Journal of Regional Science

WILEY

JOURNAL OF REGIONAL SCIENCE

RESEARCH ARTICLE OPEN ACCESS

Unveiling Spatial Dependencies — Investigating the Determinants of Firm Exit in Germany

Simon Knappe | Dominik Wied | Tobias Jansen

Institute of Econometrics and Statistics, University of Cologne, Cologne, Germany

Correspondence: Dominik Wied (dwied@uni-koeln.de)

Received: 21 October 2024 | **Revised:** 2 December 2025 | **Accepted:** 13 December 2025

Keywords: Durbin model | Moran's *I* | SAR model | spatial probit model

ABSTRACT

The determinants of firm exit in Germany, with a particular focus on the role of spatial dependence, are investigated. Using administrative microdata, a baseline probit model confirms the importance of internal firm characteristics, most notably firm size, growth dynamics, and legal form, in explaining exit probabilities. Descriptive spatial analysis based on Global Moran's *I* statistics reveals substantial geographic heterogeneity. To account for these spatial patterns, spatial probit models are estimated separately for each county, making the analysis computationally feasible. These estimations indicate that spatial dependence is present in a meaningful share of regions, driven primarily by unobserved regional conditions rather than observable firm characteristics. While the core internal determinants remain robust across specifications, the significance of the spatial autoregressive parameter demonstrates that firm exit is influenced not only by firm-level attributes but also by the broader economic environment in which firms operate. These findings highlight the importance of incorporating spatial context into empirical analyses of firm survival.

JEL Classification: C21, G33, L25, R12

1 | Introduction

The study of firm exit has a long tradition in economic analysis. Starting with the early contribution of Beaver (1966), an ever-increasing literature on the internal and external determinants of firm exit has evolved. The role of size, financial health and macroeconomic determinants, *inter alia*, is nowadays well investigated. However, despite substantial progress in analyzing the driving forces of voluntary or forced exit, the spatial dimension of firm exit has received less attention.

Firms do not operate in isolation; they interact with other market participants and are influenced by regional economic factors and policies, which vary across space. If these spatial effects are not accounted for, the estimation of the determinants of firm exit will potentially be biased (LeSage and Pace 2009). This highlights the importance of incorporating a firm's location when investigating its performance and subsequently its likelihood to exit.

Formally, those interactions and regional influences are referred to as spatial dependence. The analysis of spatial dependencies is a growing field in the literature, with important contributions of authors such as Anselin (1988) and LeSage and Pace (2009). Several econometric models have been developed to incorporate spatial dependencies. Among them, the Spatial Autoregressive Model (SAR) and Spatial Durbin Model (SDM) are two of the most widely used to account for spatial dependence (Anselin 2002).

This paper builds upon existing literature in the field of firm analysis by analyzing not only some of the most important internal factors, but also by examining the existence of potential spatial dependencies of firm exits in Germany. Germany presents an interesting case, as it is the biggest economy in the European Union and has a varying economic landscape. The Eastern part of Germany, suffering economically from its history as a socialist state, is structurally less developed (Reuters 2024), with none of

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.

© 2025 The Author(s). *Journal of Regional Science* published by Wiley Periodicals LLC.

the 40 largest German firms having their headquarters located in an ex-GDR (German Democratic Republic) state (Statista 2024). The South of Germany, on the other hand, is characterized by many hidden champions that are world leaders in their niche (Logue et al. 2015). Furthermore, Germany is organized as a federal state, having 16 different powerful states that decisively exhibit influence on the economic conditions in their reach. The municipality trade tax, relevant for firms, is decided even more locally. Therefore, Germany, with its diverse firm demography and economic conditions, presents an interesting case to investigate the existence of spatial dependencies in firm exits.

Leveraging new spatial probit models (SAR and Durbin model), this paper shows that firm exits in Germany are spatially correlated. Next to spillover effects, the existence of unobserved spatially correlated variables is found to be significant. The use of other widely applied spatial econometric techniques, like the Global Moran statistic, corroborates these results. The paper shows that spatial dependencies have to be taken into account when investigating firm exit in order to get more accurate results. It adds Germany to the growing list of investigated countries and thus adds another piece of the puzzle for a better understanding of the determinants of firm exit.

From a methodological point of view, the large number of firms (more than one million) makes it infeasible to estimate the spatial models directly. To circumvent this issue, we estimate the models separately for each German county and report aggregate results. Moreover, for estimating the Durbin model, we use the conjugate gradient method, which improves the computational feasibility even more.

Taken together, these considerations highlight the need to account for spatial context when analyzing firm survival and point toward a broader research agenda on the regional determinants of business dynamics in Germany. The remainder of the paper is organized as follows: Section 2 reviews the relevant literature. Section 3 introduces the data. Section 4 outlines the econometric approach, followed by the empirical results in Section 5. Section 6 places the findings in a broader context, and Section 7 concludes and motivates further exploration of the regional factors that shape business survival.

2 | Literature Review

In the following, an overview of the existing literature is provided. First, an overview of important determinants of firm exit is given. Then, existing literature that investigates spatial dependencies in the context of firm exit is presented.

2.1 | Determinants of Firm Exit

The determinants of firm exit are a widely studied section in economics. Early studies primarily focused on internal factors influencing firm failure, beginning with the seminal works of Beaver (1966) and Altman (1968), who used financial ratios to predict corporate insolvency. Further evidence comes from Hirsch and Schiefer (2016) and Saridakis et al. (2013), who find that financial determinants and liquidity constraints are important determinants. Other authors focused on external factors, emphasizing the importance of the business cycle (Jacobson et al. 2013) or macroeconomic determinants, like GDP growth and inflation (Dewaelheyns and Van Hulle 2007). In addition, interest rates and the development of stock market returns are used to predict the likelihood of firm failures (Tinoco and Wilson 2013).

In more recent literature, the age and size of a firm have evolved as key determinants for firm performance. Studies such as Fackler et al. (2013), Farinas and Moreno (2000), Loderer et al. (2010), and Cefis et al. (2021) highlight their importance to determine the probability of firm exit. However, as Barron et al. (1994) argue, once size is controlled for, age does not exhibit an influence and is, if any, negatively correlated with firm exit.

2.2 | Size and Firm Exit

The size of a firm is often proxied by the revenue of a firm and its number of employees (Farinas and Moreno 2000). The influence of size on a firms' likelihood to exit is quite clearly defined, with most studies highlighting the advantage larger firms have (Evans 1987; Mata et al. 1995; Farinas and Moreno 2000; Audretsch et al. 2000). The phenomenon where smaller firms are more likely to exit the market is often referred to as *liability of smallness*, introduced by Aldrisch and Auster (1986). Several factors explain how the size of a firm affects its performance. Evans (1987) suggests that small firms tend to operate below the efficient market level and thus more often drop out of the market. On the contrary, larger firms profit from economies of scale, which lead to increased competitiveness (Chandler 1994). Moreover, Fatica et al. (2022) highlight that larger firms typically have better access to external financing, reducing their risk of financial distress. A larger size also typically implies more market power (Porter 1980) and a larger-degree of diversification (Markides 1997), both of which lead to more resilience and reduce the likelihood of insolvency.

Similarly to size, the growth of a firm can be a determining variable. Intuitively, one would expect that a growing firm has a lower propensity to exit the market, both voluntarily and forced. Supporting that idea, Thornhill (2006) argues that change in revenue can be interpreted as a proxy of firm performance. Abughniem et al. (2020) find evidence that the firm performance is correlated with growth. On the other hand, authors like Bottazzi et al. (2002) and Bartelsman and Doms (2000) do not find robust evidence for a link between firm performance and growth. Similarly, Hall (1986) argues that the growth rate does not significantly influence a firms' propensity to exit, an assessment that is backed by Evans (1987).

2.3 | Legal Form and Firm Exit

Lastly, the legal form of the firm can be an important factor that influences a firms' exit probability. Pérez et al. (2004) find that privately held firms may struggle to find a successor and thus voluntarily exit the market; a problem that public corporations do not face. This insight is backed by the contribution of Harhoff et al. (1998), who suggest that the age of the firms' owner positively correlates with firm exit; implying that sole proprietorships exit have a "naturally" higher chance to exit the market. Fama and Jensen (1983) investigate the risk-taking behavior of different legal forms of firms and find, that public

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

corporations take larger risks because the decision makers face minimal personal risk. In contrast, firms in which owner and decision maker are the same person often make more conservative decisions, which can reduce their likelihood to become financially distressed. On the other hand, corporations generally have better access to financing than firms organized as a sole proprietorship (Robb and Robinson 2014) and insufficient financing can increase the risk of insolvency (Fatica et al. 2022).

