Regional Innovation Networks & High-Growth Entrepreneurship

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Abstract
We investigate the influence of regional innovation networks (RINs) on high-growth entrepreneurship within the framework of the knowledge spillover theory of entrepreneurship (KSTE). While previous studies have separately examined RINs' role in knowledge diffusion and the geographical characteristics of high-growth firms, the connection between these two areas remains unexplored. To address this gap, we develop a conceptual model that highlights the positive impact of RINs on high-growth entrepreneurship, moderated by regional entrepreneurial capital. Using a unique longitudinal dataset at the metropolitan statistical area (MSA) level, we employ two-way fixed effects and instrumental variables regressions to analyze the data. Our findings support the conceptual model, revealing that robust RINs facilitate high-growth entrepreneurship. Additionally, we conduct post-hoc exploratory analyses to investigate potential moderating factors, including the influence of the public policy environment.

Keywords
Gazelles; Geography of Innovation; Innovation Networks; Geography of High-Growth Entrepreneurship; Knowledge Spillover Theory of Entrepreneurship

JEL Codes: L14, M13, O12, O33, R1

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1. Introduction

Entrepreneurship, particularly through high-growth firms commonly called “gazelles”, is a pivotal driver of regional economic growth and job creation (Acs & Mueller, 2007). Scholars have explored the phenomenon of high-growth entrepreneurship—the process of starting and developing businesses with significant potential for rapid expansion (Henrekson & Johansson, 2010)—through various angles, including the characteristics of the founders (Siegel et al., 1993), industry structure (Delmar et al., 2011), firm strategy (Coad & Rao, 2008), and national public policies (Autio & Rannikko, 2016). While these perspectives offer valuable insights, the role of geographical factors has been underexplored, despite evidence of regional variations in the presence of high-growth firms (Brown et al., 2017; Sleuwaegen & Ramboer, 2020). A nascent body of research, which we refer to as the *geography of high-growth entrepreneurship* literature (Fotopoulos, 2022; Friesenbichler & Hölzl, 2020), has emerged seeking to fill this gap, but further investigation is required to identify the geographic attributes most conducive to high-growth entrepreneurship.

An important theoretical lens to understand entrepreneurship in general—and the high-growth kind in particular—is the knowledge spillover theory of entrepreneurship (KSTE), which suggests that entrepreneurs serve as conduits for integrating new knowledge created in a region into successful commercial offerings, catalyzing regional economic growth (Audretsch & Keilbach, 2008; Audretsch & Lehmann, 2005). Concurrently, the geography of innovation literature, which focuses on the characteristics of regions or specific locales, has identified several important factors, such as innovation networks, that shape a region’s capability for knowledge creation, diffusion, and transformation (Baum et al., 2010; R. A. Boschma & Ter Wal, 2007; De Noni et al., 2018). Despite the richness of these streams of literature, they have not been adequately integrated to tackle the puzzle of high-growth entrepreneurship, which is underscored by the "paucity of research linking locational characteristics to high growth firms" (Audretsch, 2012, p. 32).

We advance this area of research by addressing the research question: *How do regional innovation networks influence high-growth entrepreneurship?* Defined as sets of formal ties among inventors within a region (Flemin & Frenken, 2012; Singh, 2005), regional innovation networks (RINs) may play a vital function in diffusing knowledge, which can ultimately enhance the capacity of a region to foster high-growth entrepreneurship. Such networks are important to consider within the KSTE because they reflect the degree to which knowledge is being *diffused* in a region. This differs from the traditional approach focusing on the amount of knowledge that is *produced* in a region. Given that high knowledge production alone does not guarantee successful knowledge spillovers (Agarwal et al., 2007), exploring how knowledge diffuses through RINs may yield novel insights regarding a potential regional path to high-growth entrepreneurship.

Building on the KSTE's pivotal insight regarding the role of entrepreneurs in facilitating knowledge spillovers, we develop a conceptual model depicting a positive effect of RINs on high-growth entrepreneurship that is amplified by regional entrepreneurial capital, or the number of entrepreneurs willing to take risks and start new businesses (Audretsch et al., 2008). Our empirical strategy draws on a diverse set of databases and the development of a unique longitudinal dataset containing information at the U.S. metropolitan statistical area (MSA) level. Utilizing two-way fixed effects and instrumental variables regressions, while controlling for a host of potential confounding contextual factors, our findings are consistent with our conceptual model. Furthermore, we conduct post-hoc exploratory analyses to examine additional factors that might moderate the relationship between RINs and high-growth entrepreneurship, including the public policy environment.

