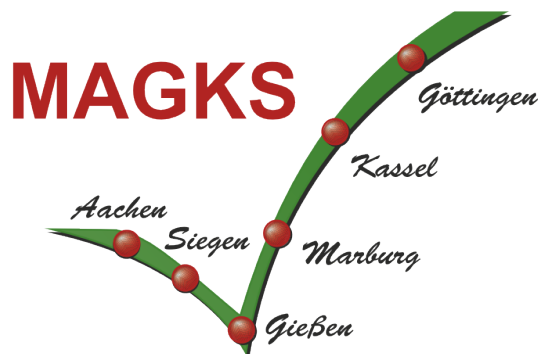




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More Than the Sum of Its Parts: Migration, Diversity, and Greenfield FDI in German Districts

K. Peren Arin* David Hardt[†] Oliver Lorz[‡] Josep Marti[§]

September 16, 2026

Abstract

This paper studies how cultural diversity shapes greenfield FDI location across 400 German NUTS-3 districts, 2003–2019. We compare foreigner share, cultural heterogeneity, and religious heterogeneity using fixed-effects Spatial Durbin Models, estimated statically and dynamically by quasi-maximum likelihood. Cultural heterogeneity delivers the most robust finding: its local effect is insignificant, but spillovers to neighboring districts are positive and highly significant. This spillover persists after accounting for investment dynamics and nearly doubles in the long run, suggesting regional rather than local channels. Spillovers from foreigner share and religious diversity disappear in dynamic models, indicating that they mainly reflect accumulated investment dynamics.

Keywords: Foreign direct investment; cultural diversity; migration; Spatial Durbin Model; spillovers; Germany

JEL classifications: C23; F21; F22; R12

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1 Introduction

Foreign direct investment (FDI) is widely recognized as a key channel through which capital, technology, and managerial expertise cross borders. It contributes to host-country productivity growth, employment, and innovation (Borensztein et al. 1998). Understanding what drives the location decisions of multinational enterprises is therefore important for economists and policymakers seeking to create investment-friendly environments. This study focuses on greenfield FDI, i.e., newly established ventures in the host location, which are particularly suitable for analyzing location decisions by international firms. A sizable literature has identified various determinants of FDI location, including market size, labor costs, taxes, and human capital.¹

Apart from these conventional location factors, international firms may also consider “soft” characteristics of a region’s business environment. International cultural diversity may be one such characteristic shaping a location’s attractiveness for foreign investors. Underlying mechanisms include complementarities across skill sets and knowledge bases, greater problem-solving capacity in heterogeneous teams, and the diffusion of ideas across cultural boundaries. To the extent that these productivity effects are visible regionally, culturally diverse districts can become more attractive destinations for multinational investment. Alesina et al. (2016) demonstrate that birthplace diversity positively predicts long-run economic prosperity across countries. Bove & Elia (2017) document growth-enhancing effects of cultural heterogeneity. In a regional context, Ottaviano & Peri (2006) find that cultural diversity raises the productivity of natives in U.S. cities. Meanwhile Niebuhr (2010), Südekum et al. (2014), Trax et al. (2015) identify diversity effects with respect to regional innovation outcomes and productivity for the German case. In the light of these findings, one might expect that cultural diversity attracts foreign investments. However, diversity can also generate frictions that work in the opposite direction. Greater heterogeneity in a host region may raise uncertainty for foreign investors about local norms, institutions, and social coordination, increasing the perceived risks of entry (Dow et al. 2016). Whether diversity ultimately promotes or impedes FDI inflows is therefore an empirical question—and one that may depend on how diversity is defined and measured.

¹For surveys of the vast literature on the location of international firms, see, e.g. Blonigen (2005), Nielsen et al. (2017), Paul & Feliciano-Cestero (2021).

Following Alesina et al. (2016), this paper distinguishes between three dimensions of diversity. The first is the foreigner share (the number of foreigners relative to the local population), which captures heterogeneity between the foreign and native populations. The second is a cultural heterogeneity index (CHI), which measures diversity within the foreign population and is constructed analogously to a fractionalization index across nationalities of foreigners. A region's diversity may thus increase through a larger foreign community or greater fragmentation within it. Separating these two dimensions allows us to identify the channels through which diversity may be relevant for international investments – either the presence of foreigners per se or the fragmentation within the foreign population that may attract or deter foreign investors in a certain region. We complement these measures with a religious heterogeneity index (RHI) within the foreign population. Religious heterogeneity is an aspect of cultural diversity that may influence cross-border investment decisions (Dow et al. 2016, Hong et al. 2023). It does not coincide with national-origin fragmentation: a community of foreigners from different countries may be religiously homogeneous, and vice versa. Contrasting cultural and religious heterogeneity therefore helps identify which aspect of diversity carries information for location decisions.

Our empirical approach uses a spatial econometric framework to account for regional spillovers. Theoretical models of multinational firms emphasize multi-plant economies, shared firm-level inputs, vertical linkages, and cross-country production networks as factors generating interdependence across locations.² These linkages imply that neighboring districts' economic performance can influence a district's attractiveness to foreign investors. Another strand of the literature draws on agglomeration effects, arising from technical spillovers between firms or factor market externalities that shape where multinationals locate (Head et al. 1995, Crozet et al. 2004, Alfaro & Chen 2014). Furthermore, economic shocks and policy changes often have regional rather than purely local effects, creating spatial correlation in unobserved determinants of FDI. Ignoring spatial relationships in such a setting can lead to biased coefficient estimates and incorrect inference (Anselin 1988, LeSage & Pace 2009). Empirical studies of subnational FDI consistently find prominent spatial patterns within national borders.³

²See, e.g., Markusen (1984), Helpman (1985), Venables (1996), Yeaple (2003), Ekholm et al. (2007), Baltagi et al. (2007), Tintelnot (2017).

³See Spies (2010) on Germany, Gutiérrez-Portilla et al. (2019), Maza et al. (2020) on Spain and Basile et al. (2008), Villaverde & Maza (2015), Krisztin & Piribauer (2021), Tsiapa et al. (2025) on European regions.

This paper integrates migration-related diversity into a unified spatial econometric framework at the German district level. German districts form a highly differentiated regional structure with heterogeneity in economic performance, demographic composition, labor market conditions, and socio-cultural characteristics. Meanwhile, Germany provides regional data systematically available over time. This high regional granularity makes Germany particularly well suited for analyzing subnational FDI location patterns and regional investment attractiveness.

Our results show that cultural diversity matters for FDI at the regional rather than the local level: While own-district effects of all diversity measures are insignificant, diversity generates positive and highly significant spillovers to neighboring districts. For the CHI, these spillovers persist after accounting for investment persistence and nearly double from the short to the long run.

This paper makes three contributions to the literature. First, we add to the spatial FDI literature by operating at the subnational level. Compared to studies using country-level data (Blonigen et al. 2007, Regelink & Elhorst 2015), exploiting variation across districts recovers within-country heterogeneity and yields more credible identification of spatial spillover mechanisms (Casi & Resmini 2014). Second, we are among the first to integrate cultural diversity variables into a spatial econometric model of FDI location. Previous research on the relationship between migration and FDI focuses on labor supply effects or on the reduction of informational frictions via co-ethnic networks.⁴ Our diversity hypothesis is conceptually distinct: What matters in our case is not the bilateral link between investors and foreigners from a specific origin country, but the general cultural variety of the host region's population. Our analysis is more similar to Dow et al. (2016), who find that linguistic and religious diversity in the target country reduces foreign acquirers' equity shares in cross-country acquisitions, and Feng et al. (2022), who document a non-linear effect of dialect diversity on FDI across Chinese provinces.⁵

Neither of these studies embeds diversity in a spatial econometric framework nor examines greenfield FDI. Third, we employ static and dynamic Spatial Durbin Models (SDM) (Belotti et al. 2017, Elhorst 2014) to distinguish short-run effects from long-run effects and direct effects from spatial spillovers. Using proper impact measures (LeSage & Pace 2009) corrects for the bias

⁴See, e.g. Foad (2012), Javorcik et al. (2011), Burchardi et al. (2019), Mayda et al. (2022), Li (2015).

⁵Related studies include Lucke & Eichler (2016) on diversity differences between host and home countries and FDI, Hong et al. (2023) on religious distance, diversity, and FDI, and Buch et al. (2006) on links between migration, FDI, and foreigners from other countries.

that arises when spatial feedback is ignored when interpreting regression coefficients. The joint reading of the static and dynamic decompositions allows us to diagnose whether and to which degree a spillover reflects a contemporaneous structural relationship or rather the accumulated legacy of past investment — a distinction that proves central to interpreting the diversity results.