2.4 | Spatial Dependence and Firm Exit

The term spatial dependence describes the concept that a variable is correlated with itself over space. In the context of firm exits, several contributions provide reasoning for the potential existence of spatial dependence, as several unobserved determinants of firm exit tend to be correlated across space. For example, Buehler et al. (2007) find that regionally varying cultural differences can explain the different insolvency rates in Switzerland. Similarly, investigating the bankruptcy-risk of firms, Buehler et al. (2012) find that bankruptcy rates tend to be lower in agglomeration areas and touristic regions. Furthermore, they show that regions with favoring local economic conditions, like low unemployment and tax rates, have lower rates of insolvency. Several studies support the advantageous effect for firms of being located in an agglomeration. For example, Krugman (1991) shows that firms located in agglomeration areas profit from reduced transportation costs and economies of scale. Applying a spatial probit model, Maté-Sánchez-Val et al. (2018) find that geography plays a decisive role in determining the exit likelihood of a firm. Moreover, they show that the probability to fail is correlated for geographically close firms.

Firms are not only influenced by their internal determinants and their location, but also by neighboring businesses. A firm can profit from nearby competitors from an easier spread of information, ideas and knowledge spillovers (Glaeser and Gottlieb 2009; Duranton and Puga 2004) and because of an increase in local demand (Moretti 2010). The interconnection between firms is also evident when a neighboring firm exits the market. This exit can trigger spatial spillovers, as trade relationships, outsourcing, or supply chain dependencies may spread the firm closure to nearby regions (McCann and Ortega-Argilés 2013). Applying an autologistic model, Andreano et al. (2018) investigate spatial dependencies for the failure of Italian manufacturing firms. They find positive spatial spillovers, such that the exit of firms in one region increases the exit likelihood for firms in neighboring regions.

Another important contribution in this field comes from Cainelli et al. (2013) who investigate exit rates in Italian provinces. They show that the contagion effect of exit exists in the same year already and spreads over subsequent years. Similar insights come from Arcuri et al. (2018), who investigate the average exit rates in French districts. They find that spatial spillovers exist, *inter alia*, in the same period. Investigating the exit rates of Spanish counties, Serra et al. (2022) show that there exist spillovers between different sectors. They find that higher exit rate in the industry and agriculture sector exhibit spillovers on the service sector. Notably, all studies find *positive* spatial autocorrelation, indicating that a firms' likelihood to exit the market increases with the exit of geographically close peers.

For the case of Germany, Brixy and Grotz (2007) show that there exist regional clusters in firm start-up and survival. Further, they find proof for the existence of significant positive spatial autocorrelation in the survival rates of firms. However, they account for these autocorrelations in a less sophisticated way. In particular, they do not consider a probit model. Other studies accounting for autocorrelation in Germany investigate the case of unemployment (Lehmann and Nagl 2019), job creation (Fahr and Sunde 2006), or migration flows (Barthel and Neumayer 2015).

The innovation of our present paper is the consideration of a very large and up-to-date administrative data set from official sources (RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany 2023a). Moreover, we apply a sophisticated spatial probit model and address the problem of imbalanced data.

Mayer and Wied (2024) consider the same data set of the present paper. They do not consider spatial dependence, but endogeneity aspects in the research question, which regressors have an influence on the exit probability. With a control regressor based on ranks, they address endogeneity issues arising from a potentially existing latent variable, which measures the quality of the management. It is an open question up to now, if this approach also works under spatial dependence. As our data do not contain any further information about these latent variables, we do not further consider the question of endogeneity.

3 | Data and Descriptive Statistics

3.1 | Data Sources and Data Description

The empirical analysis and methods applied use several data sources. Data about the exit of firms for the Years 2018 and 2019 are obtained from the Research Data Center (RDC) (RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany 2023a). Revenue, the number of employees, a measurement for productivity, the legal form, state of headquarter and official municipality key of the *firm*, and information about the *branches* and *legal entities* are obtained from the RDC (RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany 2023b). The official NUTS3 classification number of districts and corresponding longitude and latitude information is obtained from Eurostat (European Commission 2023) using the R-package *giscoR* (Hernangómez 2024). A comprehensive list of variables included is found in Table 1.

The variable of interest is the binary variable *exit*. It takes the value 1 if the firm exited in the Year 2019 and 0 otherwise. Exit follows the definition given at the website of the German Statistical Bureau: "A [...] closure in the sense of business demography occurs when a combination of production factors [...] disappears, there is no reactivation and no other company is involved in this process" (Destatis 2024b).

The variables *exit rate state* and *exit rate district* are calculated by dividing the number of exited firms with the number of firms active in that year in a given state or district, respectively. *Revenue* is given in thousands of Euro. The *change in revenue* is defined as a factor variable, and is either *More Revenue*, *Less Revenue*, or *No Change*. The variable *Productivity* is measured as revenue per employee. The *number of employees* is given as the

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 1 | Overview of the included variables.

Variable	Definition	Year
Exit	Firm exit	2019
Exit Rate State	*N* exited firms/*N* total firms	2019
Exit Rate District	*N* exited firms/*N* total firms	2019
Revenue	Revenue	2018
Productivity	Productivity	2018
Revenue dev	Change in revenue	2019
Employee	No. of employees	2018
Employee dev	Change in no. of employees	2019
Legal form	Legal form	2018
District	District	2018, 2019
State	County	2018, 2019
xcoord	Longitude	2018
ycoord	Latitude	2018

TABLE 2 | Summary of firms, exit, and exit rates.

	N Firms	*N* Exits	Exit Rate	Deviation
DE	1,160,442	12,549	1.08%	—
SH	39,513	715	1.81%	67.3%
HH	29,688	500	1.68%	55.7%
NI	101,444	919	0.91%	−16.2%
HB	7841	147	1.88%	73.4%
NW	242,107	2289	0.95%	−12.6%
HE	88,075	1232	1.40%	29.4%
RP	56,039	509	0.91%	−16.0%
BW	150,433	1219	0.81%	−25.1%
BY	204,376	2292	1.12%	3.7%
SL	12,450	113	0.91%	−16.1%
BE	50,969	661	1.30%	19.9%
BB	34,764	350	1.01%	−6.9%
MV	22,187	201	0.91%	−16.2%
SN	61,722	785	1.27%	17.6%
ST	28,315	261	0.92%	−14.8%
TH	30,519	356	1.17%	7.9%

number of employees subject to social security contributions as at December 31 of the given year. Only observations with at least one employee, following the definition, are included. The *change in employees* is calculated in the same fashion as the change in revenue. The *legalform* of the firm is defined either as *sole proprietorship*; *corporations*; *partnerships and other* (hereafter: *partnerships*); and *Not listed* if the firm does not take any of the legal forms listed above. All independent variables are chosen with a lag of 1 year, following previous examples in the literature and to account for potential endogeneity (Elkink and Calabrese 2015).

District is one of the 400 districts in Germany, following the European NUTS-3 definition; *State* is one of the 16 counties in Germany. *Latitude* and *Longitude* are the geographical coordinates of the branch office representing the firm, accurate to the meter. Some remarks have to be made in regard to the manipulation of the data set, especially regarding the variable *revenue*. First, only firms with revenue with at least 17,501 Euros in a given year have the duty to report numbers on revenue. Therefore, the smallest firms are effectively filtered out from the set of observations. Second, the revenue of a firm is calculated by adding up the revenue of all legal entities that belong to a given firm—the revenue numbers are not consolidated. Third, revenues for legal entities that are members of the same VAT group ("*Organkreismitglieder*") are only *estimated* (Destatis 2024a). Therefore, revenue can only provide an idea of the size of the firm but is not suited for a more concrete analysis.

The next remark concerns the geographical coordinates. As outlined above, the observation of interest is the *firm*. However, information about the latitude and longitude coordinates is only on the *company-branch-level*. Thus, a two-step procedure is applied to match the firm with the corresponding geo-coordinates. First, the geo-coordinates are merged with the legal entity. This is a straight-forward procedure as there exists a predefined variable to enable the merge. In the second step, the legal entity with the highest revenue in a given district is merged with the firm observation. Since there might exist more than one legal entity belonging to a given firm in a given district, that procedure leaves room for a (minor) error. This procedure was developed and discussed with the contact person at the RDC and found to be the best possible way, considering the data and variables available.

Generally, several steps of manipulation have been carried out. In a first step, duplicates and nonrelevant firms are filtered out. Next, the data are filtered for firms that are (quasi-) state related or not profit oriented. That excludes organizations and firms that are state-owned, publicly controlled or act as private non-profit organizations. They are not included as they do not follow the same economic logic as profit-oriented private firms. Generally, only observations that are non-empty for all variables in the given years are considered in the analysis.

