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How does social capital encourage entrepreneurship? Evidence from Facebook data

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Abstract
This article examines how social capital influences entrepreneurial activity by analyzing the structure of social ties across U.S. counties. Building on Granovetter's weak ties theory, we assess the role of economic connectedness (cross-class friendships) and social cohesiveness (dense local networks). Using data on Non-Farm Proprietorships from the U.S. Bureau of Economic Analysis and social capital indicators from Facebook's Social Capital Atlas, we estimate a Spatial Durbin Error Model to account for spatial dependence. Results show that economic connectedness is positively associated with local entrepreneurship, but this correlation weakens once neighboring conditions are considered. In contrast, social cohesiveness exhibits a uniformly negative but generally statistically inconclusive relationship. Findings suggest that diverse, outward-facing networks better support entrepreneurship than tightly clustered local ties.

Keywords: social capital, entrepreneurship, Facebook data, spatial econometrics
JEL Classification Codes: L26, R11, Z13

1. Introduction

Self-employment is a key driver of economic dynamism, contributing to productivity, innovation, and employment growth (Acs & Armington, 2006). Yet self-employment rates differ markedly across regions, even among areas with similar economic conditions (Cheng & Li, 2011), raising the question of which local factors shape entrepreneurial activity. Self-employment is influenced by a broad set of economic, demographic, and individual characteristics, and a substantial body of research has examined these factors at the micro level (Walter et al., 2015; Simoes et al., 2016; Molina, 2020). However, individual determinants

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alone do not fully account for why self-employment rates differ as evidence shows that peer effects and social norms significantly influence entrepreneurial decisions (Velilla et al., 2018; Giménez-Nadal et al., 2019). This suggests that broader features of the local social environment may play a role. In this regard, social capital—long recognized as a key determinant of economic outcomes—offers a useful lens for understanding how individuals access information, opportunities, and resources (Loury, 1977; Granovetter, 1985; Jackson, 2020).

Classic network theories highlight distinct mechanisms through which social capital shapes economic behavior. Granovetter's (1973) weak ties and Burt's (2018) structural holes emphasize the advantages of diverse and bridging connections, which facilitate access to novel information and opportunities. In contrast, the cohesive networks described by Lin et al. (1981) and Coleman (1988), and studies on immigrant and ethnic entrepreneurship (Kerr & Mandorff, 2023), underscore the value of dense ties for mobilizing support and resources. Together, these perspectives suggest that different social structures may have opposing effects on entrepreneurial activity.

Self-employment also exhibits a spatial dimension: regional outcomes depend not only on local entrepreneurial conditions but also on those of neighboring areas (Cueto et al., 2015). This aligns with the view that entrepreneurship should be analyzed through a spatial lens for three reasons (Pijnenburg & Kholodilin, 2014): (i) knowledge diffusion and labor-market interactions are spatially bounded; (ii) entrepreneurial activity tends to cluster geographically; and (iii) entrepreneurship capital in nearby regions can foster competition and economic development (Audretsch & Feldman, 1996; Audretsch & Keilbach, 2004; Audretsch & Lehmann, 2005). Despite these insights, only a limited number of studies incorporate broader societal structures and local environments into the analysis of entrepreneurship (Jack & Anderson, 2002; Estrin et al., 2013; Kibler et al., 2017).