Our study offers several important contributions. First, by uncovering that strong RINs facilitate high-growth entrepreneurship, we shed new light on the puzzle of penetrating the "knowledge filter" (Qian & Jung, 2017) through the diffusion of knowledge. Relatedly, we extend the KSTE framework (Acs et al., 2009) by emphasizing that knowledge diffusion and connectivity (De Noni et al., 2018; Huggins & Thompson, 2015) matter beyond sheer knowledge production (Motoyama, 2014; Sleuwaegen & Ramboer, 2020; Yu & Fleming, 2022). Further, we unpack interdependencies and temporal complexities regarding the effects of RINs. First, we illustrate that their impact depends on the level of regional entrepreneurial capital, adding depth to the notion of entrepreneurs as knowledge spillover agents (Audretsch & Keilbach, 2008; Audretsch & Lehmann, 2005). We also consider multi-year RINs, acknowledging that inventors may collaborate differently over time. Our findings underscore that current knowledge diffusion is paramount for high-growth firms, addressing an overlooked aspect of temporal dynamism in knowledge diffusion studies (Ejermo & Karlsson, 2006; Malecki, 2021). Finally, by employing an instrumental variable approach, we offer the first attempt to establish a causal link between RINs and high growth entrepreneurship.

2. Theoretical Framework

Combining insights from the geography of innovation and KSTE literatures, we advance the conceptual model depicted in Figure 1. First, we posit that RINs are a key mechanism for knowledge diffusion, enabling high-growth entrepreneurship (H1). Additionally, we propose that thise relationship is not homogenous across regions but rather is conditional on the level of entrepreneurial capital (H2).

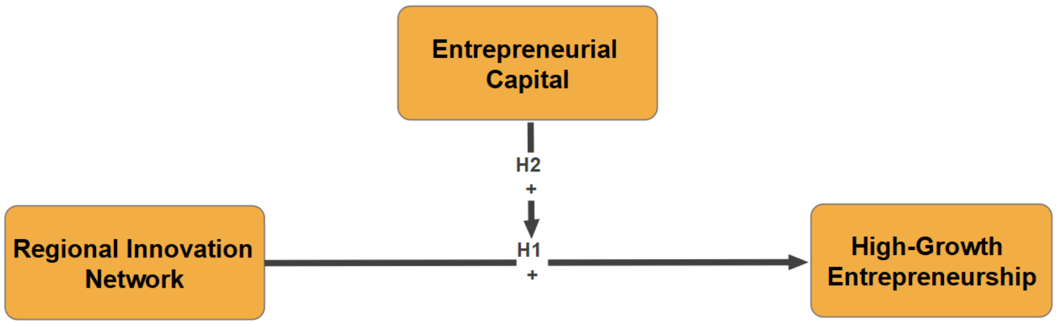

Figure 1: Conceptual Model

2.1 Knowledge Diffusion as The Nexus Between the KSTE and the Geography of Innovation

Central to the KSTE is the concept of the “knowledge filter,” representing the barriers and frictions that impede the flow of knowledge from its origin to its commercialization through entrepreneurship. According to this approach, knowledge generated through research, innovation labs, or other forms of intellectual activity does not automatically flow into commercial use. Instead, this process passes through a series of filters, which can be influenced by regional conditions (Acs & Plummer, 2005; Qian & Jung, 2017). The more “clogged” the filter is, the less knowledge successfully passes through it to become commercialized or economically productive.

Entrepreneurs play a crucial role in this framework as they are the “conduits” who identify opportunities within extant knowledge and act to secure resources and execute their plans in the hopes of turning this knowledge into successful products, services, or processes (Acs et al., 2009). However, a gap remains in our understanding regarding the mechanisms enabling entrepreneurs to penetrate the knowledge filter (Qian & Jung, 2017). For instance, one approach considers the amount of knowledge produced in a region, given that a greater pool of knowledge could generate more opportunities for entrepreneurs to successfully complete the spillover process (Fotopoulos, 2022; Li et al., 2016; Sleuwaegen & Ramboer, 2020).

We extend the focus beyond mere knowledge production to explore the dynamics of knowledge diffusion. We offer a detailed analysis of RINs and examine how they enable entrepreneurs to navigate the knowledge filter more effectively. Our theoretical framework draws from the geography of innovation literature, which has substantially enriched our understanding of spatial influences on innovation processes (e.g., Audretsch & Feldman, 1996; Backman & Lööf, 2015). Among the key findings in this literature is the role of different kinds of proximity—cognitive, social, geographic, institutional, and organizational—in fostering the development of knowledge ties among the actors in a network (Boschma, 2005; Sorenson et al., 2006). This motivates our interest in studying the connectivity among inventors through RINs.

Our focus on innovation networks aligns with previous work on the geography of innovation. For example, Boschma and Ter Wal (2007) showed that knowledge networks can be instrumental in the innovation performance of firms. Similarly, Cooke et al. (1997) proposed that regional innovation systems—interdependent actors and institutions that collaborate to expedite knowledge spillovers and innovation—are a pivotal mechanism for innovation within regional clusters. More recent studies have also reiterated the significance of innovation networks for regional innovation performance (Breschi & Lenzi, 2016; De Noni et al., 2018; Lyu et al., 2019) and for regional economic development (Huggins & Thompson, 2015). Collectively, these studies corroborate the idea that networks and proximity elements can provide a valuable lens through which we can better understand the dynamics of knowledge diffusion among inventors and its potential impact on high-growth entrepreneurship (Malecki, 2021).