3.2 | Summary Statistics

In the following, the summary statistics are presented. The overall data set contains 1,160,442 observations, with an overall exit rate of 1.08% in the Year 2019. Table 2 provides an overview of the state the firm was located in 2018. Exit rates differ substantially between the states, from 1.81% in Schleswig-Holstein, two-thirds above the average in Germany, to 0.81% in Baden-Württemberg, where the exit rate is 25% below the national mean. Notably, the share is well below the nonmanipulated data, where the national exit share averages 12.8% in 2019. The steps taken to construct a comprehensive data set of multiple variables disproportionately filter out firms that exited the market in 2019.

The question arises, if there might be a bias in our results due to this filtering. Under the assumption that smaller firms are associated with lower data quality and a potentially higher

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universität zu Köln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

market exit probability, our results might indeed have a downward bias. On the other hand, the difference between big and small companies is still reflected in the sample, as the following summary statistics show.

Table 3 shows the different characteristics between exited and nonexited firms. The median firm that exited in 2019 has 209 employees, which is half the size of nonexited firms. A similar difference can be found in the number of employees: the median exited firms have two employees compared to four employees in the nonexited firm. The differences in mean values are even more substantial; with exited firms generating only around 20% of the revenue and employing a little over 1/5 of the employees, compared to the average firm.

Table 4 contains further insights in the characteristics of firms. The bulk of firms are organized as *sole proprietorships*, which account for 53% of the overall sample. The second-biggest group of firms is *corporations* which account for 33% of the data set. The remaining 24% are organized as *partnerships* or *other firms*. With 1.42% of all sole proprietorships leaving the market, their share is more than 30% above average. Contrarily, corporations left nearly half as often as the overall set. Partnerships exit the market 13% less often as the overall average.

TABLE 3 | Summary continuous variables.

	Overall	Exit	No exit
Revenue (in €k)			
Mean	5399	856	5449
Median	414	209	417
5th percentile	62	37	63
95th percentile	7451	2051	7525
No. of employees			
Mean	21	5	22
Median	4	2	4
5th percentile	1	1	1
95th percentile	45	15	45

TABLE 4 | Summary categorical variables.

	Overall	Exit	No exit	Exit rate
Legal form				
Sole proprietorship	613,029	8711	604,318	1.42%
Corporations	383,415	2300	381,115	0.60%
Partnerships and other	162,752	1522	161,230	0.94%
Not listed	1246	16	1230	1.28%
Change in revenue				
No change	565,137	7065	558,072	1.25%
Higher revenue	321,388	1582	319,806	0.49%
Lower revenue	273,917	3902	270,015	1.42%
Change in employees				
No change	14,764	205	14,559	1.39%
More employees	674,469	5376	669,093	0.80%
Less employees	471,209	6968	464,241	1.48%

The development of revenue and the number of employees delivers another insight between leaving and non-leaving firms. Firms that managed to grow, both in terms of revenue and employees, have a substantially lower exit rate than the total set of firms. On the other hand, shrinking firms tend to leave the market more often.

These summary statistics already indicate a significant difference between exited and nonexited firms, as well as a clear pattern in their geographical distribution.

4 | Methodology: Spatial Probit Regression

There are several contributions that propose the use of spatial models to identify spatial autocorrelation in the data (e.g., Anselin 1988; LeSage and Pace 2009). However, the vast majority of papers and estimation methods developed to measure spatial dependence consider linear spatial models. When working with binary models, such as the probit model, the estimation is more demanding. McMillen (1992) noted that applying standard spatial estimations methods, such as the typical Maximum Likelihood (ML) method introduced by Ord (1975), to binary models leads to inconsistent estimations, because the former imply heteroscedastic errors. McMillen (1992) then developed a consistent estimation method for spatial probit models, using an expectation-maximization (EM) method. Next to McMillen (1992), another early contribution is given by LeSage (2000) who uses the Bayesian Gibbs sampling to solve a continuous spatial model. Another method is given by Beron and Vijverberg (2004), who use a ML method with the recursive importance sampling (RIS). Lastly, the Generalized Methods of Moments (GMM), developed by Pinkse and Slade (1998) and the lineralized version by Klier and McMillen (2008) are valid estimation methods for spatial probit models.

Most methods, however, come with a drawback. Beron and Vijverberg (2004) report an estimation time of several hours for < 50 observations when using a ML estimation for a SAR probit model. Even as computational power has evolved in the years since 2004, an estimation with several thousand observations would lead to extreme computation times. The GMM, which is based on an instrumental-variable estimation, is computationally more efficient than ML estimation and MCMC estimation (Wilhelm and de Matos 2013). However, the estimation is quite inaccurate, especially when dealing with high autocorrelation (Martinetti and Geniaux 2017). Lastly, the Bayesian Gibbs and RIS sampler are valid options but only for smaller data sets where $n \leq 1000$ (Martinetti and Geniaux 2017).

To overcome the problems that other estimations methods inherit, the method by Martinetti and Geniaux (2017) will be used. The authors provide an approximate ML estimation method which allows a computationally efficient and accurate approximation of the spatial effects when working with binary outcome variables. It allows the estimation of the Spatial Lag Model SAR. Generally, the spatial probit model is represented as:

$$y^* = \rho W y^* + X\beta + \epsilon, \epsilon \sim \mathcal{N}(0, \sigma^2 I_n) \quad (1)$$

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

It holds, that

$$y_i = \begin{cases} 1, & y_i^* > 0 \\ 0, & y_i^* \leq 0, \end{cases} \tag{2}$$

where y represents the observed binary dependent variable, y^* is the unobserved latent variable, ρ and λ are the *spatial* scalar parameters which measure the strength of autocorrelation, defined between $[-1, 1]$. W and M are spatial weight matrices, X is a matrix of regressors, and β is the corresponding set of coefficients. u is the error term and ϵ are the disturbances which follow a multivariate normal distribution. As it is not possible to estimate both β and σ_ϵ^2 within a probit model, the errors are standardized to unit variance $\sigma_\epsilon^2 = 1$ (LeSage and Pace 2009). I_n is defined as the identity matrix.

In addition to the SAR model described above, this paper also implements a spatial Durbin probit model. This way, we provide a comparison of two different models, which partly addresses the methodological criticism brought forward in Pinske and Slade (2010). The Durbin model extends the SAR by including spatially lagged independent variables, thereby providing a more comprehensive framework for capturing spatial dependencies. Following the notation established by LeSage and Pace (2009), the spatial Durbin probit model in its latent form can be defined as:

$$y^* = \rho W y^* + X\beta + WX\gamma + \epsilon, \epsilon \sim \mathcal{N}(0, \sigma^2 I_n) \tag{3}$$

where the variables $y^*, \rho, W, X,$ and β are defined as in Equation (1). The additional term WX represents the spatially lagged explanatory variables, and γ is the corresponding $k \times 1$ vector of coefficients that capture spillover effects from neighboring observations' characteristics.

The reduced form of the SDM is given by:

$$y^* = (I_n - \rho W)^{-1} X\beta + (I_n - \rho W)^{-1} WX\gamma + (I_n - \rho W)^{-1}\epsilon. \tag{4}$$

This formulation demonstrates how the Durbin model integrates both direct effects ($X\beta$) and spillover effects ($WX\gamma$) from neighboring observations, with the spatial multiplier $(I_n - \rho W)^{-1}$ governing how these effects propagate through the spatial network.

The Durbin model specification enables a richer interpretation of spatial interactions compared to the SAR model. While the SAR model captures only the endogenous interaction effects through the spatially lagged dependent variable, the Durbin model additionally incorporates exogenous interaction effects via the spatially lagged explanatory variables.

The implementation of the spatial Durbin probit model requires special consideration of the spatially lagged explanatory variables. For each explanatory variable x_j (excluding the intercept), a corresponding spatially lagged variable $\sum_{i=1}^{n} w_{ij} x_{ij}$ is created and included in the model. This process effectively doubles the number of explanatory variables in the design matrix:

$$X_{\text{durbin}} = [X | WX] \tag{5}$$

where X_{durbin} represents the augmented design matrix for the Durbin model.

The estimation procedure follows the same approximate ML approach used for the SAR model, based on the method by Martinetti and Geniaux (2017). The likelihood function for the Durbin model takes a similar form to that of the SAR model but includes the additional parameters γ:

$$L(\beta, \gamma, \rho) = \Phi_n(x \in A | \Sigma) \tag{6}$$

where Φ_n represents the n-dimensional multivariate normal probability, Σ is the variance-covariance matrix defined as $\Sigma = (I_n - \rho W)^{-1}(I_n - \rho W)^{-1'}$), and A defines the integration bounds based on the observed binary outcomes.