2 Data

The empirical analysis relies on a panel of 400 German districts at the Nomenclature of Territorial Units for Statistics level 3 (NUTS-3), comprising 106 independent cities and 294 regional districts.⁶ NUTS-3 districts are the lowest administratively consistent regional level for which comprehensive socio-economic data are systematically available over time. The high level of regional granularity, combined with the high quality of district-level data in Germany, makes the NUTS-3 level particularly well-suited for analyzing subnational FDI location patterns and regional investment attractiveness in this paper. The panel structure allows us to exploit both cross-sectional and intertemporal variation in the analysis while controlling for unobserved regional heterogeneity and time-specific effects. To ensure a representative time period, we consider data from 2003 to 2019. The selected observation period captures the pre-financial crisis expansion, the 2008–2009 global financial crisis, as well as the subsequent recovery period. This accounts for substantial changes in macroeconomic and investment conditions over time.

Greenfield FDI project data were obtained from the *fDi Markets* database (fDi Intelligence 2026), while regional socio-economic information at the German NUTS-3 level comes from the *INKAR* database (BBSR 2026) and from *GENESIS-Online* of the *German Federal Statistical Office* (Destatis 2026). No missing observations occurred for the variables obtained from *GENESIS-Online* and the *INKAR* database over the sample period.

The *fDi Markets* database provides project-level information on announced greenfield FDI. To construct a district-level dataset, each project location was assigned to its corresponding district and the project-level observations were then aggregated to obtain the annual number of FDI projects per district and year. 48 districts recorded no FDI inflow projects during the entire

⁶For simplicity, we refer to all 400 NUTS-3 units as districts.

period, while others had no projects in specific years. These observations were coded as zero resulting in a balanced district-year panel of FDI projects for all 400 German NUTS-3 districts over the period 2003 to 2019.

Several German districts experienced administrative boundary reforms during the observation period, most notably between 2007 and 2013, which resulted in mergers and territorial re-classifications at the NUTS-3 level. To ensure intertemporal consistency, all data were harmonized to the 2024 territorial classification of German NUTS-3 districts (Eurostat 2024).⁷ The unit of observation is district j in year t . The final dataset comprises 400 NUTS-3 districts observed over 17 years, resulting in a total of 6,800 district-year observations.

Table 1 provides an overview of all used variables, reporting their respective definition, abbreviation, unit of measurement, transformation, roles in the model, underlying theoretical concept, expected effects, and data source.

The attractiveness of a location for FDI can generally be measured using the number of FDI projects or the aggregate value of these investments. While the investment value captures the financial magnitude of FDI, the number of projects appears to be a more consistent indicator of FDI activities for our purpose. At the local level a small number of large-scale projects often dominates other projects, thereby obscuring the broader pattern of investment activities across regions. The number of FDI projects is less sensitive to such outliers and, as a result, provides a more stable measure of the regional attractiveness as an investment destination for foreign firms. Accordingly, the dependent variable in this study is defined as the number of announced greenfield FDI projects located in district j in year t . Since the distribution of FDI projects is highly skewed across districts and since several district-year observations record zero projects, the regression analysis uses the natural logarithm of the project count plus one, i.e., $\ln(1 + FDI_{jt})$.⁸

⁷The regional indicators obtained from the INKAR database already follow a time-harmonized territorial reference consistent with the NUTS-3 2024 classification. For variables sourced from GENESIS-Online, the harmonization to the 2024 district boundaries was conducted manually using the official correspondence information provided by BKG (2025).

⁸As robustness checks, we verify that the results are not sensitive to the transformation of the FDI count nor to the choice of FDI measure. Replacing the log of the FDI project count with its inverse hyperbolic sine transformation yields similar results, and re-estimating the model with inward FDI capital inflows (in millions of EUR) preserves the immigration-diversity relationship, the share of foreigners and the diversity indices (CHI, RHI) retain a positive and statistically significant association with inward FDI, operating primarily through the indirect (spillover) channel.

Table 1: Variable Definitions

Variable	Abbreviation	Unit	Transformation	Role	Theoretical Concept	Expected Effect	Source
Number of FDI projects	FDI_{jt}	Projects	Log	Dep	Regional investment attractiveness	/	fDi Markets
Share of foreign residents	$Foreigners_{jt}$	Share (0–1)	Level	Ind	Socio-cultural heterogeneity	+	GENESIS
Cultural heterogeneity of foreign residents	CHI_{jt}	Index (0–1)	Level	Ind	Socio-cultural heterogeneity	+	GENESIS
Religious heterogeneity of foreign residents	RHI_{jt}	Index (0–1)	Level	Ind	Socio-cultural heterogeneity	+	GENESIS
Share of self-employed	$Self\ Employed_{jt}$	Percent	Log	Con	Entrepreneurial activity	+	INKAR
Nominal gross domestic product	GDP_{jt}	EUR	Log	Con	Market size	+	INKAR
Nominal gross domestic product per capita	$GDP\ pc_{jt}$	EUR per inhabitant	Log	Con	Market size; Costs	+/–	INKAR
Share of graduates with Abitur	$Abitur_{jt}$	Percent	Log	Con	Human capital	+	INKAR
Average population age	Age_{jt}	Years	Log	Con	Demographic structure	–	INKAR
Tax revenue per capita	$Taxes\ pc_{jt}$	EUR per inhabitant	Log	Con	Fiscal strength	+	INKAR
Average business tax rate	$Business\ Tax_{jt}$	Percent	Log	Con	Tax burden	–	GENESIS

Notes: j denotes the NUTS-3 district in Germany and t the respective year.
Expected effects refer to the anticipated impact on FDI projects as discussed in the paper.

Figure 1 illustrates the spatial distribution of FDI activity across German NUTS-3 districts by showing the aggregate number of FDI projects over the entire period 2003–2019.

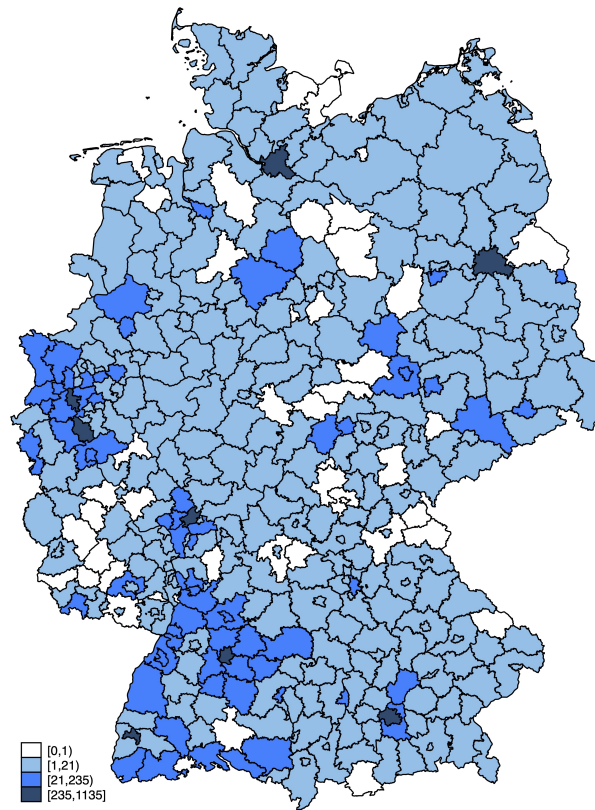


Figure 1: Number of FDI Projects in German NUTS-3 districts, 2003-2019

The map reveals substantial spatial heterogeneity in the distribution of FDI. A total of 48 districts recorded no FDI projects during the entire observation period. Meanwhile, FDI activity is strongly concentrated in several regional clusters. Higher numbers of projects can be observed in groups of neighboring districts, particularly in the Rhine–Ruhr metropolitan region, northern Baden–Württemberg, and districts located near the Swiss border. In addition, eight urban districts record exceptionally high levels of FDI activity, each hosting at least 234 projects during the sample period. Seven of these districts are among Germany’s largest cities—Munich, Berlin, Frankfurt am Main, Düsseldorf, Hamburg, Stuttgart, and Cologne—alongside Freiburg. The map also indicates an East–West pattern: Districts in West Germany generally exhibit higher levels of FDI activity than those in East Germany.

The main explanatory variables capture different dimensions of migration-related diversity at the district level. Information on foreigners by country of origin as well as on the total population was obtained from the *GENESIS-Online* database. The variable $Foreigners_{jt}$ reflects the proportion of residents without German citizenship in district j in year t . Figure 2 illustrates the spatial distribution of foreigners across German NUTS-3 districts by displaying the mean share of foreign population from 2003 to 2019.