2.2 Regional Innovation Networks and High-Growth Entrepreneurship

Building on previous arguments, we contend that RINs are instrumental to penetrate the knowledge filter and unclog the knowledge spillover process, thereby facilitating opportunities for the emergence of regional high-growth entrepreneurship. Strong RINs are characterized by well-connected members, frequent collaboration, and effective and swift knowledge sharing. This creates an environment that not only fosters collaborative innovation, but also facilitates the rapid flow of ideas and expertise within a region. Conversely, weak RINs are characterized by limited connections and collaboration among their members, leading to infrequent sharing of knowledge and ideas across the region, potentially serving as a filter limiting knowledge diffusion (Breschi & Lenzi, 2016; Flemin & Frenken, 2012; Singh, 2005). This is consistent with previous studies suggesting that highly connected networks are a vital source of knowledge diffusion in a region (R. A. Boschma & Ter Wal, 2007; Owen-Smith & Powell, 2004).

We posit that a key mechanism connecting innovation networks to the emergence of high-growth entrepreneurship within a region is the streamlined access to cutting-edge innovation and technology. In regions with strong innovation networks, the transfer and exchange of new knowledge and technological discoveries occurs more rapidly as inventors share information about their latest research and development with other actors (e.g., inventors) within the network (Breschi & Lenzi, 2016; Singh, 2005). This knowledge has the potential to not only diffuse throughout the innovation network, but also reach other actors, including entrepreneurs alert to potentially innovative ideas (Kirzner, 1973). In contrast, regions with weaker RINs offer limited scope for entrepreneurs to access such fresh ideas, making it more challenging to find and translate new knowledge into a competitive advantage that fuels firm growth.

In summary, we posit that RINs are instrumental in disseminating knowledge and fostering high-growth entrepreneurship in a region. Strong RINs serve as vital channels for disseminating advanced innovation and technology. Through these networks, entrepreneurs have richer avenues to tap into and leverage new ideas, amplifying their ventures' growth prospects. Conversely, regions with weak RINs experience limited knowledge diffusion, constraining knowledge spillovers and curtailing opportunities for high-growth entrepreneurship. We, therefore, hypothesize that:

> **H1:** *Stronger regional innovation networks are associated with more high-growth entrepreneurship in a region.*

2.3 The Moderating Role of Regional Entrepreneurial Capital

While we posit that RINs increase the potential accessibility of knowledge within a region, knowledge diffusion may be a necessary but insufficient condition to unclog the knowledge filter. Without entrepreneurial actors alert and willing to take the risks associated with converting new knowledge into a commercial offering, knowledge may be shared but remain “clogged” in the network (Agarwal et al., 2007; Michelacci, 2003). In line with the KSTE, our framework underscores the pivotal role of entrepreneurs in the complex act of transforming innovation into commercial entrepreneurial offerings by examining the role of regional entrepreneurial capital as an important contextual factor in understanding the dynamics of knowledge spillovers.

We argue for a synergistic interaction between RINs and regional entrepreneurial capital in facilitating high-growth entrepreneurship. Regions with high entrepreneurial capital are characterized by a large pool of entrepreneurs with an appetite for risk-taking and a greater willingness to explore innovative ideas (Audretsch et al., 2008). We posit that the presence of high levels of regional entrepreneurial capital is a crucial factor in the ability of regions with strong innovation networks to generate high-growth entrepreneurship because it increases the likelihood that the knowledge and ideas diffusing within a region will reach entrepreneurs with the alertness (Kirzner, 1973) and capacity (Qian & Jung, 2017) to convert that knowledge into commercial offerings with high-growth potential.

Conversely, in regions where there is low entrepreneurial capital, even a strong innovation network that rapidly diffuses knowledge may be insufficient because there are not enough entrepreneurs with access to, and the willingness to act on, the knowledge created within the network (Michelacci, 2003). Thus, although RINs have the potential to generate positive effects, the lack of sufficient entrepreneurial capital can limit the region's ability to translate this knowledge into new businesses, products, and services. In such cases, the knowledge may fail to spillover. That is, the knowledge may fail to be appropriated by the local entrepreneurs with the willingness to use this knowledge as potential fuel for the growth of their ventures. As a result, knowledge remains confined within the network, only exchanged between inventors and their organizations.