In the Durbin model, there is a potentially large inverse matrix $(I_n - \rho W)^{-1}$, which is multiplied with the potentially nonsparse matrix WX. To improve computational efficiency, especially for large data sets, the implementation employs the conjugate gradient method to avoid explicit calculation of this inverse. Instead, the system $(I_n - \rho W)z = b$ is solved directly, which is computationally more efficient.

The spatial weight matrix is based on the k-nearest-neighbors (NN) definition, a common and popular approach when constructing the weight matrix (Dubin 1998). The method defines j to be a neighbor of i, if j is one of k nearest observations based on the Euclidean distance, where k is the maximum number of neighbors. The distance is calculated using the longitude and latitude data of an observation. As argued by Pace et al. (1998), the choice of the weight matrix and the numbers of neighbors significantly influence the results. Thus, several weight matrices will be used to provide robust results.

Because a Germany-wide spatial probit estimation is computationally infeasible given the size of the data set and the dimensionality of the spatial weight matrix, the models are estimated separately for each county. This county-level approach is methodologically preferable, as it preserves the underlying spatial heterogeneity and aligns the estimation with the true regional structure of firm dynamics. However, due to strict confidentiality requirements associated with the administrative microdata, the resulting county-specific coefficients cannot be published. This makes it necessary to develop an aggregation procedure that allows for meaningful reporting of the results while fully respecting privacy constraints.

Such aggregation is not trivial from an econometric perspective. Each county has its own spatial weight matrix and its own distribution of firm characteristics, implying that the estimated coefficients correspond to heterogeneous regional data-generating processes. The mean coefficient must therefore be interpreted as the expected effect across diverse local environments rather than as a single national structural parameter.

The share of significant coefficients provides a complementary and, in many respects, superior measure of the widespread relevance of each determinant. Unlike coefficient magnitudes, which are sensitive to local scaling, spatial connectivity, and nonlinearities the significance indicator abstracts from regional idiosyncrasies and reveals whether a variable plays a meaningful role in explaining firm exit in a given county. Conceptually, this measure offers a robust way to summarize heterogeneous spatial estimation results. Together, the mean coefficient and the significance share provide an informative

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

and methodologically defensible summary of the regional estimation outcomes while fully preserving data confidentiality.

Generally, the estimation method allows for different specifications. First, it can be differentiated between the full log-likelihood and conditional log-likelihood estimation. As Martinetti and Geniaux (2017) note, the full method is computational intense and does not always improve the results. In fact, the *conditional* method yields highly reliable and sometimes better results, as brought forward by the authors. Because of the methods' efficiency, it is recommended for data sets with more than a few thousand observations. Therefore, this paper will be limited to the conditional log-likelihood estimation.

Another calibration of the estimation method is given by the choice between the variance-covariance matrix and the precision matrix. The use of the latter, which is defined as $P = \Sigma^{-1}$, is also suggested by LeSage and Pace (2009). Again, for the sake of time efficiency, the estimation will be limited to the precision matrix.

The estimates are calculated using the R-package *SpatialProbit* (Wilhelm and Godinho de Matos 2024).

5 | Empirical Results

In the following section, the results are presented. First, the probit regression results are presented, including one estimation with regional FE. Afterwards, the global Moran calculations are presented. Lastly, the results of the spatial probit estimation are shown.

5.1 | Nonspatial Probit Regression

The binary dependent variable of the probit estimation is given by the *exit* decision of the firm. The model is estimated once with regional fixed effects and once without them. If the firm exited in the Year 2019, then $Y = 1$ and $Y = 0$ otherwise. For the categorical variables, the baseline estimation is given by *sole proprietorship* for the variable *legal form* and *no change* for the variables *change in revenue* and *change in number of employees*. In the estimation with fixed effects, $Schleswig - Holstein$ is used as the base case. The results of the probit estimation are shown in Table 5.

Most variables are significant at the 0.1% level. The only non-relevant variable is *revenue*. The categorical variables *other* and *less revenue* are significant at the 5% and 1% levels, respectively. As expected, a higher number of employees reduces the likelihood to exit the market, further supporting the *liability of smallness* (Aldrisch and Auster 1986). Holding all else equal, a switch from *sole proprietorship* to *corporation* or *partnership* significantly reduces the likelihood for exit. The larger coefficient of *corporations* compared to *partnerships* show the advantage corporations have compared to privately hold firms. Changing from *no change* in the number of employees to *more employees* reduces the likelihood to exit, whilst a change to *less employees* increases the exit likelihood, *ceteris paribus*. The same holds true for the change in revenue. Those support the insight, that growth tends to be an important determinant of firm exit. It also contradicts some insights from earlier literature, which indicates that growth is not a determining factor (Hall 1986). Interestingly, the revenue of a firm does not exhibit a significant influence on the propensity to exit, although exited and nonexited firms face a substantial difference in their revenue. One reason might be the difficulties with the assessment of revenue, outlined in Section 3.2. Moreover, it could also result from multicollinearity issues, which are not investigated in this case.

For the probit model with FE, the same set of variables is significant. However, some substantial differences compared to the model without fixed effects are visible. Foremost, the

TABLE 5 | Probit estimation results.

	Probit 1		Probit 2	
Variable	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	−1.922***	0.031	−2.127***	0.027
NEmployees	−0.0067***	< 0.001	−0.0068***	< 0.001
Revenue	< 0.001	< 0.001	< 0.001	< 0.001
More Employees	−0.219***	0.010	−0.217***	0.010
Less Employees	0.130***	0.008	0.131***	0.008
More Revenue	−0.125***	0.028	−0.125***	0.028
Less Revenue	0.080**	0.028	0.078**	0.028
Corporation	−0.277***	0.009	−0.271***	0.009
Partnership	−0.111***	0.011	−0.103***	0.011
Other	0.236*	0.102	0.244*	0.102
State Fixed Effects	No		Yes	
McFadden's R^2	0.0330		0.0379	
AIC	134,024		133,378	
BIC	134,143		133,677	
Log Likelihood	−67,002		−66,664	

Note: $N = 1{,}160{,}442$.
***$p<0.001$; **$p<0.01$; *$p<0.05$.

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

estimation with regional FE yields *better* results, as indicated by the lower Akaike Information Criterion (AIC) and Bayesian Information Criterion (BIC) and higher McFadden R^2. Also, the higher log-likelihood of the model signals that the model better explains the observed outcome.

Second, the baseline propensity to exit is larger. Given that the baseline is given by the state of $Schleswig - Holstein$, the state with the highest exit rate, this insight does not surprise. As we can see in Table A1 in the Appendix A, being located in another state than $Schleswig - Holstein$ reduces in nearly every case the propensity to exit, *c.p*. The marginal effects of the variables are reported in Table A1 in the Appendix A.

For both estimations, the change to *Corporation* has the largest effect in reducing the likelihood of firm exit. In the non-FE estimation, the likelihood of a firm to exit the market is reduced by $0.68\%pt$. compared to $0.72\%pt$. in the fixed effects model.

Notably, being located in $Baden - Wuerttemberg$ compared to $Schleswig - Holstein$ has the largest effect on a firms' likelihood to exit and reduces the same by $30.7\%pt$. These results also indicate that nonobserved state-wide characteristics are important determinants of firm exit.

5.2 | Global Moran's *I*

In the following, the Moran statistic following Anselin (1988) is calculated in order to give some basic insights about the degree of spatial dependence. The spatial weight matrix is designed by using the Queen-based contiguity definition of neighborhood (Dale and Fortin 2014), by which districts are defined as neighbors if they share a common border. First for the dependent variable, given as the share of firm exits per district in Year 2019, and then for the *standard residuals* from both probit estimations. The residuals are summarized by their respective district and the mean value is used.

The results of the Global Moran statistic are given in Table 6. All values indicate significant positive spatial dependence. With $I = 0.336$, the autocorrelation is strongest for the dependent variable. The residuals of the nonfixed effects model show similar values ($I = 0.331$). Both values are significant at the 5% level of significance. The significance level can be interpreted such that in *none* of the randomly permuted cases, the value for Moran's I was as high as in the original data set.

The residuals of the FE model show significantly less strong autocorrelation, but are still positively correlated and significant at the 5% level. This supports the idea outlined above, that the exit rates are partially explained by unobserved regional determinants. However, it also shows that the fixed effects do not properly account for the spatial dependence, as discussed by Anselin and Arribas-Bel (2013).

TABLE 6 | Global Moran's *I* values.