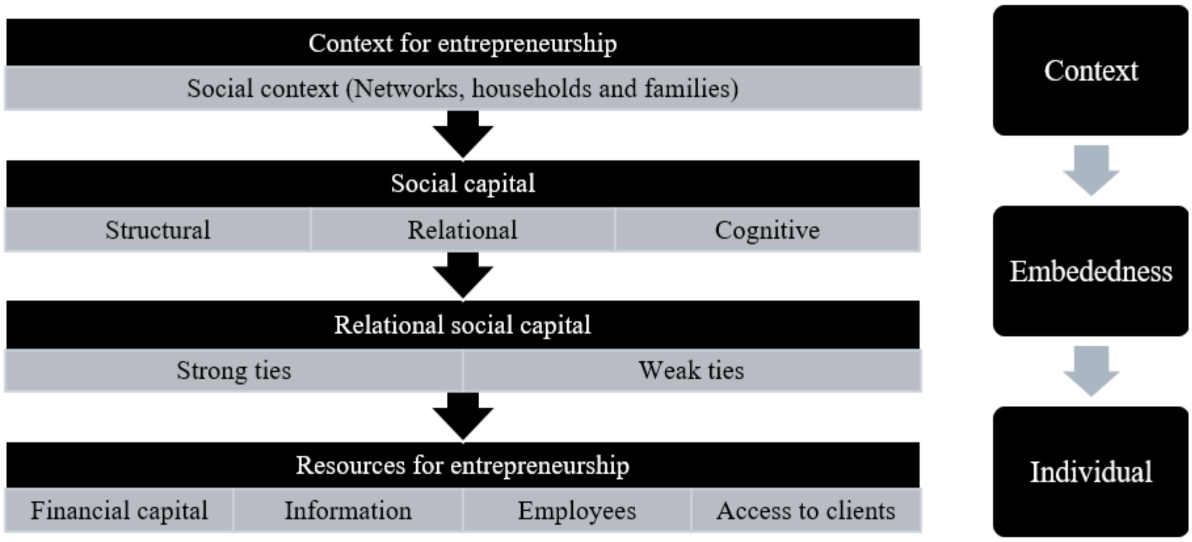
Therefore, this article adopts a contextual approach, viewing entrepreneurship as embedded within institutional, social, spatial, and economic environments (Welter, 2011). We focus on the relational dimension of social capital—namely, the quality and structure of interpersonal ties (Nahapiet & Ghoshal, 1998)—and examine how two key dimensions identified in the U.S. Social Capital Atlas (Chetty et al., 2022a, 2022b), economic connectedness and cohesiveness, influence self-employment while explicitly accounting for spatial dependence. Our results show that cross-income ties support entrepreneurship, whereas dense, local cohesion may inhibit it. These findings highlight the spatially bounded nature of social capital and its importance in shaping entrepreneurial activity.

The paper is structured as follows: Section 2 presents methods underlying the research. Section 3 provides a presentation of the data used in this analysis, with a particular focus on data obtained from Facebook. Section 4 outlines the main results. Finally, Section 5 concludes the article.

2. Methods

Entrepreneurship is a socially and geographically embedded phenomenon shaped by local interactions and contextual conditions (Welter, 2011). Social capital operates through structural, cognitive, and relational dimensions (Crowley & Barlow, 2022), and this study focuses on the relational dimension, which reflects the quality of interpersonal ties—strong or weak—and their influence on access to entrepreneurial opportunities. Strong ties foster localized trust and support but may limit exposure to new ideas and resources. In contrast, weak ties bridging diverse social circles facilitate access to non-redundant information and markets (Granovetter, 1973; Burt, 2018). These mechanisms are shaped by spatial context. Proximity reinforces cohesive networks, whereas weak ties may span broader areas, generating spatially bounded spillovers (Sternberg & Wennekers, 2005; Kibler et al., 2017; Almeida et al., 2021; Crowley & Barlow, 2022). Consequently, entrepreneurial outcomes depend on local social capital structures and neighboring conditions, consistent with evidence that entrepreneurship functions as a local process (Fotopoulos & Storey, 2017; Novosák et al., 2023). We conceptualize social capital as a multidimensional and spatially contingent phenomenon shaped by regional norms, demographic composition, and inter-group connectedness. Understanding how these social and spatial elements interact is essential for explaining geographically patterned variation in self-employment across U.S. counties.

Figure 1. Theoretical framework of entrepreneurial context and social capital



Note: Own elaboration from concepts by Granovetter (1985), Jack & Anderson (2002), Welter (2011) and Kautonen et al. (2014).

Consistent with the spatial mechanisms outlined above, we estimate a Spatial Durbin Error Model (SDEM). This specification (LeSage, 2014) captures local spillovers through the spatially lagged covariates WX and accounts for spatial correlation in unobserved regional conditions, while avoiding the global feedback effects implied by the SDM's spatial lag of the dependent variable Wy and the SLX model's omission of spatial error dependence. The model is defined as:

$$Y = X\beta + WX\theta + u, u = \lambda Wu + \varepsilon \quad \text{with} \quad \varepsilon \sim (0, \sigma_\varepsilon^2 IN) \tag{1}$$

Where Y is our dependent variable (percent of Non-Farm Proprietorship Employment), X are the explanatory variables, and u captures the unobserved factors. The coefficients β and θ represent direct and indirect effects, respectively, while λ reflects spatial autocorrelation in the error structure. ε is an $n \times 1$vector of disturbances. The model is estimated by maximum likelihood.