In sum, regional entrepreneurial capital represents an important moderator between RINs and high-growth entrepreneurship. Regions rich in entrepreneurial capital are better poised to harness knowledge from RINs, setting the stage for high-growth entrepreneurship. In contrast, regions lacking in entrepreneurial capital might struggle to utilize knowledge from these networks, thus constraining the prospects for high-growth entrepreneurship. We hypothesize, therefore, that:

H2: *The positive relationship between regional innovation networks and high-growth entrepreneurship is enhanced in regions with higher entrepreneurial capital.*

3. Data & Methods

3.1 Research Context

Considering that both high-growth entrepreneurship and innovation networks are regional phenomena, the context for our empirical analysis is a large longitudinal sample of MSAs, a county-based concept designed by the U.S. Office of Management and Budget using local commuting data to capture the boundaries of regional economies. MSA's are "key engines and incubators of new knowledge creation processes because they facilitate intellectual linkages among individuals through social proximity and face-to-face contacts" (Breschi & Lenzi, 2016, p. 67). Our analysis includes 358 MSAs and spans the period 2003-2014. Table 1 summarizes the variables used in our analysis. Appendix Table B2 provides a pairwise correlation matrix of the variables.

3.2 Regional Innovation Networks

We operationalize RINs using U.S. patent data to develop a measure of the strength of connections, both direct and indirect, between inventors in a region. Specifically, we use detailed utility patent data provided by the PatentsView Project, a collaborative effort between the U.S. Patent and Trademark Office (USPTO) and several universities and private-sector organizations. These data are constructed from the USPTO records, covering both granted patents (1976-present) and patent applications (2001-present). This database facilitates the study of innovation networks because it applies a disambiguation algorithm to every patent's inventor(s), assignee(s), lawyer(s), and location (based on the residential address of the inventor(s)). The disambiguated data can then be merged and linked to more than 60 data fields, allowing for a

Table 1: Variable Descriptions, Summary Statistics, and Sources

Variable	*Description*	*Mean*	*SD*	*Min*	*Max*	*N*	*Source*
High-growth entrepreneurship	The number of firms on the annual *Inc. 5000* list of fastest-growing privately held companies in the U.S. per 10,000 firms.	37.10	47.30	0.00	482.13	4,296	Inc. Magazine; BDS
Regional innovation network (RIN)	The internal social proximity metric for patent authors during a given year (or years).	1.59	3.69	0.00	98.66	4,296	PatentsView Project
Entrepreneurial capital	The ratio of the number of nonfarm proprietors to the number of nonfarm wage employees.	18.74	3.80	8.79	35.03	4,296	Bureau of Economic Analysis
Business churn	The ratio of the sum of the establishment entries and exits to the number of existing establishments.	18.95	3.34	10.90	34.00	4,296	BDS
Net job creation rate	The ratio of the difference between the number of jobs created and the number destroyed from all establishments during a year (including startups) to the existing number of jobs.	1.11	3.51	-24.80	29.50	4,296	BDS
R&D investments	The sum of real R&D expenditures by colleges and universities and federally funded R&D facilities (in 1,000s), normalized by the number of business establishments.	11.99	33.84	0.00	416.06	4,296	National Science Foundation; BDS
Venture capital	Inflation-adjusted venture capital investments (in 1,000s), normalized by the number of business establishments.	1.35	4.19	0.00	112.80	4,296	Dow Jones Venture Sources; BDS
Net migration rate	The net flow of migrants (migrants less emigrants) to a region per 10,000 residents during a year.	-152.33	108.23	-914.35	121.46	4,296	IRS Statistics of Income database

Variable	*Description*	*Mean*	*SD*	*Min*	*Max*	*N*	*Source*
Government size	Size of government index, comprised of three variables: (1) government consumption expenditures; (2) government transfers and subsidies; and (3) insurance and retirement payment by the government. Each variable expressed as a percentage of personal income and transformed to a 0-10 score, with higher values reflecting more limited government. Index is derived as the mean of three transformed variables.	6.55	1.11	2.26	9.09	4,296	Stansel (2019)
Tax freedom	Tax freedom index, comprised of three variables: (1) income and payroll tax revenue; (2) sales tax revenue; and (3) revenue from property and other taxes. Each variable expressed as share of personal income and transformed to a 0-10 score, with higher values reflecting less taxation. Index is derived as the mean of three transformed variables.	5.90	0.75	2.05	8.18	4,296	Stansel (2019)
Labor market freedom	Labor market freedom index, comprised of three variables: (1) Minimum Wage (full-time income as a percentage of per capita personal income); (2) Government Employment; and (3) Private Union Density. Latter two expressed as share of total employment. Each variable transformed to a 0-10 score, with higher values reflecting fewer distortions. Index is derived as the mean of three transformed variables.	7.31	1.00	3.31	9.73	4,296	Stansel (2019)
Patent rate	The number of utility patents to residents of a region per 10,000 residents.	4.46	6.56	0.00	102.02	4,296	PatentsView Project and Census Bureau
Innovation grants	Inflation-adjusted small business innovation research (SBIR) and small business technology transfer (STTR) awards, normalized by the number of business establishments.	0.33	0.85	0.00	9.33	4,296	U.S. Small Business Administration

