: Own estimations based on county level data from the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

We continue with the best distance decay parameters γ = 0.9 in the high-tech and γ = 1.0 in the manufacturing industry. The estimated intertemporal and spatial autoregressive coefficients τ and ρ appear in Table 2, where Panel I shows the results for high-tech and Panel II for manufacturing start-ups. Column (1) provides the baseline estimates based on the preferred model. The estimates of τ and ρ are positive and significant at the 1%-level in both industries. Spatial spillovers are particularly large. When the start-up rate in the high-tech industry in neighboring municipalities increases by 1 percent (spatially weighted average), the rate increases by 0.72 percent in the focal county. In manufacturing, the spatial spillover effect is significantly smaller, but still 0.33 percent. The intertemporal spillovers are 0.17 in high-tech and 0.09 in manufacturing, so again they are significantly larger in high-tech. In both industries, $\tau + \rho < 1$, so the processes are stable (Lee and Yu, 2010c).

Table 2: Intertemporal and spatial spillovers of regional start-up rates

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel I: High-tech industry							
Intertemporal autoreg. coeff. τ	0.178***	0.109***	0.112***	0.198***	0.341***	0.178***	0.252***
	(0.013)	(0.017)	(0.017)	(0.016)	(0.025)	(0.013)	(0.012)
Spatial autoregressive coeff. ρ	0.719***	0.426***	0.485***	0.572***	0.335***	0.714***	0.847***
	(0.047)	(0.106)	(0.098)	(0.071)	(0.105)	(0.047)	(0.026)
Log-likelihood	1766	1098	1038	1369	889	1784	-4431
Cutoff distance	None	None	None	None	None	460km	None
Panel II: Manufacturing industry							
Intertemporal autoreg. coeff. τ	0.093***	0.057***	0.059***	0.128***	0.267***	0.091***	0.130***
	(0.013)	(0.016)	(0.016)	(0.016)	(0.026)	(0.013)	(0.013)
Spatial autoregressive coeff. ρ	0.328***	0.210*	0.210*	0.384***	0.302***	0.261***	0.456***
	(0.082)	(0.113)	(0.113)	(0.092)	(0.105)	(0.066)	(0.073)
Log-likelihood	861	729	705	1148	1066	909	-3713
Cutoff distance	None	None	None	None	None	225km	None
Panel III: Model description (for high-tech and manufacturing)							
Cross-sectional units	402 counties	402 counties	402 counties	258 labor market regions	96 spatial planning regions	402 counties	402 counties
Time period	1996-2011	2001-2011	2001-2011	1996-2011	1996-2011	1996-2011	1996-2011
Control variables	Baseline	Extended	Baseline	Baseline	Baseline	Baseline	Baseline
Variables in logs	Yes	Yes	Yes	Yes	Yes	Yes	No

Notes: The dependent variable is the log annual start-up rate in the high-tech industry (Panel I) or in the manufacturing industry (Panel II). Level instead of log in specification (7). The spatial weighting matrix is a power inverse distance matrix with exponent γ=0.9 in the high-tech and γ=1.0 in the manufacturing industry. In all estimations, region and time fixed effects are eliminated. The coefficients of the baseline and extended sets of control variables are shown for specifications (1) and (2) in Table A 2 in Appendix A. We estimate dynamic Spatial Durbin Models using a Quasi Maximum Likelihood dynamic spatial panel estimator with bias correction (Lee and Yu, 2010b). Standard errors are in parentheses. Stars (*/**/***) indicate significance at the 10%/5%/1% levels.
Sources: Own estimations based on the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

In model (2), we extend the set of control variables and their spatial lags at the cost of having a shorter time period of data available beginning in 2001 instead of 1996. In (2), the point estimates of τ and ρ are smaller than in (1), but remain positive and significant. At first sight, one might suspect that the influence of characteristics of neighboring counties omitted in (1) are responsible for the larger estimate of ρ in (1). However, as shown in Table A 2 in Appendix A, all spatial lags of the additional control variables turn out to be insignificant, and among the additional own characteristics of the focal counties, only the share of workers in the services industries is marginally significant at the 10% level for high-tech start-ups. To be sure, in (3) we re-estimate the model using the shorter time period, but without the additional control variables and obtain similar estimates as in (2). The results thus suggest that intertemporal and spatial spillovers became smaller over time. Public start-up subsidies for the unemployed rolled out in Germany in 2003 (Caliendo and Künn, 2011) may play a role, because this policy triggered start-ups out of necessity, whereas intertemporal and spatial spillovers may be more related to opportunity entrepreneurship and may have manifested themselves more strongly during the New Economy period of the late 1990s. Unfortunately, we cannot investigate this in more detail because we cannot further reduce the number of time periods for a consistent estimation of the spatial panel model, and we leave this topic for future research. For our baseline model in this paper, we prefer using the longer estimation period as in (1), which spans several business cycles and is more suitable for a consistent estimation of the general intertemporal and spatial autocorrelation of start-up activity.