Because entrepreneurial activity is spatially concentrated, we model spatial interaction through proximity-based weight matrices. We rely on a smoother distance-decay structure. Our baseline matrix uses inverse–squared–distance weights, which assign higher influence on nearby counties and ensure a continuous decay with distance. To preserve sparsity and avoid excessively large neighborhoods, we impose a 150 km cutoff, guaranteeing that each county has at least one neighbor while maintaining a realistic notion of local interaction (Kelejian & Prucha, 1998, 1999; Lee, 2004). Moreover, geographically defined matrices may generate spatial dependence mechanically rather than through meaningful economic interactions (Gibbons & Overman, 2012; Debarsy & Le Gallo, 2025), motivating the use of alternative specifications. To assess robustness, we re-estimate the model using four alternative matrices: (i) inverse-distance weights; (ii) a standard geographic KNN matrix; (iii) a Facebook KNN matrix retaining the seven strongest inter-county friendship ties[1]; and (iv) an industry-similarity KNN matrix based on Euclidean distances in sectoral employment shares, also restricted to seven neighbors. The choice of seven links is supported by sensitivity checks showing that estimates remain stable for neighborhood sizes commonly used in the literature. All matrices are row standardized.

3. Analysis and results

We measure social capital with the Social Capital Atlas (Chetty et al., 2022a, b), which aggregates Facebook friendships for more than 21 million U.S. users aged 25–44 who have ≥100 U.S.–based friends and valid ZIP codes. Friendships are mutual and capped at 5,000, providing a reliable proxy for offline networks. Economic connectedness (EC) captures cross-socioeconomic status (SES) ties. For individual i, let f_{Qi} be the share of friends in socioeconomic quantile Q and w_i its population weight. Exposure is $IEC_{Qi} = \frac{f_{Q,i}}{w_i}$. County-

[1] The Facebook social-proximity matrix is constructed using the Social Connectedness Index (SCI) from Bailey et al. (2018), publicly available through the Humanitarian Data Exchange.

level EC is the average exposure of low-SES residents to high-SES friends:

$$EC_C = 2\frac{\sum_{i\in L\cap C} IEC_{Qi}}{N_{Lc}}, \tag{2}$$

where N_{Lc} is the number of low-SES individuals in county *c*.

Network cohesion (clustering) reflects how much a person's friends are also friends with one another. With adjacency matrix $A \in \{0,1\}^{nxn}$ where $A_{ij} = 1$ implies the existence of a friendship relationship between individuals i and j. The individual coefficient is:

$$Cohesiveness_i\ (A) = \sum_{k\ j\ \in N_i(A),\ k<j} \frac{A_{kj}}{d_i(A)(d_i(A)-1)/2} \tag{3}$$

where $N_i(A)$ represents the friendship relationships of individual i, and $d_i(A)$ represents the total number of friendships of individual i. At the county level c, this measure is calculated as follows:

$$\mathrm{Cohesiveness}_c = \frac{\sum_{i\in C} \mathrm{Cohesiveness}_i\ (A)}{N_c} \tag{4}$$

Economic Connectedness (EC) captures bridging ties: friendships between low-SES and high-SES individuals that connect residents to socially distant groups. These cross-class links provide non-redundant information, external resources, and access to opportunities, so EC reflects outward-oriented, weak-tie network structure. Network Cohesiveness (clustering) instead reflects bonding ties: dense, locally embedded friendship structures where friends of a person are also friends with each other. High cohesiveness indicates strong local trust, reciprocity, and shared norms. Together, these measures summarize the neighborhood relational environment. EC represents openness to external groups, while Cohesiveness represents internal density—two dimensions that could, in principle, underpin an endogenous social-interaction matrix.