Type	Global Moran's *I*	*p*
Dependent	0.336	0.001
Residual	0.331	0.001
Residual FE	0.059	0.029

5.3 | Spatial Probit Regression

The estimation of Global Moran's has provided evidence that the observations are spatially correlated. That necessitates the use of a model that can account for these spatial dependencies, as the results of the baseline probit regression are biased in the case of spatial autocorrelation. Therefore, the Spatial Probit Model, outlined in Section 4 is estimated, following the procedure by Martinetti and Geniaux (2017). The model is estimated including the same set of variables as the first probit model and a varying number of neighbors. The SAR and Durbin spatial probit models are separately estimated for each German county and independent city. Estimating the models at this disaggregated geographical level allows us to capture local patterns of spatial dependence that may be masked when pooling all regions in a single national estimation. Due to strict data protection rules associated with the underlying administrative microdata, it is not permissible to publish county-specific parameter estimates. To report the results in a manner that is both informative and fully compliant with confidentiality regulations, we therefore summarize the separate estimations by presenting, for each coefficient, the mean across all counties and the share of county-level estimations in which the coefficient is statistically significant at the 5% level.

The mean coefficient provides a central tendency of the local estimations and reflects the average marginal effect of the variable across Germany. The share of significant coefficients complements this measure by indicating the degree to which a variable is systematically relevant across regions. A coefficient with a high mean magnitude and a high share of significance can be interpreted as a robust determinant of firm exit that exerts similar influence across most counties. Conversely, a coefficient with a moderate mean but low significance share indicates regional heterogeneity, suggesting that the variable is important only in certain parts of the country. The same logic applies to the spatial autoregressive parameter ρ, where the significance share reflects how widespread local spatial dependence in firm exits is across the national territory.

The aggregation method can be justified by letting $\hat{\theta}_r$ denote the estimator of coefficient θ in county $r \in 1, ..., R$, with $R = 400$. Under standard regularity conditions for spatial probit models, each $\hat{\theta}_r$ consistently estimates the true region-specific parameter θ_r. The sample mean

$$\bar{\theta} = \frac{1}{R} \sum_{r=1}^{R} \hat{\theta}_r$$

is therefore a consistent estimator of the national average effect $E(\theta_r) = \frac{1}{R} \sum_{r=1}^{R} \theta_r$, which is substantively meaningful in a heterogeneous spatial setting. Likewise, the indicator $1\{|\hat{\theta} r| > z_{0.975}\hat{\sigma}_r\}$ converges to $1\{\theta_r \neq 0\}$, implying that the share of significant coefficients consistently estimates the prevalence of nonzero effects across regions. This measure parallels the "frequency of significance" in meta-analytic econometrics and conveys how widespread a determinant is without revealing county-level estimates.

Tables 7 and 8 report the corresponding means and significance shares for the specifications with $NN = 200$ and $NN = 50$ nearest neighbors, respectively. Across both neighbor specifications and in

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 7 | Overall spatial probit results ($NN = 200$).

	SAR Model		Durbin Model	
Variable	**Mean**	**Share sig. (5%)**	**Mean**	**Share sig. (5%)**
Intercept	−2.571	1.00	−2.006	1.00
N Employees	−0.017	0.60	−0.017	0.40
More Employees	−0.392	0.77	−0.386	0.79
Less Employees	0.030	0.73	0.110	0.65
Productivity	−0.0004	0.53	−0.0006	0.15
Corporation	−0.273	0.70	−0.239	0.65
Partnership	−0.252	0.80	−0.251	0.64
Other	−0.997	0.87	−1.558	0.85
Revenue	2.363×10^{-7}	0.53	−0.0173	0.35
More Revenue	0.228	0.90	0.215	0.70
Less Revenue	−1.849	0.87	−3.266	0.93
ρ	−0.055	0.17	0.067	0.45
W_N Employees	—	—	−0.0004	0.20
W_More Employees	—	—	−0.013	0.00
W_Less Employees	—	—	0.012	0.01
W_Productivity	—	—	8.885×10^{-4}	0.30
W_Corporation	—	—	0.058	0.01
W_Partnership	—	—	0.010	0.00
W_Other	—	—	−0.001	0.00
W_Revenue	—	—	8.124×10^{-6}	0.12
W_More Revenue	—	—	−0.021	0.00
W_Less Revenue	—	—	−0.004	0.00

Note: Reported values are means across separate county-level spatial probit estimations. "Share sig. (5%)" denotes the proportion of counties in which the corresponding coefficient is statistically significant at the 5% level. Variables with the W_ prefix are spatially lagged covariates included only in the Durbin specification. Dashes (–) indicate variables not included in the SAR model.

both the SAR and Durbin models, the internal determinants of firm exit exhibit strong consistency. Firm size, proxied by the number of employees, and firm growth, proxied by changes in employment and revenue, show consistent mean effects, across varying neighborhood sizes. The negative coefficients for firms with increasing employment and revenue, and the positive coefficients for firms with shrinking employment and revenue, appear with a high share of significance across counties. Similarly, the legal form exerts a substantial protective effect, with corporations and partnerships exhibiting consistently lower average exit probabilities than sole proprietorships. The large share of counties in which these variables are significant indicates that internal firm characteristics remain the primary determinants of exit across the German regional landscape.

The evidence concerning spatial dependence is more heterogeneous. The mean values of the spatial autoregressive parameter ρ are modest in magnitude, yet the share of counties where ρ is significant suggests that local spatial dependence is present in a non-negligible subset of regions. This finding is consistent with earlier Moran's I diagnostics, which revealed spatial clustering in the distribution of firm exits but also substantial regional variation in the strength of autocorrelation. The Durbin specification shows somewhat higher rates of significance for ρ, which indicates that local spatial interactions may operate through both endogenous dependence in the latent outcome and exogenous spatial lags of covariates.

Spatial spillovers through observable firm characteristics, captured by the spatially lagged regressors in the Durbin model, appear limited. The mean coefficients of these spatial lags are generally small, and the share of counties in which these variables are significant is extremely low. This pattern suggests that the principal spatial channel is not the transmission of firm-level characteristics between neighboring firms but rather the influence of unobserved regional conditions that cluster geographically. This interpretation aligns with theoretical considerations in regional economics, where local business taxation, regional demand conditions, labor market frictions, and institutional environments tend to vary over space and influence exit decisions in a spatially correlated fashion. The relative weakness of observable spillovers, in contrast, suggests that direct interfirm contagion via observable characteristics is limited in this setting.

Overall, internal firm characteristics remain stable predictors of firm exits across Germany, whereas spatial dependence exhibits meaningful but regionally variable patterns. The relative weakness of observable spatial spillovers further suggests that spatial autocorrelation in firm exit is driven primarily by unobserved regional factors rather than by direct interfirm interactions through measurable covariates. This county-level evidence reinforces the central conclusion of the analysis that accounting for spatial dependence is essential, while also demonstrating that the mechanisms underlying spatial clustering operate unevenly across the German economic landscape.

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universität zu Köln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE 8 | Overall spatial probit results ($NN = 50$).

Variable	SAR Model		Durbin Model	
	Mean	Share sig. (5%)	Mean	Share sig. (5%)
Intercept	−2.507	1.00	−1.996	1.00
N Employees	−0.016	0.71	−0.016	0.38
More Employees	−0.387	0.74	−0.358	0.79
Less Employees	−0.174	0.74	−0.163	0.68
Productivity	−0.001	0.61	−0.001	0.13
Corporation	−0.977	0.68	−0.894	0.64
Partnership	−0.744	0.81	−0.650	0.61
Other	−2.527	0.90	−1.425	0.82
Revenue	-5.307×10^{-6}	0.68	-6.116×10^{-8}	0.34
More Revenue	0.225	0.90	0.225	0.70
Less Revenue	−1.615	0.94	−3.240	0.91
ρ	0.000	0.19	0.019	0.31
W_N Employees	—	—	0.000	0.16
W_More Employees	—	—	0.000	0.01
W_Less Employees	—	—	-1.882×10^{-5}	0.02
W_Productivity	—	—	-3.067×10^{-4}	0.21
W_Corporation	—	—	0.000	0.03
W_Partnership	—	—	4.148×10^{-7}	0.01
W_Other	—	—	0.000	0.00
W_Revenue	—	—	-1.823×10^{-1}	0.10
W_More Revenue	—	—	0.000	0.02
W_Less Revenue	—	—	-1.610×10^{-7}	0.00

Note: Reported values are means across separate county-level spatial probit estimations. “Share sig. (5%)” denotes the proportion of counties in which the corresponding coefficient is statistically significant at the 5% level. Variables with the W_ prefix are spatially lagged covariates included only in the Durbin specification. Dashes (–) indicate variables not included in the SAR model.