How do the estimates change if we use larger regional units for the analysis? When we move from counties to larger labor market regions (column 4 in Table 2) and then to the even larger spatial planning regions (column 5) based on the long time period, we observe that the estimated intertemporal autoregressive coefficient τ becomes increasingly larger in comparison to model (1) in both industries. Moreover, in the high-tech industry, the spatial autoregressive coefficient ρ decreases, while it does not change much in the manufacturing industry. As argued in Section 2, we prefer the county level for this analysis because of the large differences in start-up rates in neighboring counties we observe even within the same labor market regions. Our estimation results thus indicate that using regional units that are too large may lead to an overestimation of intertemporal and underestimation of spatial spillovers. This is in line with Rosenthal and Strange (2003), who conclude from their analysis that spillovers in the context of firm births should be studied at a fine grained geographical level.

Does the introduction of a cutoff distance in the spatial weighting matrix further improve the spatial model of start-up activity? When the distance between two regions exceeds the cutoff distance, their influence on one another is assumed to be zero. To explore the effect on the model fit, we start from model (1) based on the county data and introduce different cutoff distances (see Figures B5 and B6 in Appendix B for the two industries). The log-likelihood values reach their maximums when the cutoff distance is 460km in the high-tech and 225km in the manufacturing industry, but they remain similarly high for larger cutoff distances. The estimated coefficients τ and ρ are fairly stable when further increasing the cutoff distances beyond their optimal values. In specification (6) in Table 2, we introduce the best cutoff distances in the inverse distance matrices and find that this does not change the estimation results significantly in comparison to (1) without a cutoff distance. Thus, a cutoff distance does not significantly improve the spatial model of start-up activity.

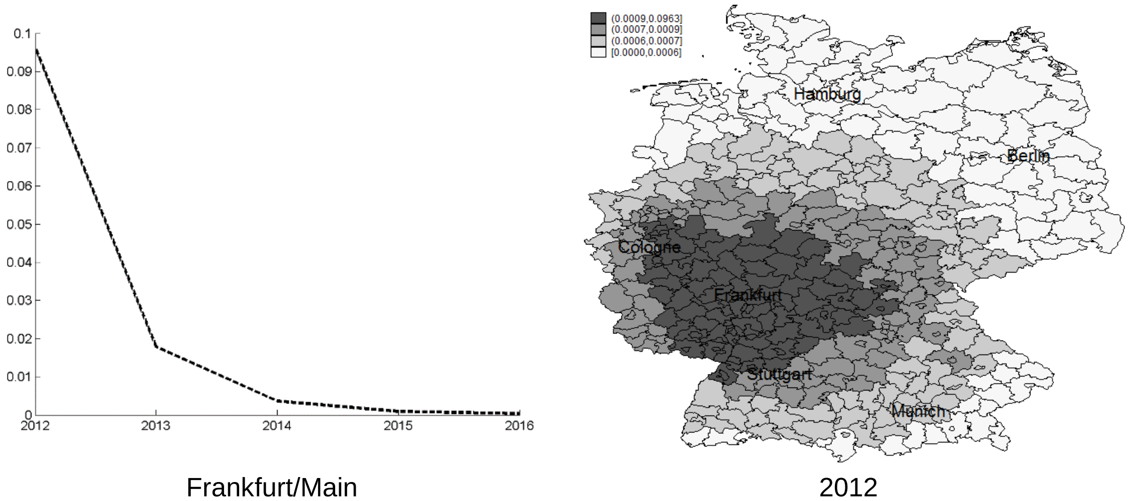
As a final sensitivity check in column (7), we include all variables in levels instead of logs. This increases the point estimates of τ and ρ somewhat in both industries in comparison to (1), but also decreases the log likelihood value substantially in both industries, indicating a worse model fit.[15] Therefore, we prefer the log model, also because it reduces the influence of outliers.

[15] In the high-tech industry, the point estimates actually sum up to more than one in specification (7), which *per se* indicates an explosive process. We follow the suggestion of Lee and Yu (2010c) in case of unstable models and additionally estimate a Spatial First Differences model, where each variable is taken in deviation of its spatially lagged value to eliminate the time fixed effects. We implement the model using the estimator with spatial fixed effects proposed by Yu et al. (2008). The results still indicate an unstable model for the high-tech industry. However, because we do not observe exploding start-up rates in the data, we take these results as another indication that the model in levels is misspecified and the log model is preferable.