Entrepreneurship is measured using 2020 Bureau of Economic Analysis data on the ratio of non-farm proprietorships to all workers. Non-farm proprietorship data is extensively used in U.S. entrepreneurship and self-employment research (Shrestha, Goetz & Rupashinga, 2007; Goetz & Rupashinga, 2009; Rupasingha & Goetz, 2013; Carree, Congregado, Golpe, & van Stel, 2015; Debbage & Bowen, 2018; Bignall & Debarge, 2020). To measure the entrepreneurial activity of a county, we use Bureau of Economic Analysis (BEA) data to obtain the 2020 ratio of non-farm proprietorships to all full- and part-time workers. This measure identifies self-employed individuals, encompassing not only those primarily engaged in self-employment but also those earning income from it, even if their primary income is derived from wage employment. We control for county-level sociodemographic characteristics using 2020 U.S. Census 5-year data. Control variables include education levels, labor force participation, income, unemployment, internet access, housing value, poverty rates, total population, and racial/ethnic composition. See Table 1 for full details.

Table 1. Summary statistics

VARIABLES	(1) Mean	(2) S.D
Non-Farm Sole Proprietorships (%)	24.505	6.458
Unemployment Rate (%)	5.173	2.373
Labor Force Participation (%)	58.431	7.703
Female Labor Force Participation (%)	54.226	6.832
Median Age of the Population (Years)	41.488	5.258
Per Capita Income (dollars)	29.025	6.925
Median Earnings of Workers (thousand dollars)	32.438	5.830
People and Families Below the Poverty Threshold (%)	10.462	5.268
Median Home Value (thousand dollars)	160.354	98.813
Owner-Occupied Housing (%)	72.196	8.016
Economic Connectedness	81.253	17.674
Cohesion	11.601	1.938
High School Graduates or More (25 years and older) (%)	87.614	5.808
Bachelor's Degree or More (25 years and older) (%)	22.519	9.562
Households with Internet Connection	78.718	7.962
Total Population (thousands)	108.487	340.629
White (%)	82.396	15.956
African American (%)	8.929	14.109
Asian (%)	1.326	2.434
Hispanics (%)	9.489	13.745
Foreign-born (%)	4.658	5.507
Agriculture, Forestry, Fishing, and Mining (%)	5.907	6.175
Construction (%)	7.593	2.425
Manufacturing (%)	12.517	6.995
Wholesale Trade (%)	2.359	1.216
Retail Trade (%)	11.155	2.344
Transportation and Warehousing, and Utilities (%)	5.710	2.061
Information (%)	1.305	0.819
Finance, Insurance, Real Estate, Rental, and Leasing (%)	4.652	1.961
Professional, Scientific, Administrative, Waste Management (%)	7.176	3.356
Educational Services, and Health Care and Social Assistance (%)	23.401	4.522
Arts, Entertainment, Recreation, Accommodation, Food (%)	8.109	3.367
Other Services, Except Public Administration (%)	4.693	1.316
Public Administration (%)	5.423	2.864

Note: Data corresponds to the year 2020 from the Census Bureau. The data for Non-Farm Sole Proprietorships has been obtained from the Bureau of Economic Analysis (BEA). These are available for 2956 counties in the United States; the states of Puerto Rico, Alaska, and American Samoa are not considered. Figures related to Economic connectedness and Cohesion Support Index are derived from available data in the Social Capital Atlas.

4. Results

Figures 2–5 illustrate spatial patterns of social capital and entrepreneurial activity across U.S.

counties. A clear contrast emerges: rural Southern counties tend to exhibit high social cohesiveness but low economic connectedness, while urban areas in the Northeast and West Coast show stronger cross-income ties but lower local clustering. This suggests that while rural regions promote tight-knit, localized social structures, urban areas may better foster the diversity and reach needed for entrepreneurial activity.

Figure 2. Cohesiveness vs Economic connectedness

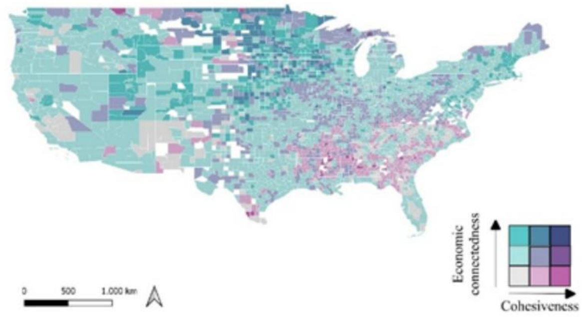


Figure 3. Non-Farm Proprietorship vs Economic Conectedness

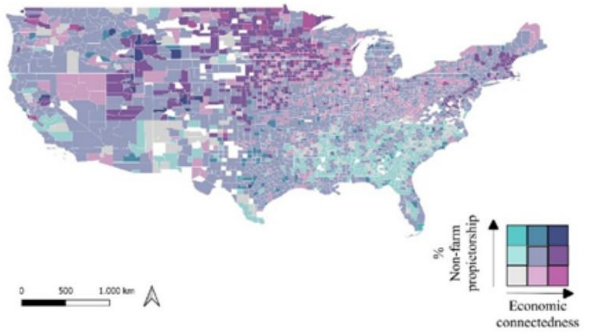


Figure 4. Non-Farm Proprietorship by County in the U.S.