Variable	*Description*	*Mean*	*SD*	*Min*	*Max*	*N*	*Source*
Cluster strength	The employment location quotient, which captures the extent that employment in related clusters is over-represented in the region.	0.51	0.12	0.05	0.87	4,296	U.S. Cluster Mapping Project
Creative class	Fraction of all jobs in the region that are in creative industries, as defined by Markusen et al. (2008).	2.22	1.66	0.00	11.96	4,296	Quarterly Census of Employment and Wages.
Agglomeration index	Ellison-Glaeser index of agglomeration based on establishment-level data; 0 indicates a random or "dartboard" pattern of firm location; positive and larger values indicate greater	0.05	0.14	-0.11	7.07	4,296	Ellison and Glaeser (1997) and National Establishment
Human capital	The percentage of residents aged 25 and older holding at least a bachelor's degree.	24.93	7.82	9.66	58.37	4,296	American Community Survey
Organizational patent share	Fraction of total patents awarded in the region that are granted to inventors affiliated with organizations.	84.92	13.97	0.00	100	4,296	PatentsView
Large organization concentration	Fraction of all establishments in the region with 250 or more employees.	0.36	0.16	0.02	1.18	4,296	National Establishment Time Series
Female CEO establishments	Fraction of all publicly traded establishments in the region with a female CEO	17.70	2.50	8.87	27.66	4,296	National Establishment Time Series

nuanced view regarding each patent record.[1] Over our sample period, we identified more than 100,000 unique organizations that were granted patents, with 94.4% of inventors residing in MSAs, suggesting that patented innovation in the U.S. is an urban phenomenon driven largely by inventors affiliated with organizations.[2]

To measure RIN strength, we utilized Breschi and Lenzi's (2016) internal inventor social proximity metric, which gauges the set of ties between individuals and organizations in a given population. Individual inventors within MSAs are treated as distinct nodes in the network and are assumed to be directly connected if they collaborated on a patent in year *t*. We first calculated the geodesic social distance (i.e., shortest path from inventor A to inventor B using all the connection paths in the network) for each pair of inventors within the same MSA. We then derived a composite measure of the size and strength of the innovation network in MSA *m* in year *t* using equation 1, where d_{jk} denotes the geodesic distance between inventors *j* and *k*, or the smallest number of intermediaries separating this pair of inventors, and *n* is the total number of distinct inventors residing in MSA *m*. Appendix Figure A2 illustrates two hypothetical RINs – one strong and one weak – to depict how the direct and indirect ties between inventors in each region translate into a measure of network strength. Appendix Figure B1 details the calculations for these two networks.

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[1] The USPTO's raw, publicly available data treat inventors and assignees on patent applications as a single observation. Neither inventors nor assignees are tracked over time. The current disambiguation algorithm applied by the PatentsView project began in 2015. It uses a series of algorithms to generate a unique identification code so that both inventors and assignees can be tracked over time. Technical details of the disambiguation algorithms may be found at:
<<https://s3.amazonaws.com/data.patentsview.org/documents/PatentsView_Disambiguation_Methods_Documentation.pdf>>.

[2] Over our sample period, 1,285,063 patents were awarded to 774,208 inventors in the U.S. Approximately 61 percent of these patents were authored by more than one inventor, suggesting that a significant amount of innovation is collaborative. Regarding the regional distribution, nearly 95 percent of inventors live in MSAs and 40 percent of all co-authored patents are from inventors who live in the same MSA. Interestingly, for patents with three or more authors, 80 percent have all co-authors but one living in the same MSA.

$$RIN_{m,t} = \frac{\sum_{j=1}^{n} \sum_{k=1}^{n} \frac{1}{d_{jk}}}{n-1}, j \neq k \qquad (1)$$

By construction, our innovation network measure ranges from 0 (i.e., no inventor collaborates with any other inventor in the region) to n (i.e., all inventors who reside in an MSA directly collaborate with every other inventor in the region). In other words, larger values of our network measure indicate greater collaboration between inventors within a region. Figure 2 illustrates the distribution of innovation network strength by MSA for 2014. The median score across MSAs was 0.92 and approximately one-third of the MSAs had a score between 1 and 3. Most MSAs, therefore, exhibited a relatively low degree of inventor collaboration in 2014. Twenty-five MSAs had scores above 5, indicative of hot spots for innovation collaboration relative to other regions.[3] Appendix figure A1 displays the change in the three-year average RIN score from the beginning (i.e., 2003-2005) and end (i.e., 2012-2014) of our sample period, demonstrating that there have been meaningful changes in network strength within some regions.

Additionally, we take into consideration that inventors may collaborate with different peers in different years such that networks take time to develop and exert an effect. As such, we anticipate the existence of temporal dynamism in innovation networks. We therefore also calculated RIN strength using two- and three-year time windows. For example, the contemporaneous RIN score for 2008 measures inventor connections limited to patents awarded in 2008. The two-year RIN score for 2008 measures inventor connections on patents awarded in 2007 and 2008, while the three-year measure uses patents awarded in 2006, 2007, and 2008.