A clear East–West pattern emerges: districts in East Germany exhibit considerably lower shares of foreigners compared to those in West Germany. Furthermore, districts with higher shares of foreign population coincide with several of the previously identified clusters of FDI activity. Metropolitan regions, such as the Rhine–Ruhr area, large cities, and parts of southern Germany display both higher numbers of inward FDI projects and higher shares of foreign residents. A small number of districts show particularly high levels of migration-related diversity, with an average foreigner share of 25 percent or more over the observation period: Offenbach, Frankfurt am Main, Munich, Ludwigshafen, Stuttgart, Heilbronn, Düsseldorf, and Mannheim.

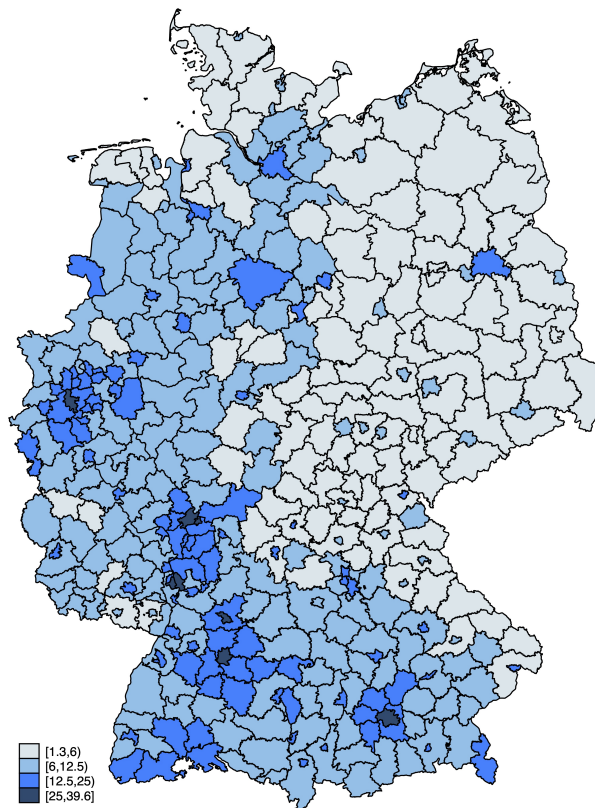


Figure 2: Average share foreign population German NUTS-3 districts 2003-2019

The CHI is derived following the fractionalization index as employed by Alesina et al. (2003). To construct the variable CHI_{jt} , the share s_{cjt} of foreign residents with citizenship c in the total foreign population of district j is first computed and the index is then calculated as

$$CHI_{jt} = 1 - \sum_{c=1}^C s_{cjt}^2,$$

where C denotes the number of countries of origin. The index ranges from 0 to 1, with higher values indicating more cultural diversity within the foreign population of a district.

In a similar fashion, we construct the RHI, which measures the diversity of religious affiliations among foreign residents in a district. Residents with foreign nationality are first grouped according to the predominant religion in their country of origin.⁹ Based on this classification, the number of foreign residents associated with a religion r in district j in year t is obtained by aggregating foreigners from all countries assigned to this religion and the RHI_{jt} is computed.

The empirical models include a set of time-varying district-level control variables that capture key dimensions of regional attractiveness, including market conditions, labor market characteristics, human capital and demographics, and the fiscal environment. These control variables are entered into the estimations in logarithmic form to mitigate the influence of extreme values, capture non-linear relationships, and facilitate interpretation in proportional terms.

This study employs two market size variables measured by the gross domestic product (GDP), GDP_{jt} and $GDP pc_{jt}$. The former represents the nominal GDP generated in district j in year t and the latter represents nominal GDP per capita. These variables represent the size of the regional market and the overall economic activity in a district measured in nominal terms. GDP per capita can also be interpreted as an indirect measure of production costs. Cost-sensitive firms may avoid booming regions in their search for lower costs, particularly with respect to land and labor.

⁹Information on the majority religion of each country is obtained from Hackett et al. (2025). The majority religion reported for the year 2010 is used consistently for all years in the dataset. Countries are assigned to one of the following seven religion categories: Buddhism, Christianity, Hinduism, Judaism, Islam, Other Religions, and Religiously Unaffiliated.

The variable $Self\ Employed_{jt}$ measures the percentage of self-employed individuals relative to the total number of employed individuals in district j in year t . It captures entrepreneurial activity in a district and reflects the local business environment. Regions with a high self-employment share have a more dynamic business environment. This variable is based on workplace location, meaning that employment is assigned to the district where people work rather than where they reside.

As an indicator of a district's human capital endowment, we use the variable $Abitur_{jt}$, which measures the percentage of school graduates who obtained the university entrance qualification (Abitur), the highest school graduation level in Germany. To retain observations with zero values while reducing skewness, we use the transformation $\ln(1 + Abitur_{jt})$. This variable reflects the educational attainment of the local population and serves as a proxy for the availability of highly skilled labor, which may increase the attractiveness of a region for foreign investors.

We also incorporate the average age of residents in a district Age_{jt} to account for the demographic structure of the local population. Regions with younger populations may benefit from a larger and more dynamic workforce, while older populations may indicate demographic aging and potential labor shortages.

To capture the fiscal capacity of local governments, the empirical models include tax revenue per capita $Taxes\ pc_{jt}$ at the district level. This variable reflects the financial resources available to municipalities and municipal associations at the district level. These resources can influence the provision of local public goods and public infrastructure, for example.

In Germany, a local business tax (Gewerbesteuer) is levied at the municipal level, and each municipality sets its own tax multiplier (Hebesatz). These municipal decisions determine the local tax burden on corporate profits and may thereby influence the location choices of foreign investors. Since districts consist of several municipalities, the variable $Business\ Tax_{jt}$ is calculated at the district level as a weighted average of these municipal tax multipliers.

The descriptive statistics in Table 2 provide an overview of the distribution of the variables used in the empirical analysis. Table 3 reports the pairwise correlation matrix.

Table 2: Descriptive Statistics

Variable	Mean	SD	Min	Max	N
FDI_{jt}	1.7	7.8	0	156	6,800
$Foreigners_{jt}$	0.096	0.06	0.007	0.472	6,800
CHI_{jt}	0.91	0.052	0.61	0.97	6,800
RHI_{jt}	0.55	0.056	0.21	0.71	6,800
$Self\ Employed_{jt}$	11.2	2.7	2.7	20.6	6,800
GDP_{jt}	6.86e9	1.07e10	8.34e8	1.57e11	6,800
$GDP\ pc_{jt}$	31,438	15,211	8,434	195,836	6,800
$Abitur_{jt}$	29.2	9.9	0	70.3	6,800
Age_{jt}	43.5	2.1	36.9	50.5	6,800
$Taxes\ pc_{jt}$	876.4	367.8	202.3	3,599.1	6,800
$Business\ Tax_{jt}$	374.9	49.1	223	893	6,800

The descriptive statistics in Table 2 show substantial variation across German district-year observations. Greenfield FDI projects are highly unevenly distributed: while the average number of projects is 1.7, the standard deviation is 7.8 and the maximum reaches 156, indicating that FDI activity is concentrated in a relatively small number of observations. The cultural diversity variables also display meaningful variation. The foreigner share averages 9.6 percent, but ranges from 0.7 to 47.2 percent, suggesting large differences in the size of the foreign population across districts. The CHI is high on average, with a mean of 0.91 and values between 0.61 and 0.97, indicating that foreign populations tend to be culturally diverse. The RHI has a lower mean of 0.55 and ranges from 0.21 to 0.71, pointing to more moderate variation in religious heterogeneity.

Table 3 shows that FDI is most strongly correlated with regional economic size, measured by the nominal GDP. Among the diversity variables, the foreigner share has the strongest positive correlation with FDI ($r = 0.482$), whereas the correlations with the CHI ($r = 0.119$) and the RHI ($r = 0.054$) are positive but weak. The foreigner share is negatively correlated with both heterogeneity indices, while the CHI and the RHI are only moderately correlated with each other ($r = 0.303$). Overall, the tables suggest that the size of the foreign population, cultural heterogeneity, and religious heterogeneity capture distinct dimensions of migration-related diversity.