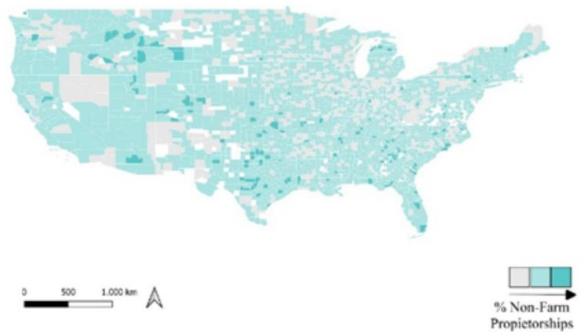
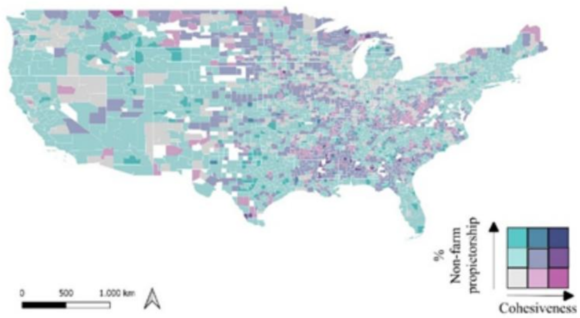


Figure 5. Non-Farm Proprietorship vs Cohesiveness



Local Moran's I confirm that the spatial patterns in Figures 2–5 are statistically significant, with clear high–high and low–low clusters in entrepreneurship and both social capital measures (see Table 2).

Table 1 shows descriptive statistics. On average, 40.6% of the friends of low-income individuals are high-income, yielding an Economic Connectedness score of 81.253. Network cohesiveness—defined as the proportion of an individual's friends who are also friends with each other—is 11.6% at the county level, indicating relatively sparse cohesiveness across the full sample. The average rate of non-farm proprietorship, our proxy for entrepreneurship, is 24.5% across counties.

Table 3 reports the SDEM estimates under five alternative spatial-weight specifications. Across all models, Economic Connectedness exhibits a positive and statistically significant local association with the non-farm proprietorship rate, with coefficients ranging from 0.042 to 0.091. This suggests that counties with more diverse, outward-oriented social networks exhibit higher self-employment, consistent with Granovetter's weak-ties hypothesis. The spatially lagged term for economic connectedness is small and sensitive to the choice of spatial weights: it is negative and statistically significant in the KNN and inverse-squared-distance specifications, but close to zero and statistically insignificant in the remaining matrices. This heterogeneity suggests that, under definitions of neighborhood based on close geographic proximity, connectedness in neighboring counties may dampen local entrepreneurship—although this pattern is not robust across all weighting schemes. Some of this heterogeneity may stem from the spatial clustering of economic connectedness itself (Table 2), which may partially overlap with proximity-based weight matrices and limit the ability to cleanly separate local and neighboring effects.

Table 2. Local Moran's I cluster classification (percent of counties)

Variable	Moran's I	High–High (HH)	Low–Low (LL)	High–Low (HL)	Low–High (LH)	Not significant
Self-employment	0.125	12.3	17.8	5.8	5.2	58.9
Economic connectedness	0.461	27.8	29	2.4	4.5	36.3
Cohesiveness	0.278	23.4	20.5	2.5	4.7	48.9

Note: Moran's I statistics are computed using the inverse–squared–distance spatial-weight matrix. HH and LL denote high–high and low–low clusters, respectively, while HL and LH correspond to spatial outliers. Percentages indicate the share of counties belonging to each cluster, based on Local Moran's I significance at the 5% level.