4.2 Impulse response functions

To illustrate the strength and reach of the estimated intertemporal and spatial spillovers, we simulate the response to a local and temporary shock to the start-up rate in Frankfurt/Main in 2012. We first look at the high-tech industry and compare with the manufacturing industry thereafter. In the simulation referring to the high-tech industry, we define an exogenous impulse that has the size of 10% of the observed high-tech start-up rate in Frankfurt/Main in 2011. For the simulations we use the estimated model shown in column (1) of Table 2. The response is the relative difference between the simulated high-tech start-up rates in the scenario with the initial impulse in Frankfurt/Main and the baseline scenario without the impulse.[16]

Figure 5: Specific impulse responses to a shock in *high-tech* start-up rates in Frankfurt/Main

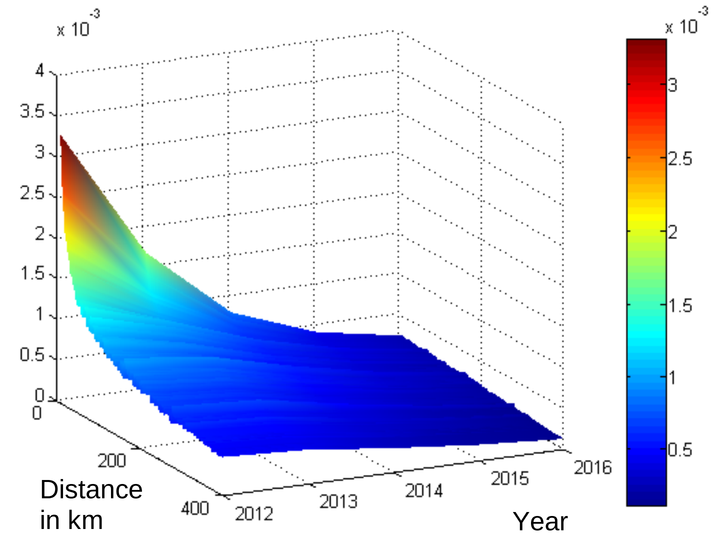


Notes: The figures show the simulated impulse response to a shock to the start-up rate in the high-tech industry that temporarily hits Frankfurt am Main in 2012. The impulse has the size of 10% of the observed 2011 start-up rate in high-tech in Frankfurt am Main. The left panel shows the impulse response over time for Frankfurt am Main. The right panel shows the spatial impulse response in all municipalities in 2012. In both graphs, the response shown is the relative difference in the high-tech start-up rates between the scenario with the initial impulse in Frankfurt/Main and the baseline scenario without the impulse. The simulations are based on the estimated model shown in column (1) of Table 2.
Sources: Own estimations based on county level data from the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

[16] E.g., 0.1 means a 10% higher start-up rate in high-tech due to the impulse. In 2011, Frankfurt/Main saw 213 start-ups in high-tech, which translates into a start-up rate of 4.56 per 10.000 working-age inhabitants.

The left panel of Figure 5 displays the response to the impulse in Frankfurt/Main over time and shows that in 2013, the year after the exogenous impulse, the start-up rate in high-tech is still higher by about a fifth of the initial impulse in comparison to the scenario without the initial impulse. After that, the response gradually vanishes. The right panel shows the spatial response in 2012. One can see that large parts of south-western Germany respond to the impulse in Frankfurt/Main, including large cities like Cologne and Stuttgart.

Figure 6: General impulse response to a shock in *high-tech* start-up rates in Frankfurt/Main



Notes: The figures show the simulated impulse response to a shock to the start-up rate in the high-tech industry that temporarily hits Frankfurt am Main in 2012. The impulse has the size of 10% of the observed 2011 start-up rate in high-tech in Frankfurt am Main. The vertical axis shows the relative difference in the high-tech start-up rates between the scenario with the initial impulse in Frankfurt/Main and the baseline scenario without the impulse. The axis labeled "Distance in km" shows the distance of counties to Frankfurt/Main. We exclude Frankfurt/Main from the graph because the relatively large local impulse would be dominating. The simulations are based on the estimated model shown in column (1) of Table 2.
Sources: Own estimations based on county level data from the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

Figure 6 shows the joint intertemporal and spatial impulse response function. To draw this graph we order all counties by their geographical distance to Frankfurt/Main. The figure shows that most of the impulse response in high-tech is limited to counties within a distance of about 200km to Frankfurt/Main and to a period of about two years after 2012, the year of the shock. However, in the model best describing the data, entrepreneurship still exerts small spillovers to even more distant regions, as shown by the optimal cutoff distance of 460km for the high-tech industry (see above).

Figures B7 and B8 in Appendix B provide results from analogous simulations for the manufacturing industry. In comparison, both the intertemporal and the spatial impulse responses are substantially smaller than in the high-tech industry (note the different scales). This suggests that knowledge spillovers, which are likely to be more crucial in the high-tech industry than in the general manufacturing industry, may be a key component of intertemporal and spatial entrepreneurial spillovers.

5 Conclusion

We provide evidence of significant intertemporal and spatial spillovers of start-up activity in the high-tech and manufacturing industries. The evidence is based on dynamic spatial panel estimators that take into account unobserved regional and time fixed effects and control relevant variables of the focal regions and their neighbors.