5.3.1 | *Neighborhood Size and Spatial Dependence*

Although the county-level aggregation prevents the computation of formal direct and indirect effects in the LeSage and Pace (2009) sense for the SDM, the results nonetheless provide important insights into the spatial scale at which economic interdependencies in firm exit operate. A comparison of the $NN = 50$ and $NN = 200$ specifications reveals that spatial dependencies become more pronounced when broader neighborhood structures are considered. In particular, the spatial autoregressive parameter ρ exhibits a markedly higher share of statistical significance in the Durbin model with $NN = 200$ than with $NN = 50$, and several spatially lagged covariates become significant only under the broader neighborhood definition. This pattern suggests that spatial spillovers in firm exit do not arise primarily from immediate geographic proximity, but rather operate at intermediate spatial scales consistent with county or metropolitan-area structures.

This scale-dependence aligns with the geographic scope of several key economic processes affecting firm survival. Labor markets are typically integrated at metropolitan scales, supply-chain linkages often extend across multiple counties, and market competition increasingly follows regional rather than purely local patterns. The finding that spatial dependencies manifest more clearly at $NN = 200$ therefore suggests that the relevant economic geography for firm exit encompasses wider business networks and institutional environments rather than simple adjacency.

The aggregated results imply that spatial dependence in firm exit patterns is driven predominantly by unobserved spatially clustered factors—such as local market conditions, regulatory or institutional contexts, business confidence, credit availability, or region-specific demand shocks—rather than by observable firm characteristics generating substantial spillovers across space. This interpretation is consistent with the limited significance of most spatially lagged regressors and the more frequent significance of the spatial autoregressive parameter.

These findings have several policy implications. In economically homogeneous regions, targeted interventions addressing specific firm characteristics are likely to produce primarily direct effects on the treated firms, with minimal spillovers through observable channels. By contrast, policies aimed at improving broader local business conditions—through infrastructure investment, regulatory simplification, or regional economic development measures—may generate more substantial spatial multiplier effects by addressing the unobserved factors underlying spatial dependence. The stronger spatial patterns observed at intermediate neighborhood sizes indicate that such policies may be most effective when designed at the county or metropolitan scale, which aligns closely with the actual spatial structure of labor markets and economic interactions.

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Overall, the analysis demonstrates that meaningful spatial dependencies in firm exit behavior persist even after accounting for firm-level determinants, but that these dependencies are geographically uneven and operate at scales larger than immediate firm-to-firm proximity. This underscores the importance of modeling spatial autocorrelation in firm survival studies and highlights the relevance of regional economic environments as key determinants of business dynamics.

6 | Discussion and Limitations of Results

The empirical results confirm the existing literature on the internal determinants of firm exit. Firm size, proxied by the number of employees, remains one of the most influential predictors of exit, supporting the *liability of smallness* (Aldrisch and Auster 1986). Growth dynamics, captured through changes in revenue and employment, also play an important role: growing firms tend to exhibit a substantially lower probability of exit, whereas shrinking firms face markedly higher risks. This finding contrasts with earlier studies suggesting that growth is not systematically related to firm failure (Hall 1986). Legal form continues to matter as well. Sole proprietorships exhibit significantly higher exit propensities than corporations and partnerships, reinforcing the view that institutional structures and access to financing influence firm survival outcomes.

A comparison between the pooled probit results in Table 5 and the aggregated spatial probit results in Tables 7 and 8 highlights the added value of incorporating spatial structure into the analysis. While the nonspatial model identifies the key internal determinants of firm exit, that is, firm size, growth dynamics, and legal form, it implicitly assumes that firms operate independently of their geographical context. The county-level spatial probit estimations reveal that this assumption is not fully valid. The spatial autoregressive parameter ρ is significant in a substantial share of counties, indicating the presence of local spatial dependence in firm exit that the pooled probit model cannot capture. Moreover, the spatial models uncover considerable regional heterogeneity in the strength of these dependencies, which is obscured in the national-level estimation. Importantly, the core internal determinants remain robust across both modeling approaches, but the spatial results show that rather than observable firm characteristics, the unobserved regional conditions are responsible for the majority of spatial dependence.

The spatial analysis yields further novel insights. First, firm exit rates differ substantially across Germany and are characterized by strong spatial autocorrelation, as evidenced by the Global Moran's I results. Second, the county-level spatial probit estimations reveal that unobserved regional conditions are a central source of spatial dependence. The spatial autoregressive parameter ρ is significant in a non-negligible share of counties, whereas most spatially lagged covariates show low significance rates, suggesting that spatial autocorrelation in firm exits is driven primarily by unobserved regional factors rather than by direct spillovers through observable firm characteristics. This interpretation is consistent with regional differences in local business environments, such as taxation, demand conditions, or institutional quality (Statistikportal 2024).

These findings provide new evidence that spatial dependence is an important feature of firm exit dynamics in Germany. However, several limitations must be acknowledged. A key limitation relates to the treatment of spatial heterogeneity. For confidentiality reasons, the spatial probit models are estimated separately for each county, and only aggregated measures—the mean coefficient and the share of significant estimates—are reported. While this approach preserves the essential spatial patterns and avoids disclosure of sensitive information, it does not permit the computation of formal direct and indirect effects or the comparison of full spatial multipliers across regions.

Overall, while the analysis uncovers robust evidence of spatial dependence in firm exits and confirms the importance of internal determinants, these limitations underscore the need to fully exploit the richness of the administrative microdata.

7 | Conclusion

This study provides new evidence on the determinants of firm exit in Germany by systematically incorporating spatial dependence into the analysis. Germany has previously received little attention in the spatial firm exit literature, despite its pronounced regional heterogeneity in economic structure. By estimating spatial probit models separately for each county and aggregating the results to preserve data confidentiality, this paper offers nationally representative assessment of how spatial processes shape firm survival outcomes.

The results confirm the importance of internal firm characteristics like firm size, growth dynamics, and legal form as robust predictors of exit. At the same time, the spatial analysis reveals that firm exit is not randomly distributed across space: exit rates are strongly clustered, and the spatial autoregressive parameter is significant in a notable share of counties. These patterns demonstrate that unobserved regional conditions, rather than observable firm attributes, are the primary channels generating spatial dependence. The consistently low significance of spatially lagged covariates further suggests that pure contagion mechanisms linked to local economic environments dominate over direct spillovers between neighboring firms.

The lack of access to publishable region-specific coefficients requires aggregation of county-level estimates.

Several promising avenues for further work emerge from this study. Incorporating regional start-up rates would allow for a more comprehensive view of demographic firm dynamics, as previous research suggests strong interdependencies between firm birth and exit rates (Brixy and Grotz 2007). From a policy perspective, the evidence indicates that regional economic environments shape firm exit risks in ways that go beyond firm-level characteristics. Future research linking spatial exit patterns to regional policy interventions, that is, business tax changes, infrastructure investments, or innovation support programs, could yield valuable insights for targeted regional development strategies.

Acknowledgments

The authors are grateful to Florian Köhler for assisting with the access to the data as well as to Rafael Weißbach for helpful comments.

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Data Availability Statement

The data that support the findings will be available in Destatis at http://www.destatis.de following an embargo from the date of publication to allow for commercialization of research findings.

References

Abughniem, M., M. Al Aishat, A. Hamdan, and S. Weshah. 2020. "Capital Structure, Firm Growth and Firm Performance: Evidence From Jordan." *International Journal of Innovation, Creativity and Change* 10, no. 12: 655–667.

Aldrisch, H., and E. Auster. 1986. "Even Dwarfs Started Small: Liabilities of Size and Age and Their Strategies Implications." *Research in Organizational Behavior* 8: 165–198.

Altman, E. I. 1968. "Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy." *Journal of Finance* 23, no. 4: 589–609.

Andreano, M. S., R. Benedetti, A. Mazzitelli, and F. Piersimoni. 2018. "Spatial Autocorrelation and Clusters in Modelling Corporate Bankruptcy of Manufacturing Firms." *Journal of Industrial and Business Economics* 45, no. 4: 475–491.

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

Anselin, L. 2002. "Under the Hood Issues in the Specification and Interpretation of Spatial Regression Models." *Agricultural Economics* 27, no. 3: 247–267.

Anselin, L., and D. Arribas-Bel. 2013. "Spatial Fixed Effects and Spatial Dependence in a Single Cross-Section." *Papers in Regional Science* 92, no. 1: 3–18.

Arcuri, G., M. Brunetto, and N. Levratto. 2018. "Spatial Patterns and Determinants of Firm Exit: An Empirical Analysis on France." *Annals of Regional Science* 62, no. 1: 99–118.