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Table 3. Spatial Durbin error model

	Dependent variable:				
	Non-farm proprietorship rate				
	KNN	**Inv. dist**	**Inv. Dist squared**	**Social connection**	**Ec- similarity**
Economic connectedness	0.080***	0.084***	0.091***	0.044***	0.042***
	(0.012)	(0.012)	(0.012)	(0.010)	(0.010)
Cohesiveness	-0.145*	-0.084	-0.090	-0.336***	-0.331***
	(0.076)	(0.073)	(0.076)	(0.071)	(0.073)
W* Economic connectedness	-0.053**	-0.240	-0.114*	0.009	-0.004
	(0.024)	(0.259)	(0.059)	(0.021)	(0.025)
W* Cohesiveness	-0.159	-2.540	-0.299	0.219	-0.166
	(0.173)	(2.510)	(0.465)	(0.144)	(0.180)
Observations	2,956	2,956	2,956	2,956	2,956
Log Likelihood	-8,462.000	-8,465.000	-8,436.000	-8,722.000	-8,697.000
σ^2	17.500	18.000	17.300	21.400	21.000
λ	0.404***	0.904***	0.888***	-0.020	0.111***
Akaike Inf. Crit.	17,058.000	17,064.000	17,007.000	17,578.000	17,527.000
Wald Test (df = 1)	218.000***	186.000***	400.000***	0.521	10.300***
LR Test (df = 1)	194.000***	16.500***	163.000***	0.521	9.430***

Note: *p<0.10, **p<0.05, ***p<0.01. All models control for the full set of sociodemographic variables reported in Table 1 and for the relative industry shares. Each specification uses a different spatial-weight matrix: K-nearest neighbors (KNN), inverse distance, inverse squared distance, Facebook-based friendship links, and an economic KNN matrix based on sectoral similarity. To avoid excessively dense matrices, we cap the number of neighbors at seven for all KNN-based constructions (geographic, friendship, and economic similarity). For the inverse-distance matrix, we impose a 150 km cutoff so that each county has at least one neighbor while still maintaining a sparse structure.

Table 4.1 and 4.2 report the total effects of all predictors on non-farm proprietorship. Several variables display statistically significant associations: poverty, internet access, and bachelor's degree attainment show positive total correlations, whereas median earnings and the foreign-born share exhibit significant negative ones. Significant total effects also arise for some racial and ethnic groups. In contrast, total population and labor force participation show no significant total effects. For population, this reflects that county size contributes little once age structure, housing markets, and economic composition are accounted for. For labor force participation, its high correlation with unemployment and female participation leaves limited independent variation

Economic connectedness shows no statistically significant total effect once spatial spillovers are incorporated. This indicates that the benefits of diverse, outward-oriented networks are highly localized and do not translate into broader regional gains. Under proximity-based spatial weights, a plausible interpretation is that nearby counties compete for similar entrepreneurial resources, generating spatial sorting that offsets positive local associations. Cohesiveness displays uniformly negative direct, indirect, and total coefficients, although none reach statistical significance. This pattern is consistent with the idea that dense, inward-looking networks may limit exposure to novel opportunities, but the imprecision of the estimates prevents a definitive conclusion.

Findings align with our conceptual framework, showing that social effects depend on spatial structure. Economic connectedness is positively associated with local entrepreneurship, consistent with the weak-ties view that diverse networks provide non-redundant information and opportunities. However, the negative association with neighboring connectedness appears only under geographic proximity; when neighborhoods are defined through social or economic similarity, the pattern disappears. This suggests a proximity-driven sorting dynamic, whereby highly connected counties attract entrepreneurial activity from nearby neighbors. The spatial clustering of connectedness (Table 2) may further amplify this pattern by increasing overlap with proximity-based matrices. Cohesiveness, meanwhile, shows uniformly negative but statistically inconclusive effects, indicating that dense, inward-looking networks play a limited role in regional variation. Overall, weak ties promote entrepreneurship locally, whereas geographic frictions and spatial clustering shape how these advantages redistribute across space.

5. Concluding remarks

This article examines how social capital shapes entrepreneurial activity across U.S. counties by combining relational measures from the Social Capital Atlas with spatial econometric techniques. Our findings highlight economic connectedness—capturing cross-income bridging ties—as the key social-capital dimension associated with higher non-farm proprietorship. Counties with more diverse and outward-oriented networks consistently display higher entrepreneurship, aligning with Granovetter's weak-ties mechanism.