Table 3: Pairwise Correlation Matrix

	$\ln(1 + FDI_{jt})$	$Foreigners_{jt}$	CHI_{jt}	RHI_{jt}	$\ln(Self\ Employed_{jt})$	$\ln(GDP_{jt})$	$\ln(GDP\ pc_{jt})$	$\ln(1 + Abitur_{jt})$	$\ln(Age_{jt})$	$\ln(Taxes\ pc_{jt})$	$\ln(Business\ Tax_{jt})$
$\ln(1 + FDI_{jt})$	1.000										
$Foreigners_{jt}$	0.482	1.000									
CHI_{jt}	0.119	-0.121	1.000								
RHI_{jt}	0.054	-0.188	0.303	1.000							
$\ln(Self\ Employed_{jt})$	-0.263	-0.515	0.045	-0.139	1.000						
$\ln(GDP_{jt})$	0.647	0.584	0.036	0.043	-0.385	1.000					
$\ln(GDP\ pc_{jt})$	0.383	0.680	0.105	-0.074	-0.657	0.555	1.000				
$\ln(1 + Abitur_{jt})$	0.246	0.292	0.174	0.149	-0.438	0.276	0.365	1.000			
$\ln(Age_{jt})$	-0.115	-0.299	0.176	0.058	-0.022	-0.231	-0.109	0.264	1.000		
$\ln(Taxes\ pc_{jt})$	0.409	0.706	0.078	-0.235	-0.425	0.563	0.788	0.301	-0.082	1.000	
$\ln(Business\ Tax_{jt})$	0.296	0.475	-0.065	0.089	-0.554	0.409	0.309	0.391	0.049	0.314	1.000

Note: All correlation coefficients are statistically significant at the 1% level.

3 Methodology

3.1 Spatial Panel Data Models

The spatial distribution of greenfield FDI across German districts exhibits significant geographic clustering, suggesting that location decisions are influenced not only by local economic conditions, but also by economic activity and characteristics in neighboring regions. Standard panel estimators ignore this interdependence and may deliver biased coefficient estimates and invalid inference when outcomes are spatially correlated. Spatial econometric models address these limitations by explicitly incorporating spatial dependence into the empirical specification. Following Belotti et al. (2017) and Elhorst (2014), we estimate a family of spatial panel models that differ in their treatment of spatial and temporal dependence. In particular, we consider both static specifications, which capture contemporaneous spatial interactions, and dynamic specifications, which additionally account for temporal persistence in FDI and allow for a distinction between short-run and long-run effects. With $y_{jt} = \ln(1 + FDI_{jt})$ as the dependent variable, the general empirical specification can be written as:

$$y_{jt} = \delta y_{j,t-1} + \phi W y_{j,t-1} + \rho W y_{jt} + \beta X_{jt} + \theta W X_{jt} + \mu_j + \gamma_t + \varepsilon_{jt}.$$

Here, y_{jt} denotes the log-transformed number of greenfield FDI projects in district j ($j = 1, \dots, 400$) at time t ($t = 2003, \dots, 2019$). The term $y_{j,t-1}$ represents the temporal lag of the dependent variable, capturing persistence in FDI dynamics.

W is an $N \times N$ row-standardized spatial weights matrix that defines the neighborhood structure of the cross-sectional units. Accordingly, $W y_{jt}$ denotes the contemporaneous spatial lag of FDI, i.e., the weighted average FDI in neighboring districts at time t , while $W y_{j,t-1}$ captures spatio-temporal diffusion effects from neighboring districts in the previous period.

X_{jt} is a $k \times 1$ vector of explanatory variables, and $W X_{jt}$ denotes their spatially lagged counterparts, capturing spillover effects of covariates across neighboring districts. The terms μ_j and γ_t represent unobserved time-invariant district-specific effects and common time effects, respectively. Finally, ε_{jt} is an idiosyncratic error term assumed to be independently and identically distributed with zero mean and constant variance σ^2 .

The model includes six key parameters that capture different forms of spatial and temporal dependence: δ (temporal autoregressive parameter) measures the persistence of FDI over time, indicating path dependence in investment location decisions; ρ (spatial autoregressive parameter) captures contemporaneous spatial spillovers in the dependent variable; ϕ (space-time autoregressive parameter) measures dynamic spatial spillovers, reflecting the delayed diffusion of agglomeration benefits across space; β (vector of coefficients on explanatory variables) represents the effect of local characteristics on local FDI in the absence of spatial feedback; θ (vector of coefficients on spatially lagged explanatory variables) captures spillover effects from neighbors' characteristics and μ_j and γ_t control for time-invariant district heterogeneity and common time trends, respectively.

This general specification nests several well-known spatial panel models as special cases. By imposing specific restrictions on the parameters, we obtain the static Spatial Autoregressive (SAR) model, the Spatial Error Model (SEM), and the SDM, as well as the dynamic SDM, which enables us to distinguish between short-run and long-run effects.¹⁰ Table 4 summarizes these model specifications and their corresponding parameter restrictions. Because the three diversity measures are closely related by construction and partially overlapping in information content, each diversity variable enters the model in a separate specification, holding the set of control variables constant across specifications.

Table 4: Spatial Panel Model Specifications

Model	δ	ϕ	ρ	θ
Static SAR	$= 0$	$= 0$	$\neq 0$	$= 0$
Static SEM	$= 0$	$= 0$	$\neq 0$	$= -\rho\beta$
Static SDM	$= 0$	$= 0$	$\neq 0$	$\neq 0$
Dynamic SDM	$\neq 0$	$\neq 0$	$\neq 0$	$\neq 0$

¹⁰The SEM is obtained from the SDM under the common-factor restriction $\theta = -\rho\beta$, in which case the model can be rewritten with a spatially autocorrelated error term $\varepsilon_{jt} = \lambda W\varepsilon_t + u_{jt}$.

3.2 Spatial Weights Matrix

A central element of the empirical strategy is the specification of the spatial weights matrix W , which determines the extent and intensity of interactions between districts (Anselin 1988). Our baseline spatial weights matrix employs a first-order queen contiguity definition, where two districts j and i are considered neighbors if they share a common border or vertex. Formally,

$$w_{ji} = \begin{cases} 1, & \text{if districts } j \text{ and } i \text{ share a common border or vertex} \\ 0, & \text{otherwise} \end{cases} \quad j \neq i,$$

with $w_{jj} = 0$, and this matrix is then row-standardized such that $\sum_i w_{ji} = 1$. The queen contiguity structure is the natural reference for administrative districts: economic processes in geographically proximate areas tend to co-vary (Hu et al. 2020), and contiguity captures the labor market integration, commuting links, and supplier relationships that connect adjacent districts.

To assess the sensitivity of the results to the definition of spatial proximity, we additionally estimate all models using an inverse-distance weights matrix, in which connection strengths between districts decline with the Euclidean distance between their geographic centroids. This robustness check is motivated by the broader discussion on the specification of spatial interaction structures in applied spatial econometrics. In particular, Halleck Vega & Elhorst (2015) emphasize that empirical conclusions in spatial panel models may depend on how the spatial weights matrix is defined and recommend assessing whether substantive results are robust to plausible alternative specifications of spatial connectivity. The use of distance-based matrices is also supported by the observation that administrative boundaries do not necessarily coincide with economic boundaries, and that modern transportation infrastructure allows FDI spillovers to operate across considerable distances (Bottazzi & Peri 2003). The inverse-distance matrix therefore provides a complementary notion of spatial proximity to the queen contiguity matrix by allowing all districts to be connected, with interaction intensity decreasing smoothly in geographic distance. As discussed in Section 4.3, the static results are robust to this alternative structure, while the dynamic inverse-distance specifications fall outside the stationary parameter region and are therefore not interpretable; all substantive interpretation rests on the queen contiguity estimates.

3.3 Estimation

All spatial panel models are estimated using quasi-maximum likelihood (QML) methods following the approach described in Belotti et al. (2017).

For static specifications (SAR, SEM, SDM), we employ the concentrated likelihood approach, which transforms the data to remove fixed effects through the within-transformation. For the dynamic SDM, the presence of the lagged dependent variable $y_{j,t-1}$ in combination with fixed effects creates the well-known Nickell (1981) bias. To address this issue, we employ the bias-corrected QML estimator proposed by Yu et al. (2008), which produces consistent estimates when both N and T are large. We estimate both fixed effects and random effects specifications and apply a spatial Hausman test to determine the appropriate model. Given that our sample comprises the complete set of German districts rather than a random sample, and that unobserved district characteristics are likely correlated with observed covariates, we anticipate that the fixed effects specification will be preferred.

3.4 Diagnostic Tests and Model Selection

To assess the presence of spatial dependence and to guide the selection of appropriate model specifications, we conduct a comprehensive set of diagnostic tests. First, we evaluate global spatial autocorrelation using Moran’s I statistic, which tests the null hypothesis of spatial randomness against the alternative of positive or negative spatial clustering. This provides an initial indication of whether spatial interactions across districts are relevant. Complementing this approach, we also implement the cross-sectional dependence test proposed by Pesaran (2021), which extends the classical Breusch & Pagan (1980) framework to panel data settings. The statistic is based on the average pairwise correlation of the residuals, is particularly suitable for large N and moderate T panels, and does not require specification of a spatial weights matrix. In our application, the test is computed on the residuals of a non-spatial two-way fixed effects specification, so that a rejection indicates cross-sectional dependence beyond what common time effects can absorb and thereby motivates explicit spatial modeling. Under the null hypothesis of cross-sectional independence, the test statistic follows a standard normal distribution asymptotically.