A systematic grid search shows that the spatial weighting matrix that best reflects the spatial structure of start-up activity is a power inverse distance matrix with a distance decay parameter of $\gamma = 0.9$ to $\gamma = 1.0$ and a cutoff distance of more than 200km. This shows that the strengths of entrepreneurial spillovers quickly declines with geographical distance, but is still notable beyond a far distance. This is in line with Rosenthal and Strange (2003) and may indicate that knowledge spillovers by means of face-to-face communication are an important component of interaction. We also show that using regional units that are too large may lead to an overestimation of intertemporal spillovers in the analysis. By simulating impulse response functions based on our preferred estimated models, we find that most of the response to a shock in the high-tech start-up rate at a specific place and time takes place in regions within a distance of about 200km from the place and a period of about two years after the time of the shock. The spatial and intertemporal impulse response is much stronger in the high-tech than in the general manufacturing industry, which may indicate that knowledge spillovers are an important component of entrepreneurial spillovers.

Our findings demonstrate that entrepreneurship capital is a local and persistent phenomenon. The robust intertemporal and spatial spillovers we document imply positive external effects of investment in entrepreneurship capital by individual entrepreneurs and local governments. For example, local governments investing in entrepreneurship capital by establishing business parks stimulate entrepreneurship not only in their own, but also in neighboring regions. Such positive externalities may lead to underinvestment in entrepreneurship capital by local governments, who do not take into account the social returns to their investment in neighboring jurisdictions. This suggests that higher level governments may increase overall efficiency by supporting local governments in their efforts to promote local entrepreneurship. Further research should investigate specific channels of intertemporal and spatial interactions in entrepreneurship to enhance our understanding of the scope for entrepreneurship policy.

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Appendix A: Supplementary tables (online material)

Table A 1: Mean characteristics of labor market regions and spatial planning regions

	Labor market regions	Spatial planning regions
Period 1996-2011:		
Annual start-ups in high-tech per 10,000 inhabitants at working age	2.71	2.84
Annual start-ups in manufacturing per 10,000 inh. at working age	2.28	2.20
Population in 10,000	31.85	85.61
Share of population at working age in total population (in %)	62.91	63.40
Share employees without apprenticeship (in %)	17.12	16.37
Share employees with apprenticeship (in %)	64.88	63.61
Share employees with university degree (in %)	7.01	7.86
Gross value added in real thousand euro per employee	62.51	63.38
Period 2001-2011:		
Share workers in the manufacturing sector (in %)	29.89	27.47
Share workers in the services sector (in %)	67.44	70.18
Share unemployed in the working age population (in %)	7.31	7.55
Average wage per employee in 1,000 real euro	31.91	32.20

Notes: The table shows unweighted mean characteristics for all 258 labor market regions and all 96 spatial planning regions in Germany. Thus, we have 4128 (1536) annual observations in the period 1996-2011 for the labor market regions (spatial planning regions) and 2838 (1056) in the period 2001-2011. Working age refers to ages 18-65. Real euro are in prices of 2010. Concerning the education structure of the employees, the omitted base category is the share of employees without information on education. Concerning the industry structure, the omitted base category is the agricultural and mining sector.
Sources: Own calculations based on regional data from the Federal Statistical Office and the Mannheim Enterprise Panel, 1996-2011.