[3] The five most collaborative MSAs in 2014, which holds true for other years in our sample period, were Seattle-Tacoma, San Diego, Burlington VT, Minneapolis-St. Paul, and Rochester, NY.

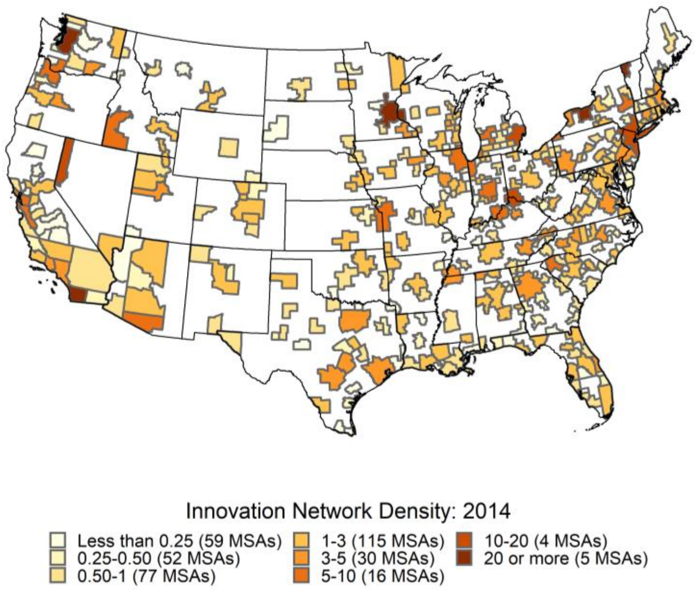

Figure 2: Regional Innovation Network Strength in 2014

3.3 High-Growth Entrepreneurship

Following recent studies, we operationalize regional high-growth entrepreneurship by looking at the incidence of high-growth firms in a region (Friesenbichler & Hölzl, 2020; Sleuwaegen & Ramboer, 2020). Specifically, we derive the MSA-level ratio of the number of firms appearing on the *Inc. 5,000* ranking of the fastest-growing privately held companies in the U.S. per 10,000 firms, as reported by the U.S. Census Bureau's Business Dynamics Statistics (BDS) database. For inclusion in the ranking, firms must meet specific growth criteria: (1) annual revenue growth of at least 20 percent over the previous three years (three-year revenue growth rate of 72.8 percent); (2) at least $100,000 annual revenue at the beginning of the three-year growth period; and (3) at least $2 million in revenue by the end of it.[4] For each year's list, we assigned the number of high-growth firms located in an MSA to the *beginning* of the three-

[4] Firms must be U.S.-based, independent, and structured as a for-profit company to be eligible for inclusion in the Inc. 5,000. Although firms must apply to be considered for inclusion in the *Inc. 5,000*, which potentially creates a selection bias in the data, the annual ranking generates significant national publicity and therefore provides firms with an incentive to apply (Markman & Gartner, 2002). Li et al. (2016) provide evidence that the spatial distribution of firms on the Inc. 5,000 list is representative of the distribution of all firms in the U.S.

year growth period used to derive it (e.g., we assigned the 2018 list, which is based on growth over the period 2014-2017, to 2014). We then normalized the number of high-growth firms by the total firm population that year. The map provided in Figure 3 shows the mean annual high-growth density of our sample by MSA.

3.4 Regional Entrepreneurial Capital

We assess regional entrepreneurial capital using the proprietorship rate, or the ratio of the number of nonfarm proprietors to the number of nonfarm wage employees. Proprietors are individuals who own and run a business and, as such, are willing to take the risk of starting a new business. Thus, regions with a high proprietorship rate exhibit a large endowment of entrepreneurs and, hence, high entrepreneurial capital. Meanwhile, regions with a low proprietorship rate exhibit a small endowment of entrepreneurs and, hence, low entrepreneurial capital. Our proprietorship rate data is from the Bureau of Economic Analysis.

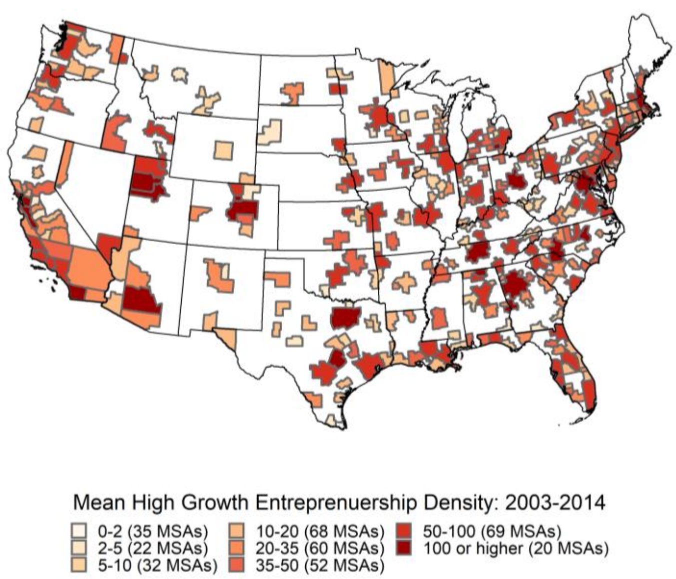

Figure 3: Mean High Growth Entrepreneurship: 2003-2014

3.5 Post-Hoc Analyses: Entrepreneurship Policy and Patent Rates

In addition to the variables incorporated in our primary analysis, several extraneous factors could potentially influence the association between RINs and high-growth entrepreneurship. To address this possibility, we include post-hoc analyses covering three aspects: two related to regional entrepreneurship policy and a third related to regional patent production.