To select between fixed effects and random effects specifications, we apply the spatial Hausman test for each specification. The Hausman test evaluates whether the district-specific effects are correlated with the explanatory variables. Under the null hypothesis of no correlation, the random effects estimator is consistent and efficient, while under the alternative hypothesis, only the fixed effects estimator remains consistent.

To select among competing spatial model specifications, we adopt a general-to-specific approach following LeSage & Pace (2009), Elhorst et al. (2010), and the spatial panel framework of Belotti et al. (2017). We begin with the SDM as the most general static specification, since it nests both the SAR and SEM as restricted cases. In particular, the SDM simplifies to a SAR model when the coefficients on the spatially lagged regressors are jointly zero ($H_0 : \theta = 0$), and to a SEM model under the common-factor restriction ($H_0 : \theta = -\rho\beta$). These nested hypotheses are evaluated using Wald and likelihood ratio tests. The preferred specification is ultimately selected based on the joint evidence from these tests and goodness-of-fit measures.

3.5 Direct and Indirect Effects

A key advantage of spatial econometric models over conventional regression models is their ability to properly measure marginal effects in the presence of spatial feedback. In spatial models, a change in an explanatory variable X_k in district j affects not only FDI in district j (the direct effect) but also FDI in neighboring districts (the indirect or spillover effect), which in turn feeds back to affect FDI in district j through the spatial multiplier process (LeSage & Pace 2009). Consequently, the regression coefficient β_k does not directly represent the marginal effect of X_k on y , and interpreting β_k as a conventional marginal effect can be highly misleading in the presence of spatial spillovers (Elhorst 2014). Instead, we compute impact measures that account for spatial feedback loops by calculating the partial derivatives of the expected dependent variable with respect to changes in the independent variables.

For static models, the impact matrix for the k -th explanatory variable depends on the model specification as summarized in Table 5. Note that the static impact measures account for contemporaneous spatial feedback through the multiplier $(I - \rho W)^{-1}$, but involve no temporal adjustment process; they are conceptually distinct from the long-run effects of the dynamic model introduced below.

Table 5: Direct and Indirect Effects for Static Models

Model	Direct Effect	Indirect Effect
SAR	$[(I - \rho W)^{-1}\beta I]^{DE}$	$[(I - \rho W)^{-1}\beta I]^{RS}$
SEM	β	—
SDM	$[(I - \rho W)^{-1}(\beta I + \theta W)]^{DE}$	$[(I - \rho W)^{-1}(\beta I + \theta W)]^{RS}$

Note: the notation *DE* indicates the average value along the matrix's diagonal, while *RS* indicates the average of the row sums excluding the diagonal elements.

Dynamic spatial panel models allow us to distinguish between short-run effects (contemporaneous impacts) and long-run effects (cumulative impacts after the system reaches equilibrium). Short-run effects measure the immediate impact of a change in X_k at time t on y at the same time t , before the lagged dependent variable adjusts. Long-run effects are obtained from the steady state of the dynamic system, in which $y_t = y_{t-1}$, so that the equilibrium multiplier combines the contemporaneous spatial lag with the temporal and space-time lags (Debarys et al. 2012, Elhorst 2012). Table 6 summarizes these effects for the dynamic SDM.¹¹

¹¹Total Effect = Direct Effect + Indirect Effect for all specifications, static and dynamic models.

Table 6: Direct and Indirect Effects for the Dynamic SDM

Model	Short-run	Short-run	Long-run	Long-run
	Direct Effect	Indirect Effect	Direct Effect	Indirect Effect
SDM	$[\Psi(\beta I + \theta W)]^{DE} [\Psi(\beta I + \theta W)]^{RS} [\Theta(\beta I + \theta W)]^{DE} [\Theta(\beta I + \theta W)]^{RS}$			

Note: where $\Psi = (I - \rho W)^{-1}$ is the contemporaneous spatial multiplier and $\Theta = [(1 - \delta)I - (\rho + \phi)W]^{-1}$ is the equilibrium multiplier of the dynamic system, obtained by imposing the steady state $y_t = y_{t-1}$ on the model of Section 3.1 (Debary et al. 2012, Elhorst 2012, Belotti et al. 2017).

The distinction between short-run and long-run effects is important for understanding how FDI spillovers and agglomeration processes evolve over time. Short-run effects capture the immediate response of a region to a change in an explanatory variable, whereas long-run effects additionally account for cumulative spatial and temporal feedback mechanisms. Through these feedback loops, an initial shock may spread across neighbouring regions and feed back into the region of origin, so that long-run effects can substantially exceed short-run effects.

Long-run multipliers are well defined only if the dynamic spatial system is stationary. For a row-standardized spatial weights matrix W , whose largest eigenvalue is equal to one, this requires $\delta + \rho + \phi < 1$ (Elhorst 2012). This condition ensures that shocks do not generate explosive dynamics but gradually dissipate as the system converges to a new equilibrium. Following Belotti et al. (2017), standard errors for all impact measures are computed using Monte Carlo simulation by repeatedly drawing parameter vectors from the asymptotic distribution of the estimated coefficients (LeSage & Pace 2009). This simulation-based approach accounts for the nonlinear dependence of the impact measures on the underlying parameters and provides a reliable basis for inference.

4 Results

4.1 Spatial Dependence and Model Selection

The distribution of greenfield FDI across German NUTS-3 districts exhibits a clear spatial structure. The Pesaran (2021) cross-sectional dependence test rejects the null of independence,¹² indicating that direct investments are systematically interrelated across districts (Table 7, Panel A). Complementing this evidence, annual Global Moran’s I statistics based on a queen contiguity matrix reveal positive spatial autocorrelation throughout most of the sample (Panel B).¹³ Spatial dependence is modest in the early years but strengthens markedly from 2008 onwards, with Moran’s I roughly doubling between 2007 and 2016.

This intensification of clustering is itself economically meaningful. The global financial crisis appears to have triggered a reallocation of cross-border investment in which multinationals concentrated activity in locations offering deeper labor markets, established supplier bases, and proximity to existing affiliates, reinforcing the relative position of agglomerations over peripheral districts. As FDI became more selective, its geography became more spatially correlated, with investment increasingly clustered. The strengthening of Moran’s I after 2008 is consistent with this account and signals that spatial interdependence has grown over time.

¹²Pesaran (2021) extends the classical Breusch & Pagan (1980) framework to panel settings. The statistic is based on the average pairwise correlation of the residuals and tests the null of cross-sectional independence.

¹³Global Moran’s I measures spatial autocorrelation, i.e. the degree to which values co-move across connected units. In line with the spatial econometrics literature, in which economic processes in geographically proximate areas tend to co-vary (Hu et al. 2020), we construct a queen contiguity weights matrix—districts sharing a border or vertex are neighbors—as the reference spatial structure for measuring inter-district correlation across Germany.

Table 7: Spatial Dependence Tests

<i>Panel A. Cross-sectional dependence test (Pesaran 2021)</i>			
Null hypothesis	Test statistic	<i>p</i>-value	Decision
H_0 : cross-sectional independence	18.905***	0.000	<i>Rejected at 1%</i>
<i>Panel B. Global Moran's I statistic (queen contiguity weights matrix)</i>			
Year	Moran's <i>I</i>	<i>z</i>-value	Significance
2003	0.026	0.890	—
2004	0.055	1.767	*
2005	0.076	2.395	**
2006	0.059	1.897	*
2007	0.037	1.224	—
2008	0.142	4.363	***
2009	0.169	4.198	***
2010	0.168	5.142	***
2011	0.168	5.146	***
2012	0.170	5.225	***
2013	0.154	4.740	***
2014	0.174	5.332	***
2015	0.192	5.858	***
2016	0.296	8.998	***
2017	0.309	9.396	***
2018	0.213	6.502	***
2019	0.278	8.468	***

Note: Panel A reports the Pesaran (2021) cross-sectional dependence test, computed on the residuals of a non-spatial two-way fixed effects specification. Under the null of cross-sectional independence the statistic follows a standard normal distribution asymptotically. Panel B reports annual Global Moran's *I* statistics for 400 German NUTS-3 districts, 2003–2019, computed using the first-order queen contiguity weights matrix (row-standardized). The *z*-values test the null of spatial randomness against positive spatial clustering. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively.