Table A 2: Regional start-up rates: Coefficients of the control variables

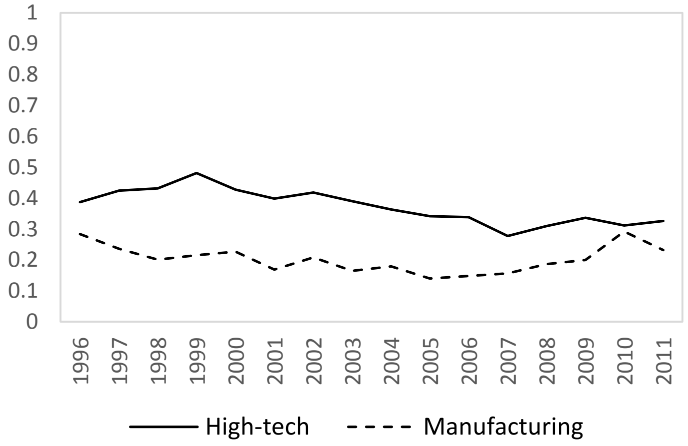
	High-tech		Manufacturing	
	(1)	(2)	(1)	(2)
Intertemporal autoregressive coefficient τ	0.178***	0.109***	0.093***	0.057***
	(0.013)	(0.017)	(0.013)	(0.016)
Spatial autoregressive coefficient ρ	0.719***	0.426***	0.328***	0.210*
	(0.047)	(0.106)	(0.082)	(0.113)
log population size	0.200	1.530***	-0.111	0.561
	(0.160)	(0.361)	(0.180)	(0.393)
log share population at working age	0.561	0.160	-1.283***	-1.476*
	(0.388)	(0.708)	(0.436)	(0.769)
log share employees without apprenticeship	-0.124*	-0.218*	-0.029	-0.210*
	(0.071)	(0.114)	(0.079)	(0.124)
log share employees with apprenticeship	0.175	-0.157	0.002	-0.005
	(0.160)	(0.265)	(0.180)	(0.288)
log share employees with university degree	0.094*	0.018	0.061	-0.026
	(0.054)	(0.095)	(0.060)	(0.103)
log gross value added per employee	-0.149**	-0.138	-0.048	-0.111
	(0.072)	(0.118)	(0.081)	(0.128)
W x log population size	-3.550**	-9.148***	-0.864	-2.172
	(1.474)	(3.241)	(1.343)	(2.830)
W x log share population at working age	-0.019	13.748**	4.810**	5.324
	(2.360)	(5.579)	(2.307)	(5.106)
W x log share empl. without apprenticeship	0.316	1.196	2.465***	3.215***
	(0.739)	(1.255)	(0.705)	(1.141)
W x log share empl. with apprenticeship	0.784	9.058***	0.947	4.013
	(1.105)	(2.905)	(1.039)	(2.520)
W x log share empl. with university degree	1.019*	-0.402	1.328**	3.392***
	(0.592)	(1.217)	(0.536)	(1.032)
W x log gross value added per employee	-0.545	1.116	0.954**	2.572***
	(0.387)	(1.071)	(0.374)	(0.954)
log share workers in manufacturing		-0.233		-0.301
		(0.213)		(0.232)
log share workers in services		-0.892*		0.082
		(0.540)		(0.588)
log unemployed in working age population		0.035		-0.024
		(0.063)		(0.068)
log average wage per employee		0.099		0.234
		(0.236)		(0.257)
W x log share workers in manufacturing		-3.223		-0.955
		(2.959)		(2.513)
W x log share workers in services		7.615		-2.120
		(7.223)		(6.168)
W x log unemployed in working age pop.		-0.219		-0.073
		(0.282)		(0.255)
W x log average wage per employee		-1.188		-2.495
		(2.078)		(1.863)
Log-likelihood	1766	1098	861	729
Cross-sectional units	402 counties	402 counties	402 counties	402 counties
Time period of annual observations	1996-2011	2001-2011	1996-2011	2001-2011
Control variables	Baseline	Extended	Baseline	Extended

Notes: The dependent variable is the log annual start-up rate. In all estimations, region and time fixed effects are eliminated. Descriptions of the variables are provided in Table 1. We estimate dynamic Spatial Durbin Models using a Quasi Maximum Likelihood dynamic spatial panel estimator with bias correction (Lee and Yu, 2010b). The spatial weighting matrix *W* is a power inverse distance matrix with exponent γ=0.9 for high-tech and γ=1.0 for manufacturing and no cutoff. Standard errors are in parentheses. Stars (*/**/***) indicate significance at the 10%/5%/1% levels.

Sources: Own estimations based on the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

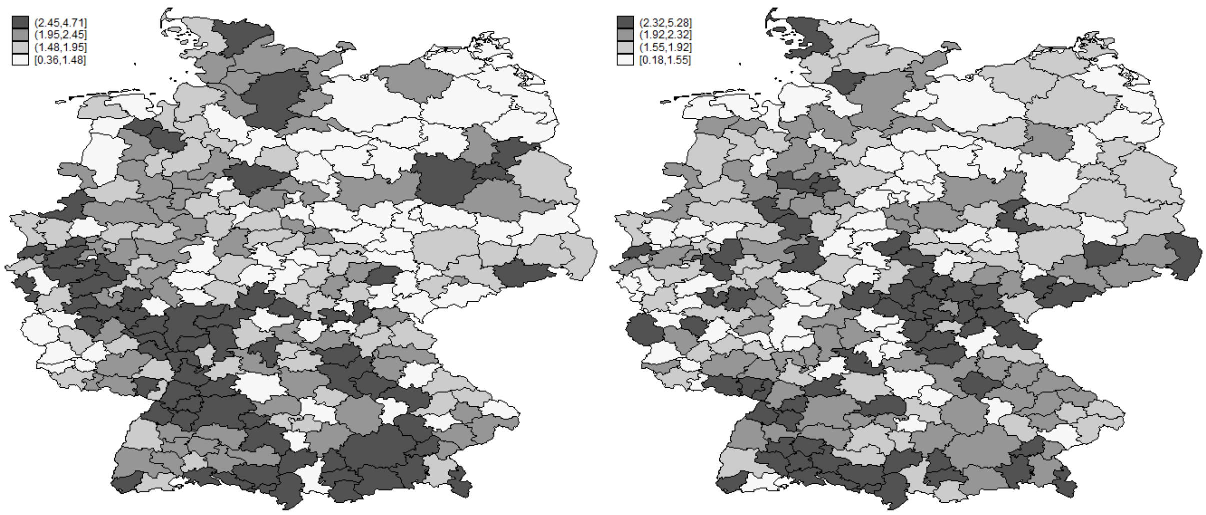
Appendix B: Supplementary figures (online material)