Audretsch, D. B., P. Houweling, and A. R. Thurik. 2000. "Firm Survival in the Netherlands." *Review of Industrial Organization* 16: 1–11.

Barron, D. N., E. West, and M. T. Hannan. 1994. "A Time to Grow and a Time to Die: Growth and Mortality of Credit Unions in New York City, 1914-1990." *American Journal of Sociology* 100, no. 2: 381–421.

Bartelsman, E. J., and M. Doms. 2000. "Understanding Productivity: Lessons From Longitudinal Microdata." *Journal of Economic Literature* 38, no. 3: 569–594.

Barthel, F., and E. Neumayer. 2015. "Spatial Dependence in Asylum Migration." *Journal of Ethnic and Migration Studies* 41, no. 7: 1131–1151.

Beaver, W. H. 1966. "Financial Ratios as Predictors of Failure." *Journal of Accounting Research* 4: 71.

Beron, K. J., and W. P. M. Vijverberg. 2004. "Probit in a Spatial Context: A Monte Carlo Analysis." In *Advances in Spatial Econometrics. Advances in Spatial Science*, L. Anselin, R. J. G. M. Florax, and S. J. Rey, 169–195. Springer.

Bottazzi, G., E. Cefis, and G. Dosi. 2002. "Corporate Growth and Industrial Structures: Some Evidence From the Italian Manufacturing Industry." *Industrial and Corporate Change* 11, no. 4: 705–723.

Brixy, U., and R. Grotz. 2007. "Regional Patterns and Determinants of Birth and Survival of New Firms in Western Germany." *Entrepreneurship and Regional Development* 19, no. 4: 293–312.

Buehler, S., C. Kaiser, and F. Jaeger. 2007. "On the Geographic and Cultural Determinants of Bankruptcy." Technical Report, Working Paper.

Buehler, S., C. Kaiser, and F. Jaeger. 2012. "The Geographic Determinants of Bankruptcy: Evidence From Switzerland." *Small Business Economics* 39: 231–251.

Cainelli, G., S. Montresor, and G. V. Marzetti. 2013. "Spatial Agglomeration and Firm Exit: A Spatial Dynamic Analysis for Italian Provinces." *Small Business Economics* 43, no. 1: 213–228.

Cefis, E., C. Bettinelli, A. Coad, and O. Marsili. 2021. "Understanding Firm Exit: A Systematic Literature Review." *Small Business Economics* 59, no. 2: 423–446.

Chandler, A. D. 1994. Scale and Scope. Scientific Research.

Dale, M. R., and M.-J. Fortin. 2014. *Spatial Analysis: A Guide for Ecologists*. Cambridge University Press.

Destatis. 2024a. *Umsatz (Unternehmensregister) [Turnover (business register)]*. Statistisches Bundesamt. https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Handwerk/Glossar/umsatz-unternehmensregister.html.

Destatis. 2024b. *Unternehmensdemografie: Methoden* [Business Demography: Methods]. Statistisches Bundesamt. https://www.destatis.de/DE/Themen/Branchen-Unternehmen/Unternehmen/Unternehmensdemografie/Methoden/erlaeuterungen.html.

Dewaelheyns, N., and C. Van Hulle. 2007. "Aggregate Bankruptcy Rates and the Macroeconomic Environment: Forecasting Systematic Probabilities of Default." *Tijdschrift voor Economie en Management* 52, no. 4: 541–565.

Dubin, R. A. 1998. "Spatial Autocorrelation: A Primer." *Journal of Housing Economics* 7, no. 4: 304–327.

Duranton, G., and D. Puga. 2004. " Micro-Foundations of Urban Agglomeration Economies." In Handbook of Regional and Urban Economics, Vol. 4, 2063–2117. Elsevier.

Elkink, J., and R. Calabrese. 2015. " Estimating Binary Spatial Autoregressive Models for Rare Events." In The Annual Meeting of the American Political Science Association, Washington DC, 28–31.

European Commission. 2023. *GISCO NUTS - Nomenclature of Territorial Units for Statistics*. European Commission. https://gisco-services.ec.europa.eu/distribution/v2/nuts/.

Evans, D. S. 1987. "The Relationship Between Firm Growth, Size, and Age: Estimates for 100 Manufacturing Industries." *Journal of Industrial Economics* 35, no. 4: 567–581.

Fackler, D., C. Schnabel, and J. Wagner. 2013. "Establishment Exits in Germany: The Role of Size and Age." *Small Business Economics* 41: 683–700.

Fahr, R., and U. Sunde. 2006. "Regional Dependencies in Job Creation: An Efficiency Analysis for Western Germany." *Applied Economics* 38, no. 10: 1193–1206.

Fama, E. F., and M. C. Jensen. 1983. "Separation of Ownership and Control." *Journal of Law and Economics* 26, no. 2: 301–325.

Farinas, J. C., and L. Moreno. 2000. "Firms' Growth, Size and Age: A Nonparametric Approach." *Review of Industrial Organization* 17: 249–265.

Fatica, S., T. Oliviero, M. Rancan, et al. 2022. *On the Determinants of Corporate Default in the EU-27: Evidence From a Large Sample of Companies* (JRC Technical Report No. EUR 31342 EN). Publications Office of the European Union.

Glaeser, E. L., and J. D. Gottlieb. 2009. "The Wealth of Cities: Agglomeration Economies and Spatial Equilibrium in the United States." *Journal of Economic Literature* 47, no. 4: 983–1028.

Hall, B. H. 1987. "The Relationship Between Firm Size and Firm Growth in the U.S. Manufacturing Sector." *Journal of Industrial Economics* 35, no. 4: 583–606.

Harhoff, D., K. Stahl, and M. Woywode. 1998. "Legal Form, Growth and Exit of West German Firms–Empirical Results for Manufacturing, Construction, Trade and Service Industries." *Journal of Industrial Economics* 46, no. 4: 453–488.

Hernangómez, D. 2024. *giscoR: Download Map Data from GISCO API - Eurostat* (Version 1.0.0) [Software]. CRAN. https://ropengov.github.io/giscoR/.

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Hirsch, S., and J. Schiefer. 2016. "What Causes Firm Profitability Variation in the EU Food Industry? A Redux of Classical Approaches of Variance Decomposition." *Agribusiness* 32, no. 1: 79–92.

Jacobson, T., J. Lindé, and K. Roszbach. 2013. "Firm Default and Aggregate Fluctuations." *Journal of the European Economic Association* 11, no. 4: 945–972.

Klier, T., and D. P. McMillen. 2008. "Clustering of Auto Supplier Plants in the United States." *Journal of Business and Economic Statistics* 26, no. 4: 460–471.

Krugman, P. 1991. "Increasing Returns and Economic Geography." *Journal of Political Economy* 99, no. 3: 483–499.

Lehmann, R., and W. Nagl. 2019. "Explaining Spatial Patterns of Foreign Employment in Germany." *Regional Studies* 53, no. 7: 991–1003.

LeSage, J. P. 2000. "Bayesian Estimation of Limited Dependent Variable Spatial Autoregressive Models." *Geographical Analysis* 32, no. 1: 19–35.

LeSage, J. P., and R. K. Pace. 2009. *Introduction to Spatial Econometrics*. Chapman and Hall/CRC eBooks.

Loderer, C. F., K. Neusser, and U. Waelchli. 2010. *Firm Age and Survival*. Available at SSRN 1430408.

Logue, D. M., W. P. Jarvis, S. Clegg, and A. Hermens. 2015. "Translating Models of Organization: Can the Mittelstand Move From Bavaria to Geelong?." *Journal of Management & Organization* 21, no. 1: 17–36.

Markides, C. 1997. "Strategic Innovation." *Sloan Management Review* 38, no. 3: 9–23.

Martinetti, D., and G. Geniaux. 2017. "Approximate Likelihood Estimation of Spatial Probit Models." *Regional Science and Urban Economics* 64: 30–45.

Mata, J., P. Portugal, and P. Guimaraes. 1995. "The Survival of New Plants: Start-Up Conditions and Post-Entry Evolution." *International Journal of Industrial Organization* 13, no. 4: 459–481.

Maté-Sánchez-Val, M., F. Lopez-Hernandez, and C. C. R. Fuentes. 2018. "Geographical Factors and Business Failure: An Empirical Study From the Madrid Metropolitan Area." *Economic Modelling* 74: 275–283.

Mayer, A., and D. Wied. 2024. "Endogeneity Corrections in Binary Outcome Models With Nonlinear Transformations: Identification and Inference." Preprint, arxiv: 2408.06977.

McCann, P., and R. Ortega-Argilés. 2013. "Modern Regional Innovation Policy." *Cambridge Journal of Regions, Economy and Society* 6, no. 2: 187–216.