Model selection follows the general-to-specific strategy of LeSage & Pace (2009), implemented within the framework of Belotti et al. (2017). The Hausman test rejects the consistency of random effects in all three specifications ($\chi^2 = 58.85, 60.48$ and 54.20 ; all $p < 0.01$), supporting fixed effects estimation throughout. Starting from the SDM as the general model, likelihood ratio and Wald tests reject both the SAR restriction ($\theta = 0$) and the SEM common-factor restriction ($\theta = -\rho\beta$) at the 1% level across all specifications (Table 8). The SDM is therefore the preferred framework.

Because the SDM admits both own-district regressors and their spatial lags, it allows each district's characteristics, including cultural diversity, to affect FDI both within the district and through neighboring districts, and it permits these two channels to be separated cleanly in the impact decomposition that follows. For the dynamic specification, we employ the bias-corrected QML estimator of Yu et al. (2008), which addresses the Nickell (1981) bias that arises in fixed effects models containing a lagged dependent variable. The estimated dynamic parameters satisfy the stationarity condition $\delta + \rho + \phi < 1$ in all three queen-contiguity specifications (with sums of 0.597, 0.557, and 0.600, respectively), so the long-run multipliers reported below are well defined.

Table 8: Spatial Model Selection

Test	(1) Foreigners	(2) CHI	(3) RHI	Preferred model
Hausman test χ^2 (H_0 : RE)	58.85***	60.48***	54.20***	FE
LR test: SAR vs. SDM	84.98***	150.65***	94.05***	SDM
LR test: SEM vs. SDM	107.05***	184.96***	120.16***	SDM
Wald test: SAR vs. SDM	85.38***	151.86***	94.51***	SDM
Wald test: SEM vs. SDM	103.58***	175.05***	115.68***	SDM

Note: The Hausman test (H_0 : random effects are consistent) rejects the null across all three specifications, supporting fixed effects. LR and Wald tests evaluate the SAR ($\theta = 0$) and SEM ($\theta = -\rho\beta$) restrictions nested within the SDM as the general specification. All tests are distributed $\chi^2(8)$. ***, **, * denote significance at the 1%, 5%, and 10% levels, respectively. The preferred specification is the SDM under fixed effects.

4.2 Coefficient Estimates

Table 9 reports the coefficient estimates from the static and dynamic SDM specifications. Due to spatial feedback effects, these coefficients do not have a direct marginal interpretation, since a change in one district-level characteristic may spill over to neighbouring districts and feed back to the origin district (LeSage & Pace 2009). The substantive interpretation therefore relies on the impact decomposition in Section 4.3; here, we focus on the main qualitative patterns.

The spatial autoregressive parameter ρ is positive and highly significant across all specifications (0.132 to 0.228), implying that districts which attract more FDI are connected to neighbors that also attract more FDI, consistent with spatial interdependence in investments across districts. In the dynamic models, the lagged dependent variable is sizable and highly significant (around 0.27), indicating investment persistence, whereby the prior number of FDI projects is an important predictor of current projects, consistent with a path-dependent nature of multinational location decisions. The space-time lag $W \cdot y_{j,t-1}$ is likewise positive and significant, confirming that this persistence also diffuses across district boundaries.

The own-district coefficients of all three cultural diversity variables—Foreigners, CHI and RHI—are statistically insignificant. This should not be interpreted as implying cultural diversity to be irrelevant. In the SDM, own-district coefficients capture only one component of a broader system of spatial interactions, and the economically relevant magnitudes emerge after spatial feedbacks are accounted for. The spatially lagged coefficients are more revealing. Among the three diversity measures, the CHI displays the most consistent pattern: $W \cdot CHI_{jt}$ is positive and highly significant in both the static and dynamic specifications, indicating that cultural heterogeneity in neighboring districts is systematically associated with higher local FDI. By contrast, $W \cdot Foreigners_{jt}$ and $W \cdot RHI_{jt}$ are significant only in the static specification and lose significance once investment persistence is introduced.

The control variables – if significant – are broadly consistent with existing evidence on regional FDI determinants. GDP is positively associated with FDI, the business tax rate negatively, while population aging and GDP per capita enter with negative own-district effects. The significant spatially lagged self-employment rate suggests that entrepreneurial activity operates at a regional rather than purely local scale, a pattern clarified by the impact decomposition.

Table 9: SDM Coefficient Estimates: Static and Dynamic Models (Queen Contiguity)

	Static SDM			Dynamic SDM		
	(1)	(2)	(3)	(1)	(2)	(3)
$y_{j,t-1}$	—	—	—	0.272*** (0.012)	0.266*** (0.012)	0.273*** (0.012)
$W \cdot y_{j,t-1}$	—	—	—	0.181*** (0.022)	0.159*** (0.023)	0.183*** (0.022)
$Foreigners_{jt}$	-0.005 (0.006)	—	—	-0.000 (0.007)	—	—
CHI_{jt}	—	-0.406 (0.258)	—	—	-0.034 (0.261)	—
RHI_{jt}	—	—	-0.095 (0.216)	—	—	0.025 (0.218)
$\ln(Self\ Employed_{jt})$	0.013 (0.157)	-0.057 (0.156)	-0.020 (0.157)	-0.000 (0.163)	-0.026 (0.162)	-0.011 (0.163)
$\ln(GDP_{jt})$	0.363** (0.171)	0.343** (0.170)	0.426** (0.170)	0.300* (0.178)	0.289 (0.177)	0.325* (0.176)
$\ln(GDP\ pc_{jt})$	-0.275** (0.140)	-0.300** (0.139)	-0.297** (0.140)	-0.245* (0.147)	-0.254* (0.145)	-0.253* (0.146)
$\ln(1 + Abitur_{jt})$	0.038 (0.042)	0.012 (0.041)	0.035 (0.042)	0.049 (0.043)	0.035 (0.043)	0.047 (0.043)
$\ln(Age_{jt})$	-3.721*** (0.516)	-3.623*** (0.474)	-3.552*** (0.485)	-1.959*** (0.557)	-1.987*** (0.506)	-1.901*** (0.516)
$\ln(Taxes\ pc_{jt})$	0.059 (0.061)	0.094 (0.061)	0.070 (0.060)	0.090 (0.062)	0.107* (0.062)	0.093 (0.062)
$\ln(Business\ Tax_{jt})$	-0.409*** (0.147)	-0.401*** (0.145)	-0.338** (0.146)	-0.353** (0.149)	-0.348** (0.148)	-0.320** (0.149)
$W \cdot Foreigners_{jt}$	0.037*** (0.009)	—	—	0.012 (0.010)	—	—
$W \cdot CHI_{jt}$	—	3.289*** (0.357)	—	—	1.509*** (0.367)	—
$W \cdot RHI_{jt}$	—	—	1.203*** (0.315)	—	—	0.419 (0.319)
$W \cdot \ln(Self\ Employed_{jt})$	0.870*** (0.217)	0.655*** (0.205)	0.628*** (0.206)	0.534** (0.230)	0.481** (0.217)	0.450** (0.218)
$W \cdot \ln(GDP_{jt})$	0.869*** (0.280)	0.706** (0.274)	1.240*** (0.272)	0.243 (0.299)	0.175 (0.288)	0.394 (0.287)
$W \cdot \ln(GDP\ pc_{jt})$	-0.273 (0.247)	-0.181 (0.245)	-0.335 (0.246)	0.131 (0.260)	0.153 (0.258)	0.095 (0.258)
$W \cdot \ln(Abitur_{jt})$	0.084* (0.047)	0.027 (0.047)	0.066 (0.047)	0.047 (0.049)	0.019 (0.049)	0.040 (0.049)
$W \cdot \ln(Age_{jt})$	3.709*** (0.780)	2.343*** (0.731)	3.179*** (0.746)	0.705 (0.819)	0.255 (0.763)	0.537 (0.778)
$W \cdot \ln(Taxes\ pc_{jt})$	-0.100 (0.093)	0.082 (0.093)	-0.122 (0.092)	0.021 (0.097)	0.110 (0.097)	0.014 (0.096)
$W \cdot \ln(Business\ Tax_{jt})$	-0.212 (0.223)	-0.065 (0.218)	0.058 (0.220)	-0.102 (0.226)	-0.061 (0.221)	0.001 (0.222)
ρ	0.227*** (0.016)	0.198*** (0.017)	0.228*** (0.017)	0.144*** (0.018)	0.132*** (0.018)	0.144*** (0.017)
Log-likelihood	-3,229.99	-3,182.83	-3,230.96	-2,867.82	-2,851.08	-2,868.43
AIC	6,495.98	6,401.65	6,497.91	5,725.34	5,693.22	5,726.60
BIC	6,618.82	6,524.94	6,620.76	5,860.62	5,828.50	5,861.88
Observations	6,800	6,800	6,800	6,400	6,400	6,400

Notes: Static SDMs are estimated by concentrated QML, while dynamic SDMs are estimated using the bias-corrected QML estimator of Yu et al. (2008), which corrects the Nickell (1981) bias. Standard errors are reported in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels, respectively.