Figure B 1: Development of Moran's I for start-up rates in German counties from 1996-2011



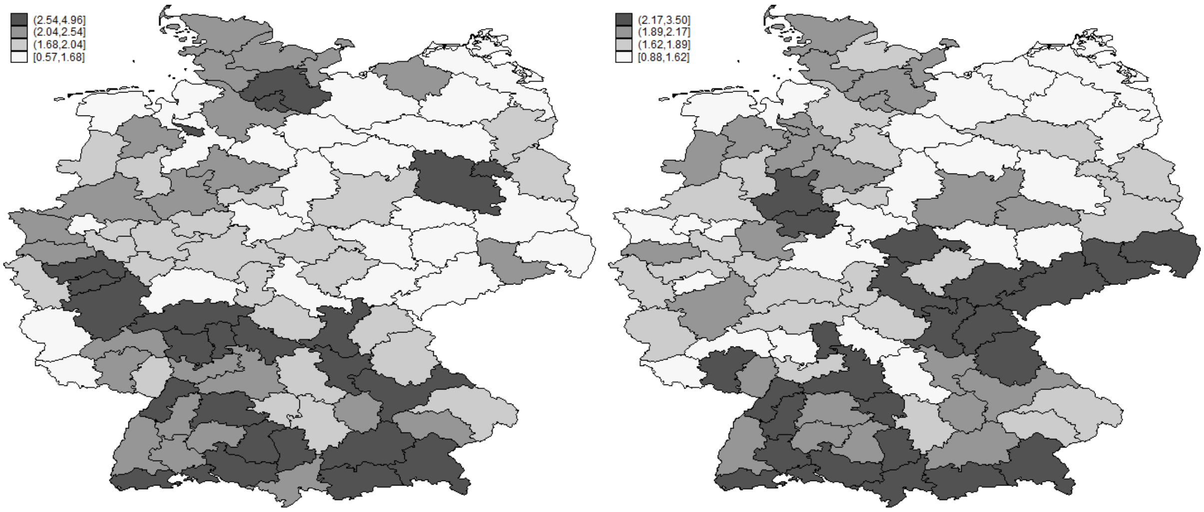
Notes: To measure spatial autocorrelation in start-up rates in German counties (NUTS 3 regions), we calculate Moran's I for each year from 1996-2011 separately for start-ups in the high-tech and manufacturing industries using a binary contiguity matrix.
Source: Own calculations based on the Mannheim Enterprise Panel, 1996-2011.

Figure B 2: Start-up rates in high-tech and manufacturing, *labor market regions* 2011



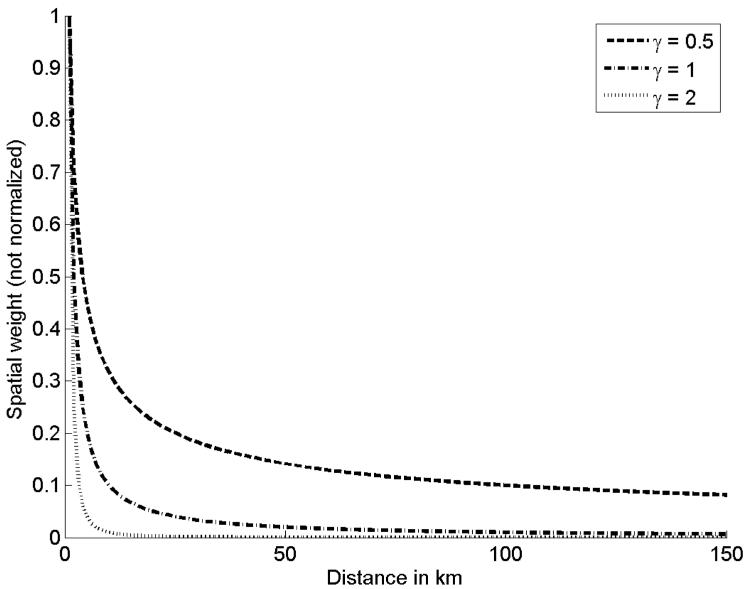
Notes: Start-ups in the high-tech industry (left panel) and in the manufacturing industry (right panel) per 10,000 inhabitants in 2011. The regions are labor market regions.
Source: Own illustration based on the Mannheim Enterprise Panel, 1996 and 2011.