Regarding regional entrepreneurship policy, we delve into two policy subtypes: bottom-up and top-down (Colombo et al., 2019). Bottom-up policy follows a market-oriented approach to generate growth in the region, whereas top-down policy aims to achieve this result via governmental programs and incentives. We measure bottom-up policy using the metropolitan area economic freedom index (MEFI) data, a measure of pro-market institutions that has been identified as an important determinant of firm formation rates (Bennett, 2021a), greater job creation among startups (Lucas & Boudreaux, 2020), innovation (Bennett & Nikolaev, 2021), and more innovation dispersion among entrepreneurs (Wagner & Pavlik, 2020). The MEFI index is comprised of three sub-indices: (1) government size; (2) tax freedom; and (3) labor market freedom (Stansel, 2019). Because recent research suggests the components of the MEFI exert heterogeneous effects on entrepreneurial activity (Bennett, 2021b), we consider the three sub-indices separately in our analysis.

To assess top-down entrepreneurship policy, we use the dollar value of innovation grants received by firms within a region. Specifically, we employ the inflation-adjusted total value of Small Business Innovation Research (SBIR) and Small Business Technology Transfer (STTR) grants awarded, normalized by the total number of business establishments in the region. The SBIR/STTR program is a large U.S. entrepreneurship program that provides phased-based competitive R&D grants to support early-stage high-tech ventures to pursue technological innovations with commercialization potential. Previous research suggests that early-stage ventures that receive innovation grants from the program have an increased likelihood of patenting their innovations and receiving subsequent venture capital to facilitate growth (Howell, 2017), and that regions receiving more innovation grants generate more high-tech startups (Qian & Haynes, 2014).

Finally, the literature shows mixed evidence on the relationship between regional knowledge production and high-growth entrepreneurship (Motoyama, 2014; Sleuwaegen & Ramboer, 2020; Yu & Fleming, 2022). We analyze both its direct effect and its interaction with our measure of RINs. We measure regional knowledge production using the patent rate, or the number of utility patents issued per 10,000 residents, and organizational patent share, or the fraction of total (utility) patents awarded to inventors affiliated with organizations.

3.6 Control Variables

The geography of high-growth entrepreneurship literature thus far examined a variety of regional contexts, including the U.S. (Li et al., 2016; Motoyama, 2014; Yu & Fleming, 2022), United Kingdom (Fotopoulos, 2022), Austria (Friesenbichler & Hölzl, 2020), and European Union (Sleuwaegen & Ramboer, 2020). We draw on this literature in selecting control variables.

Numerous studies identify human capital and agglomeration as important factors for regional high-growth entrepreneurship. We measure human capital as proportion of adults in a region with a college degree and industry agglomeration using Ellison and Glaeser's (1997) agglomeration index based on individual organization data from the National Establishment Time Series (NETS) database.[5] Two studies find the presence of a strong creative class (i.e., workers engaged in the creation of new ideas, technology, and creative content) as a positive determinant of high-growth entrepreneurship (Fotopoulos, 2022; Sleuwaegen & Ramboer, 2020).

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[5] MSA educational attainment, our measure of human capital, is only available annually starting in 2009. We imputed each MSA's fraction of the population aged 25 and older with at least a bachelor's degree for 2003 to 2008 using a linear regression that included a linear trend term and the state's population aged 25 and older with at least a bachelor's degree.

We follow Markusen et al. (2008) in measuring creative class as the proportion of all jobs in the creative industries.

The regional industry structure has also been posited as a potentially important determinant of high-growth entrepreneurship, but the results are mixed. We use two measures to represent industry structure. First, we derived large organization concentration as the fraction of organizations in the region having 250 or more employees using the NETS data. Second, we use the related industry cluster strength measure from the U.S. Cluster Mapping Project (Delgado et al., 2014). There are also mixed results concerning the role of entrepreneurial finance for regional high-growth entrepreneurship (Fotopoulos, 2022; Friesenbichler & Hölzl, 2020; Li et al., 2016; Motoyama, 2014; Yu & Fleming, 2022). We use venture capital and R&D investments as proxies for entrepreneurial finance availability.