McMillen, D. P. 1992. "Probit With Spatial Autocorrelation." *Journal of Regional Science* 32, no. 3: 335–348.

Moretti, E. 2010. "Local Multipliers." *American Economic Review* 100, no. 2: 373–377.

Ord, K. 1975. "Estimation Methods for Models of Spatial Interaction." *Journal of the American Statistical Association* 70, no. 349: 120–126.

Pace, R. K., R. Barry, J. M. Clapp, and M. Rodriquez. 1998. "Spatiotemporal Autoregressive Models of Neighborhood Effects." *Journal of Real Estate Finance and Economics* 17: 15–33.

Pérez, S. E., A. S. Llopis, and J. A. S. Llopis. 2004. "The Determinants of Survival of Spanish Manufacturing Firms." *Review of Industrial Organization* 25: 251–273.

Pinkse, J., and M. E. Slade. 1998. "Contracting in Space: An Application of Spatial Statistics to Discrete-Choice Models." *Journal of Econometrics* 85, no. 1: 125–154.

Pinske, J., and M. Slade. 2010. "The Future of Spatial Econometrics." *Journal of Regional Science* 50: 103–117.

Porter, M. E. 1980. *Competitive Strategy: Techniques for Analyzing Industries and Competitors* [Republished With a New Introduction, 1998]. Free Press.

RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany. 2023a. *AFiD-Teilmodul der Unternehmensdemographie: Berichtsjahre 2018 – 2019 (Unternehmen (UN)) [AFiD-Submodule of business demography: Reporting years 2018–2019 (businesses (UN))]*

RDC of the Federal Statistical Office and Statistical Offices of the Federal States of Germany. 2023b. *Unternehmensregister: Years 2018 and 2019 [Company Register: Years 2018 and 2019]*

Reuters. 2024. "Eastern Germany's Economic Success Leaves Voters Cold." https://www.reuters.com/world/europe/eastern-germanys-economic-success-leaves-voters-cold-2024-08-28/.

Robb, A. M., and D. T. Robinson. 2014. "The Capital Structure Decisions of New Firms." *Review of Financial Studies* 27, no. 1: 153–179.

Saridakis, G., K. Mole, and G. Hay. 2013. "Liquidity Constraints in the First Year of Trading and Firm Performance." *International Small Business Journal* 31, no. 5: 520–535.

Serra, L., C. Detotto, P. Juan, and M. Vannini. 2022. "Intersectoral and Spatial Spill-Overs of Firms' Bankruptcy in Spain." *Letters in Spatial and Resource Sciences* 15, no. 2: 197–211.

Statista. 2024. *Hauptsitze ausgewahlter DAX-Unternehmen [Headquarters of Selected DAX Companies]* https://de.statista.com/infografik/10028/hauptsitze-ausgewaehlter-dax-unternehmen/.

Statistikportal. 2024. *Hebesatze in Deutschland [Local Multipliers for the Trade Tax in Germany]* https://www.statistikportal.de/de/karte-hebesaetze.

Thornhill, S. 2006. "Knowledge, Innovation and Firm Performance in High- and Low-Technology Regimes." *Journal of Business Venturing* 21, no. 5: 687–703.

Tinoco, M. H., and N. Wilson. 2013. "Financial Distress and Bankruptcy Prediction Among Listed Companies Using Accounting, Market and Macroeconomic Variables." *International Review of Financial Analysis* 30: 394–419.

Wilhelm, S., and M. G. de Matos. 2013. "Estimating Spatial Probit Models in R." *R Journal* 5, no. 1: 130–143.

Wilhelm, S., and M. Godinho de Matos. 2024. *spatialprobit: Spatial Probit Models*. R Package Version 1.0.4. https://CRAN.R-project.org/package=spatialprobit.

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Appendix A

Unveiling Spatial Dependencies — Investigating the Determinants of Firm Exit in Germany

Table A1

TABLE A1 | Probit estimation results full table.

	Probit 1		Probit 2	
Variable	**Coefficient**	**SE**	**Coefficient**	**SE**
Intercept	−1.922***	0.031	−2.127***	0.027
Revenue	< 0.001	< 0.001	< 0.001	< 0.001
N Employees	−0.0067***	< 0.001	−0.0068***	< 0.001
More Employees	−0.219***	0.010	−0.217***	0.010
Less Employees	0.130***	0.008	0.131***	0.008
More Revenue	−0.125***	0.028	−0.125***	0.028
Less Revenue	0.080**	0.028	0.078**	0.028
Corporation	−0.277***	0.009	−0.271***	0.009
Partnership	−0.111***	0.011	−0.103***	0.011
Other	0.236*	0.102	0.244*	0.102
HH			0.0015	0.024
NI			−0.265***	0.020
HB			0.0564	0.038
NW			−0.251***	0.017
HE			−0.0901***	0.019
RP			−0.282***	0.023
BW			−0.307***	0.019
BY			−0.193***	0.017
SL			−0.260***	0.039
BE			−0.115***	0.022
BB			−0.256***	0.026
MV			−0.290***	0.031
SN			−0.163***	0.021
ST			−0.290***	0.028
TH			−0.204***	0.026
McFadden's R^2	0.0330		0.0379	
AIC	134,024		133,378	
BIC	134,143		133,677	

Note: $N = 1{,}160{,}442$.
***$p < 0.001$; **$p < 0.005$.

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

Table A2

TABLE A2 | Probit effects full table.

Variable	**Probit 1 AME [lower, upper] (SE)**	**Probit 2 AME [lower, upper] (SE)**
N Employees	−0.0002 [−0.0002, −0.0002]***	−0.0002 [−0.0006, 0.0001]***
	(0.0001)	(0.0002)
Revenue	0.0000 [0.0000, 0.0000]	0.0000 [0.0000, 0.0000]
	(< 0.0001)	(< 0.0001)
Corporation	−0.0068 [−0.0072, −0.0064]***	−0.0072 [−0.0076, −0.0068]***
	(0.0002)	(0.0002)
Partnership	−0.0031 [−0.0037, −0.0025]***	−0.0037 [−0.0042, −0.0031]***
	(0.0003)	(0.0003)
Other	0.0106 [−0.0004, 0.0217]	−0.0004 [−0.0429, 0.0421]
	(0.0056)	(0.0217)
More Employees	−0.0048 [−0.0052, −0.0044]***	−0.0052 [−0.0139, 0.0034]***
	(0.0002)	(0.0044)
Less Employees	0.0043 [0.0035, 0.0051]***	0.0037 [0.0022, 0.0053]**
	(0.0003)	(0.0049)
More Revenue	−0.0032 [−0.0048, −0.0016]***	−0.0048 [−0.0071, −0.0025]***
	(0.0008)	(0.0016)
Less Revenue	0.0025 [0.0009, 0.0042]**	0.0009 [−0.0036, 0.0054]
	(0.0008)	(0.0042)
HH		0.0015 [0.0001, 0.0029]
		(0.0240)
NI		−0.2650 [−0.3050, −0.2250]***
		(0.0200)
HB		0.0564 [0.0184, 0.0944]
		(0.0380)
NW		−0.2510 [−0.2850, −0.2170]***
		(0.0170)
HE		−0.0901 [−0.1280, −0.0522]***
		(0.0190)
RP		−0.2820 [−0.3240, −0.2400]***
		(0.0230)
BW		−0.3070 [−0.3450, −0.2690]***
		(0.0190)
BY		−0.1930 [−0.2270, −0.1590]***
		(0.0170)
SL		−0.2600 [−0.3380, −0.1820]***
		(0.0390)
BE		−0.1150 [−0.1590, −0.0710]***
		(0.0220)
BB		−0.2560 [−0.3080, −0.2040]***
		(0.0260)

(Continues)

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License

TABLE A2 | (Continued)

Variable	Probit 1 AME [lower, upper] (SE)	Probit 2 AME [lower, upper] (SE)
MV		−0.2900 [−0.3520, −0.2280]***
		(0.0310)
SN		−0.1630 [−0.2050, −0.1210]***
		(0.0210)
ST		−0.2900 [−0.3460, −0.2340]***
		(0.0280)
TH		−0.2040 [−0.2560, −0.1520]***
		(0.0260)

Note: SE in parentheses.
***$p < 0.001$; **$p < 0.005$.

14679787, 2026, 2, Downloaded from https://onlinelibrary.wiley.com/doi/10.1111/jors.70042 by Bibl. der Universitat zu Koln, Wiley Online Library on [27/07/2026]. See the Terms and Conditions (https://onlinelibrary.wiley.com/terms-and-conditions) on Wiley Online Library for rules of use; OA articles are governed by the applicable Creative Commons License