Cohesiveness, in contrast, exhibits a uniformly negative but statistically inconclusive relationship with entrepreneurship, suggesting that dense, inward-looking networks play at most a limited role in explaining regional variation. Incorporating spatial structure provides further insight: the positive effect of economic connectedness is highly localized, while neighboring counties do not experience similar gains. Indeed, under proximity-based weight matrices, the estimates suggest a proximity-driven sorting pattern, whereby highly connected counties attract entrepreneurial activity from geographically close neighbors. As a result, the total effect of connectedness across space is essentially neutral. These findings advance the understanding of how social and spatial environments jointly condition entrepreneurial outcomes. Although our design does not provide causal interpretation, the evidence points to the importance of fostering bridging social ties and reducing barriers to interaction across local groups. Policies that broaden access to heterogeneous networks may strengthen local entrepreneurial ecosystems, while excessive reliance on closed, cohesive structures appears less conducive to business creation.

Table 4.1. Direct, indirect and total effects of predictors

Variable	Direct effect	Indirect effect	Total effect
Unemployment Rate (%)	0.159***	-1.171***	-1.012*
	(0.047)	(0.367)	(0.371)
Labor Force Participation (%)	0.159***	0.141	0.300
	(0.031)	(0.243)	(0.247)
Female Labor Force (%)	-0.057*	-0.381	-0.438*
	(0.031)	(0.232)	(0.235)
Median Age of the Population	0.363***	-0.136	0.227
	(0.030)	(0.189)	(0.190)
Per Capita Income (Thousand dollars)	-0.313***	0.620**	0.307
	(0.041)	(0.276)	(0.282)
Median Earnings of Workers (Thousand dollars)	-0.109***	-0.457**	-0.567***
	(0.031)	(0.218)	(0.221)
People and Families Below Poverty Threshold (%)	0.038	0.666***	0.703**
	(0.032)	(0.249)	(0.254)
Median Home Value (Thousand dollars)	0.032***	-0.039***	-0.007
	(0.002)	(0.010)	(0.010)
Owner-Occupied Housing (%)	0.296***	-0.442***	-0.145
	(0.017)	(0.107)	(0.107)

Note: *p<0.10, **p<0.05, ***p<0.01. Standard errors in parentheses. The table reports the direct, indirect, and total effects implied by the Spatial Durbin Error Model with 7 nearest neighbors. In the SDEM, these effects correspond to the coefficients of X(direct) and WX (indirect), with total effects computed as their sum; no simulation is required because impacts do not depend on a spatial multiplier.

Table 4.2. Direct, indirect and total effects of predictors

Variable	Direct effect	Indirect effect	Total effect
Economic Connectedness	0.091***	-0.114*	-0.023
	(0.012)	(0.059)	(0.058)
Cohesiveness	-0.090	-0.299	-0.389
	(0.076)	(0.465)	(0.453)
High School Graduates (25 years and older) (%)	-0.095*	0.026	-0.069
	(0.034)	(0.196)	(0.192)
Bachelor's Degree (25 years and older) (%)	0.051**	0.380**	0.430*
	(0.026)	(0.163)	(0.163)
Households with Internet Connection	-0.024	0.431***	0.408**
	(0.019)	(0.132)	(0.131)
Total Population	0.049	0.195	0.244
	(0.031)	(0.203)	(0.205)
White (%)	-0.002	-0.004	-0.006
	(0.017)	(0.092)	(0.088)
African American (%)	0.029	0.116	0.145*
	(0.019)	(0.090)	(0.085)
Asian (%)	-0.428***	0.685**	0.256
	(0.067)	(0.340)	(0.345)
Hispanics (%)	-0.110***	0.213***	0.103*
	(0.021)	(0.065)	(0.055)
Foreign-born (%)	0.223***	-0.886***	-0.663***
	(0.044)	(0.205)	(0.199)

Note: *p<0.10, **p<0.05, ***p<0.01. Standard errors in parentheses. The table reports the direct, indirect, and total effects implied by the Spatial Durbin Error Model with 7 nearest neighbors. In the SDEM, these effects correspond to the coefficients of X(direct) and WX (indirect), with total effects computed as their sum; no simulation is required because impacts do not depend on a spatial multiplier.

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