Figure B 3: Start-up rates in high-tech and manufacturing, *spatial planning regions* 2011



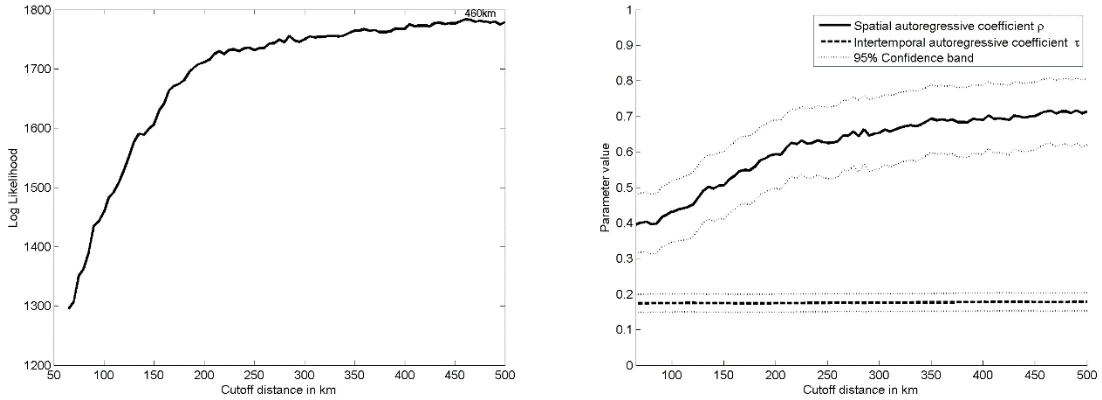
Notes: Start-ups in the high-tech industry (left panel) and in the manufacturing industry (right panel) per 10,000 inhabitants in 2011. The regions are spatial planning regions.
Source: Own illustration based on the Mannheim Enterprise Panel, 1996 and 2011.

Figure B 4: Distance decay functions for different values of γ



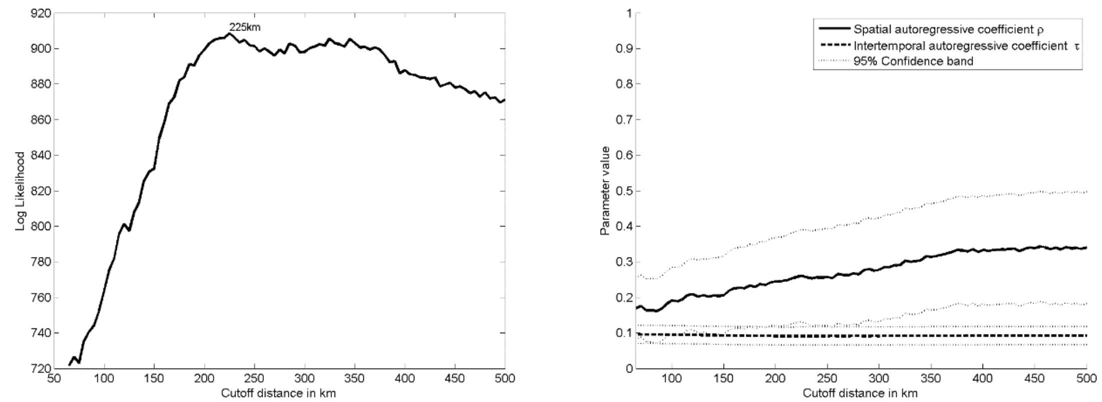
Notes: The graph illustrates how the spatial weight, i.e., the influence of a region on a neighbor, diminishes with growing distance between the regions depending on the value of the distance decay parameter γ.
Source: Own illustration adapted from Elhorst and Vega (2015).