4.3 Direct, Indirect and Total Effects

Table 10 decomposes total effects into direct (own-district) and indirect (spillover) components for the static and dynamic SDM, following LeSage & Pace (2009); for the dynamic model both short-run and long-run effects are reported.¹⁴

The two specifications recover different but reconcilable information and should be read jointly, while keeping the different sets of impact measures conceptually distinct. The static SDM impacts account for contemporaneous spatial feedback: they describe the cross-district spatial equilibrium associated with a change in a regional characteristic, without modeling the temporal adjustment process. The dynamic SDM, by conditioning on the lagged dependent variable, separates the immediate (short-run) response of FDI from the cumulative (long-run) response, where the latter additionally incorporates the adjustment of investment over time through the temporal and space-time lags. Static impacts, dynamic short-run impacts, and dynamic long-run impacts are therefore three distinct objects, and we refer to them as such in the discussion that follows.

Among the conventional determinants, GDP exerts a positive and significant direct effect, with an indirect effect roughly three times larger in the static specification. In the dynamic specification, however, the indirect effect of GDP becomes insignificant in most specifications. GDP per capita carries a negative direct effect, consistent with efficiency-seeking multinationals facing higher labor costs in wealthier districts.

The direct effect of population aging is large and negative throughout, confirming that older population structures deter inward FDI. In the static model this is offset by a positive and significant indirect effect while the indirect effect loses its significance in the dynamic model.

¹⁴The results are robust to alternative specifications of the spatial weights matrix. Re-estimating the models with k-nearest-neighbour matrices (for various values of k) in place of Queen contiguity leaves the findings for the cultural variables unchanged. Nevertheless, the controls are more sensitive to the choice of matrix, with several losing significance in their indirect effects, although their direct effects and signs remain stable. We also assessed robustness to an inverse-distance weights matrix. In the static framework the conclusions are unchanged: the CHI remains the main cultural diversity variable, retaining a positive and significant total effect on inward FDI that operates through the indirect (spillover) channel, and the sign and significance of the remaining covariates are broadly consistent across weights matrices. The dynamic models estimated with the inverse-distance matrix, however, return a spatial autoregressive parameter ρ exceeding unity. Under a row-standardized weights matrix, whose largest eigenvalue equals one, this lies outside the stationary parameter region, so the implied time-space impulse responses do not converge and the short- and long-run multipliers cannot be interpreted (Debarys et al. 2012, Elhorst 2012). All substantive interpretation is therefore based on the queen-contiguity estimates reported in Tables 9 and 10. Full results for the alternative specifications are available from the authors upon request.

Table 10: Impact Measures: Direct, Indirect and Total Effects, Static and Dynamic SDM

Variable	Static SDM			Dynamic SDM					
	Direct	Indirect	Total	Long-run			Short-run		
				Direct	Indirect	Total	Direct	Indirect	Total
Panel A: Foreigners									
$Foreigners_{jt}$	−0.004 (0.006)	0.045*** (0.010)	0.042*** (0.010)	0.002 (0.009)	0.027 (0.018)	0.029 (0.020)	0.001 (0.006)	0.013 (0.010)	0.014 (0.009)
$\ln(Self\ Employed_{jt})$	0.053 (0.143)	1.105*** (0.235)	1.158*** (0.212)	0.085 (0.213)	1.254*** (0.483)	1.340*** (0.492)	0.021 (0.157)	0.609** (0.257)	0.631*** (0.231)
$\ln(GDP_{jt})$	0.401** (0.162)	1.196*** (0.329)	1.597*** (0.334)	0.467** (0.236)	0.932 (0.683)	1.399* (0.725)	0.307* (0.172)	0.352 (0.348)	0.659* (0.341)
$\ln(GDP\ pc_{jt})$	−0.278** (0.134)	−0.436 (0.292)	−0.714** (0.311)	−0.337* (0.194)	−0.005 (0.560)	−0.342 (0.605)	−0.243* (0.140)	0.082 (0.282)	−0.161 (0.285)
$\ln(1 + Abitur_{jt})$	0.045 (0.040)	0.118** (0.055)	0.163*** (0.051)	0.076 (0.054)	0.166* (0.094)	0.242** (0.101)	0.049 (0.040)	0.064 (0.051)	0.114** (0.047)
$\ln(Age_{jt})$	−3.591*** (0.511)	3.535*** (0.874)	−0.056 (0.892)	−2.693*** (0.773)	−0.465 (1.652)	−3.159* (1.748)	−1.929*** (0.566)	0.442 (0.874)	−1.487* (0.824)
$\ln(Taxes\ pc_{jt})$	0.054 (0.057)	−0.103 (0.112)	−0.050 (0.112)	0.138* (0.083)	0.147 (0.216)	0.284 (0.223)	0.095 (0.061)	0.039 (0.113)	0.134 (0.105)
$\ln(Business\ Tax_{jt})$	−0.424*** (0.151)	−0.396 (0.270)	−0.820*** (0.299)	−0.500** (0.205)	−0.545 (0.499)	−1.046* (0.575)	−0.344** (0.145)	−0.149 (0.246)	−0.493* (0.271)
Panel B: CHI									
CHI_{jt}	−0.269 (0.258)	3.896*** (0.384)	3.627*** (0.336)	0.169 (0.331)	3.151*** (0.623)	3.320*** (0.641)	0.031 (0.246)	1.664*** (0.357)	1.695*** (0.327)
$\ln(Self\ Employed_{jt})$	−0.033 (0.142)	0.783*** (0.215)	0.750*** (0.183)	0.031 (0.209)	1.009** (0.418)	1.040** (0.413)	−0.007 (0.156)	0.538** (0.242)	0.531** (0.211)
$\ln(GDP_{jt})$	0.367** (0.160)	0.945*** (0.310)	1.311*** (0.306)	0.429* (0.230)	0.661 (0.597)	1.090* (0.618)	0.294* (0.170)	0.263 (0.331)	0.557* (0.315)
$\ln(GDP\ pc_{jt})$	−0.297** (0.133)	−0.308 (0.281)	−0.605** (0.297)	−0.341* (0.189)	0.060 (0.509)	−0.281 (0.544)	−0.250* (0.139)	0.107 (0.278)	−0.143 (0.278)
$\ln(1 + Abitur_{jt})$	0.015 (0.040)	0.037 (0.054)	0.052 (0.050)	0.050 (0.054)	0.074 (0.090)	0.124 (0.094)	0.034 (0.040)	0.029 (0.052)	0.063 (0.048)
$\ln(Age_{jt})$	−3.568*** (0.455)	1.906** (0.791)	−1.662** (0.820)	−2.779*** (0.693)	−1.163 (1.446)	−3.943*** (1.506)	−1.993*** (0.513)	−0.021 (0.817)	−2.014*** (0.770)
$\ln(Taxes\ pc_{jt})$	0.097* (0.057)	0.130 (0.111)	0.226** (0.111)	0.170** (0.082)	0.328 (0.204)	0.498** (0.208)	0.114* (0.061)	0.140 (0.114)	0.254** (0.106)
$\ln(Business\ Tax_{jt})$	−0.407*** (0.150)	−0.183 (0.250)	−0.591** (0.272)	−0.477** (0.199)	−0.373 (0.440)	−0.850* (0.501)	−0.337** (0.144)	−0.097 (0.237)	−0.434* (0.256)
Panel C: RHI									
RHI_{jt}	−0.031 (0.218)	1.504*** (0.360)	1.473*** (0.369)	0.125 (0.287)	0.987 (0.646)	1.112 (0.730)	0.059 (0.206)	0.461 (0.324)	0.519 (0.341)
$\ln(Self\ Employed_{jt})$	0.007 (0.143)	0.784*** (0.221)	0.791*** (0.192)	0.060 (0.212)	1.052** (0.457)	1.111** (0.460)	0.009 (0.156)	0.510** (0.245)	0.519** (0.214)
$\ln(GDP_{jt})$	0.481*** (0.160)	1.688*** (0.312)	2.169*** (0.307)	0.525** (0.232)	1.314** (0.641)	1.840*** (0.666)	0.336** (0.170)	0.523 (0.330)	0.859*** (0.311)
$\ln(GDP\ pc_{jt})$	−0.303** (0.134)	−0.535* (0.291)	−0.838*** (0.309)	−0.352* (0.193)	−0.099 (0.559)	−0.451 (0.602)	−0.250* (0.139)	0.040 (0.280)	−0.210 (0.281)
$\ln(1 + Abitur_{jt})$	0.040 (0.040)	0.094* (0.056)	0.135*** (0.052)	0.071 (0.054)	0.149 (0.096)	0.220** (0.103)	0.047 (0.040)	0.056 (0.052)	0.103** (0.048)
$\ln(Age_{jt})$	−3.448*** (0.473)	2.917*** (0.834)	−0.531 (0.865)	−2.658*** (0.719)	−0.797 (1.603)	−3.455** (1.705)	−1.890*** (0.525)	0.277 (0.835)	−1.613** (0.797)
$\ln(Taxes\ pc_{jt})$	0.064 (0.057)	−0.127 (0.112)	−0.062 (0.112)	0.141* (0.083)	0.137 (0.218)	0.278 (0.225)	0.097 (0.061)	0.033 (0.113)	0.130 (0.105)
$\ln(Business\ Tax_{jt})$	−0.339** (0.151)	−0.030 (0.257)	−0.369 (0.284)	−0.438** (0.203)	−0.279 (0.490)	−0.717 (0.559)	−0.307** (0.145)	−0.028 (0.242)	−0.335 (0.261)

Notes: Standard errors are reported in parentheses. Static SDM effects account for contemporaneous spatial feedback. Dynamic SDM short-run and long-run effects account for spatial and temporal adjustment. ***, **, * denote significance at the 1%, 5%, and 10% levels.

The business tax rate generates a negative total effect in most specifications, concentrated in the direct (own-district) component: the indirect effect is insignificant throughout. Local tax burdens deter FDI in the district without producing measurable competitive spillovers to its neighbors.

The self-employment rate displays a distinct profile, with insignificant direct effects but large and significant indirect effects in the static specification and at both dynamic horizons, confirming that business ecosystems operate at a regional scale. Its dynamic long-run indirect effect is roughly twice the size of the short-run effect, so the entrepreneurial spillover, like the agglomeration process itself, compounds substantially over time.

4.4 Cultural Diversity and the Geography of FDI

We now turn to the cultural diversity variables, which are the central focus of this study. Taken together, the three measures reveal a consistent message: where cultural diversity matters for FDI, it does so regionally rather than locally, and the importance of that regional effect depends on which dimension of diversity is measured.

The foreigner share exhibits a purely spatial pattern. Direct effects are insignificant in both specifications, while the static model identifies a positive and significant indirect effect that becomes insignificant once FDI persistence is modeled. Following the above interpretation, this indicates that the foreigner share is associated with FDI in surrounding districts in the spatial equilibrium, but in a manner consistent with accumulated investment dynamics rather than contemporaneous structural signals. The spillover is absorbed into the path-dependence term once the dynamic model conditions on prior FDI. Nevertheless, the static spillover remains consistent with the view that foreign populations contribute to a regional environment of greater international connectedness and openness (Buch et al. 2006). Because the foreigner share is an aggregate measure across all national origins, it does not represent bilateral co-ethnic network effects of the kind documented with country-of-origin matched data (e.g. Javorcik et al. 2011, Burchardi et al. 2019). As mentioned in the introduction, the result is better read within the broader diversity perspective of Alesina et al. (2016).

The most robust findings concerning diversity stem from cultural heterogeneity among

foreigners. The direct effects of the CHI are insignificant, but indirect effects are positive and highly significant in the static specification and in both the short- and long-run dynamic decompositions. Thus, cultural heterogeneity is associated with FDI through cross-district spillovers rather than local effects, and, crucially, these spillovers survive the introduction of path dependence, distinguishing it from the foreigner share and RHI. Even after conditioning on prior FDI, culturally heterogeneous districts are still systematically associated with higher FDI in their neighbors. This is the paper's central empirical result.

The dynamic decomposition adds two further insights: First, the significant short-run indirect effect shows that the spillover is partly contemporaneous. A change in a district's cultural heterogeneity is associated with an immediate response in neighboring districts' capacity to attract FDI, before agglomeration has had time to operate. Second, the long-run indirect effect (3.151) is almost twice as large as the short-run effect (1.664), so the association nearly doubles as it works through the self-reinforcing investment process.

In economic terms, the magnitude is substantial. The dependent variable is measured as the natural logarithm of one plus the number of greenfield FDI projects, while the CHI enters in levels, so the long-run indirect coefficient has the interpretation of a semi-elasticity. Expressed per sample standard deviation of the CHI (0.052), a one-standard-deviation increase in the cultural heterogeneity of a district's neighbors is associated with an increase of roughly 18 percent in the district's own FDI in the long run, holding other characteristics constant.¹⁵ Even allowing for the imprecision inherent in spillover estimates, an effect of this order indicates that cultural heterogeneity is a quantitatively relevant feature of the regional environment associated with FDI. The analysis cannot identify a precise mechanism, but the pattern is consistent with theoretical arguments linking cultural diversity to knowledge complementarities, international business networks, and general openness to external economic activity (Ottaviano & Peri 2006, Alesina et al. 2016, Bove & Elia 2017), and with German evidence that diversity raises regional innovation and plant-level productivity (Niebuhr 2010, Südekum et al. 2014, Trax et al. 2015).

¹⁵The corresponding figure for an illustrative 0.1-point increase in neighbors' CHI is approximately 37 percent ($e^{0.315} - 1$); since such a change amounts to almost two sample standard deviations of the index, it should be read as an upper-bound thought experiment rather than a typical shift.

The RHI stands in clear contrast. The static specification identifies a positive indirect effect, but this effect disappears once investment persistence is introduced. Neither the short-run nor the long-run dynamic effects are significant. Applying the same logic as before, the evidence for religious diversity to be an independent factor correlated with FDI at the subnational level appears to be far weaker. The dimension of diversity relevant to multinational location is cultural heterogeneity based on national origin—the variety of backgrounds, languages, and international connections captured by the CHI—rather than religious composition.

Taken together, the results on cultural diversity support a clear conclusion. Diversity is not primarily associated with FDI through local effects within individual districts but rather operates through spatial spillovers that cross district boundaries. Of the three measures, cultural heterogeneity is the most robust. It generates positive indirect effects that persist after controlling for investment dynamics and that strengthen over time. The economic effects of diversity are regional, and analyses confined to the local level are likely to understate its relation with the geography of FDI.

5 Conclusion

This paper has examined how diversity shapes the location of greenfield FDI in 400 German NUTS-3 districts from 2003 to 2019. Distinguishing three dimensions of migration-related diversity—the share of foreign residents, the cultural heterogeneity of the foreign population, and its religious heterogeneity—we embedded these measures in static and dynamic SDM estimated by bias-corrected QML under fixed effects. This framework enabled us to separate own-district effects from cross-district spillovers and contemporaneous responses from the cumulative effects that build up through the self-reinforcing investment dynamics.

Three findings stand out: First, spatial interdependence is an important major channel through which regional characteristics are connected with the geography of FDI. Second, and centrally, cultural heterogeneity within the foreign population is associated with FDI through a purely interregional channel. Its own-district effect is statistically indistinguishable from zero, while its spillover to neighboring districts is positive, highly significant, and—uniquely among the three diversity measures—robust to conditioning on investment persistence. The long-run

spillover is almost twice as large as the short-run spillover, so the contribution of cultural diversity compounds as it works through the agglomeration process. Third, jointly reading the static and dynamic decompositions provides a diagnostic for the nature of each spillover. The static spillovers associated with the foreigner share and religious heterogeneity disappear once prior investment is considered, suggesting that they reflect accumulated investment dynamics rather than contemporaneous structural relationships.

These results have implications for both research and policy. For research, they imply that non-spatial and static frameworks likely understate or miss the relationship between diversity and firm location, since the effect materializes in neighboring districts rather than at home. For policy, the existence of spatial spillovers cautions against evaluating place-based interventions at the level of the individual district. Policies that affect the composition of the regional population, the local business ecosystem, or demographic structure may generate benefits and costs that extend beyond administrative boundaries, which constitutes an argument for coordinating investment-promotion and integration policy at the level of functional economic regions rather than individual districts. The temporal amplification of the cultural heterogeneity spillover further suggests that the returns to such policies cumulate over time and may be undervalued by short-term assessments.

Several limitations qualify these conclusions and point to avenues for future research. While our estimates identify economically meaningful spatial correlations, the analysis cannot isolate a precise causal mechanism—knowledge complementarities, transnational business networks, or openness signals—through which cultural heterogeneity increases a region’s attractiveness for investments. The dependent variable measures announced greenfield FDI projects rather than realized capital expenditure, and the analysis is confined to a single country whose institutional homogeneity is an identification advantage but limits external validity. Extending the framework to other countries, to sector-level investment data capable of distinguishing knowledge-intensive from cost-driven projects, and to research designs that can identify the underlying transmission channels are natural next steps.

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