Figure B 5: Influence of a cutoff distance on estimation results for *high-tech*



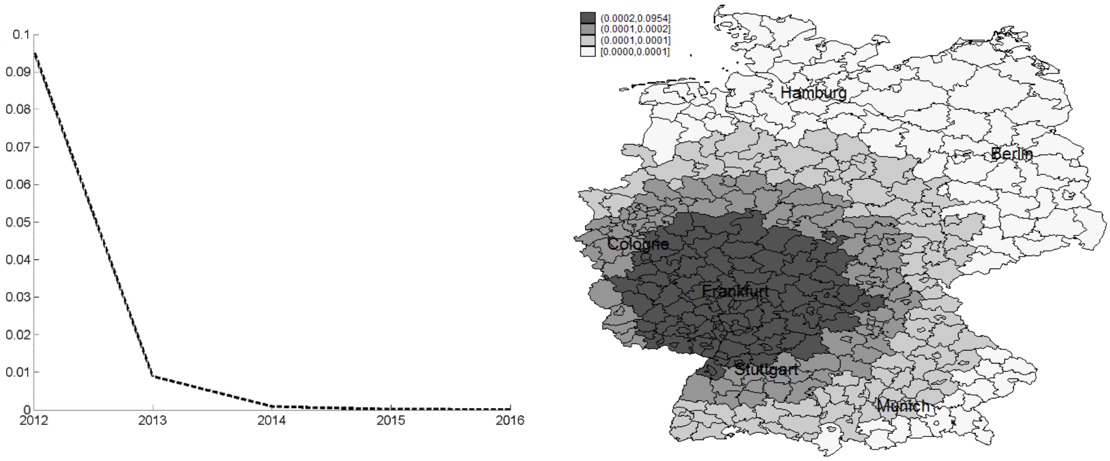
Notes: The figures show how the log-likelihood value (left panel) and the intertemporal and spatial autoregressive coefficients (right panel) change in the model of high-tech start-ups when increasing the cutoff distance in the spatial weighting matrix, beyond which neighbors are assumed to have no influence. We re-estimate model (1) repeatedly with different cutoff distances, starting with 50km and then gradually increasing the cutoff distance in steps of 5km until it reaches 500km. In all these estimations we use a power inverse distance matrix with the distance decay parameter γ=0.9, as determined for high-tech before. For the high-tech industry, the highest log-likelihood is reached when using a cutoff distance of 460km.
Sources: Own estimations based on county level data from the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

Figure B 6: Influence of a cutoff distance on estimation results for *manufacturing*



Notes: The figures show how the log-likelihood value (left panel) and the intertemporal and spatial autoregressive coefficients (right panel) change in the model of high-tech start-ups when increasing the cutoff distance in the spatial weighting matrix, beyond which neighbors are assumed to have no influence. We re-estimate model (1) repeatedly with different cutoff distances, starting with 50km and then gradually increasing the cutoff distance in steps of 5km until it reaches 500km. In all these estimations we use a power inverse distance matrix with the distance decay parameter γ=1.0, as determined for manufacturing before. For the manufacturing industry, the highest log-likelihood is reached when using a cutoff distance of 225km.
Sources: Own estimations based on county level data from the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

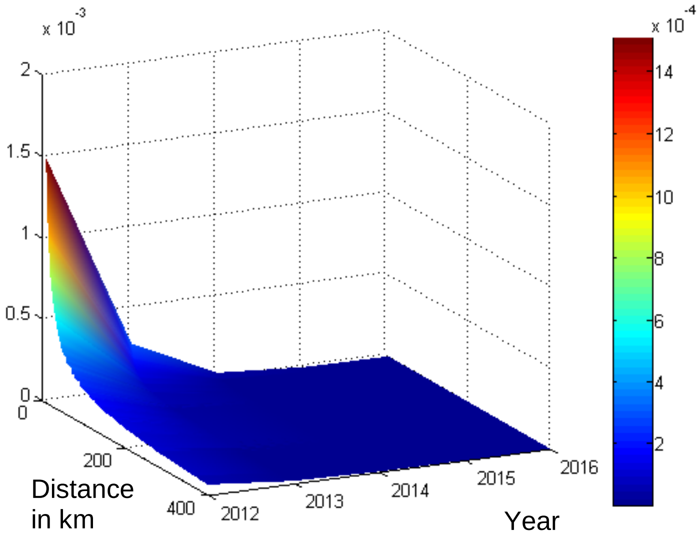
Figure B 7: Specific impulse responses to a shock in *manufacturing* start-up rates in Frankfurt/Main



Frankfurt/Main 2012

Notes: The figures show the simulated impulse response to a shock to the start-up rate in the manufacturing industry that temporarily hits Frankfurt am Main in 2012. The impulse has the size of 10% of the observed 2011 start-up rate in manufacturing in Frankfurt am Main. The left panel shows the impulse response over time for Frankfurt am Main. The right panel shows the spatial impulse response in all municipalities in 2012. In both graphs, the response shown is the relative difference in the manufacturing start-up rates between the scenario with the initial impulse in Frankfurt/Main and the baseline scenario without the impulse. The simulations are based on the estimated model shown in column (1) of Table 2.
Sources: Own estimations based on county level data from the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.

Figure B 8: General impulse response to a shock in *manufacturing* start-up rates in Frankfurt/Main



Notes: The figures show the simulated impulse response to a shock to the start-up rate in the manufacturing industry that temporarily hits Frankfurt am Main in 2012. The impulse has the size of 10% of the observed 2011 start-up rate in manufacturing in Frankfurt am Main. The vertical axis shows the relative difference in the manufacturing start-up rates between the scenario with the initial impulse in Frankfurt/Main and the baseline scenario without the impulse. The axis labeled "Distance in km" shows the distance of counties to Frankfurt/Main. We exclude Frankfurt/Main from the graph because the relatively large local impulse would be dominating. The simulations are based on the estimated model shown in column (1) of Table 2.
Sources: Own estimations based on county level data from the Mannheim Enterprise Panel and the Regional Statistical Data Catalogue for 1996-2011.