To control for a region's economic dynamism, which may be associated with environments more amenable to high-growth startups, we included three variables: (i) net job creation rate; (ii) business churn; and (iii) net migration rate. MSA net job creation and business churn measures are from the BDS database. Net migration measures are derived from the Internal Revenue Service's Statistics of Income database.[6]

Finally, using the NETS database, we include the fraction of publicly traded establishments in the region with a female CEO to adjust for observable differences in regional gender equality and business participation, which may play a role in creating a more inclusive environment for entrepreneurship (Bullough et al., 2022).

[6] The Statistics of Income data are based on year-to-year address changes on federal personal income tax returns, so they more accurately reflect the spatial reorganization of households rather than individuals. We used county-to-county address changes, ignoring migrations within the same region.

3.7 Methods

We estimate the effect of RINs on high-growth entrepreneurship using the two-way fixed effects model described by equation 2, where $HGE_{m,t}$ is our measure of high-growth entrepreneurship for MSA *m* in period *t*, $RIN_{m,t}$ is our regional innovation network measure, *EC* is the regional entrepreneurial capital, $X_{m,t}$ is a matrix of MSA-level time-varying control variables, λ_t and μ_m denote fixed year and MSA effects, respectively, and $\epsilon_{m,t}$ is an idiosyncratic error term.

$$HGE_{m,t} = \beta_0 + \beta_1 RIN_{m,t} + \beta_2 EC_{m,t} + \nu X_{m,t} + \lambda_t + \mu_m + \epsilon_{m,t} \qquad (2)$$

The year fixed effects will control for common unobserved factors that could affect high-growth entrepreneurship across all regions in a particular year (e.g., a common shock like the Great Recession). Similarly, the MSA fixed effects control for any time-invariant regional unobserved factors, such as culture or natural amenities (Li et al., 2016), that may be correlated with high-growth entrepreneurship. Another advantage of modeling these unobserved characteristics as fixed effects is that it allows them to be potentially correlated with the other control variables. It seems more plausible in this setting to assume that observed variables such as R&D investments and net migration could be correlated with regional unobserved characteristics than to assume that they are unrelated to one another, which is the (implicit) assumption in a random effects model. We also performed a Hausman (1978) test for each regression and easily rejected the null hypothesis that the random effects specifications are more efficient than the fixed effects specifications. Considering the potential for spatial spillovers across regions, we also test for residual spatial correlation via Moran's I with an inverse distance weighting matrix so that all regions are potentially interconnected.[7] All statistical analyses were performed using R.

As noted in Section 3.3, high-growth entrepreneurship is defined over a three-year period, and we assign the year in the empirical analysis to be the base year of the window. Linking the timing to the RIN scores, the regression models capture how changes in RIN scores that end in year t influence high-growth entrepreneurship over the three-year period that begins in year t.

4. Empirical Results

4.1 Main Results

Table 2 reports our main results. Model 1 is the baseline estimate of the effect of RIN on high-growth entrepreneurship, conditioning on the set of control variables. We find that, consistent with H1, RINs have a statistically significant positive relationship with high-growth entrepreneurship. A unit increase in the RIN measure is associated with 0.310 additional high-growth firms per 10,000 establishments (β = 0.310; p = 0.049; 95% CI = [0.001, 0.619]). We also find a significant positive direct effect of entrepreneurial capital on high-growth entrepreneurship. Regions with a one percentage point higher entrepreneurial capital rate have 3.25 more high-growth entrepreneurial firms per 10,000 establishments (β = 3.254; p = 0.000; 95% CI = [1.497, 5.010]).

Regarding the control variables in Model 1, we observe that regions with a higher net job creation rate, greater tax freedom, a higher fraction of female CEOs, higher levels of human capital, and a higher patent rate are associated with more high-growth entrepreneurship. Meanwhile, regions with more net migration, higher cluster strength scores, and greater industry agglomeration are associated with less high-growth entrepreneurship. Our remaining control

[7] (Inverse) distances between MSAs were computed, in miles, as the distance between the geographic centroid of each region's most populated county in the 2010 Census.

variables are not statistically significant at the 10 percent level. We also find no evidence of residual spatial correlation using Moran's I test.

Model 2 tests H2 by adding the interaction between RIN and entrepreneurial capital. The joint significance test for the overall marginal effect of RINs, shown in the row labeled p(RIN = RIN*Entrepreneurial capital = 0), is 0.039, meaning that the combined effects of RIN and its interaction with regional entrepreneurial capital are statistically significant. In terms of the individual interaction terms, the main RIN effect term enters negatively (β = -3.067; p = 0.158; 95% CI = [-7.390, 1.237]), and its interaction with entrepreneurial capital enters positively (β = 0.175; p = 0.128; 95% CI = [-0.052, 0.403]). The positive coefficient on the interaction term is consistent with H2 and indicates that—on average across the sample—the marginal effect of RINs on high-growth entrepreneurship is higher in regions with more entrepreneurial capital. We note that this effect is too imprecisely measured to conclude that it differs from zero with a high degree of confidence. Interestingly, the negative sign on the main effect term suggests that the marginal effect of RINs on high-growth entrepreneurship is only positive in regions with entrepreneurial capital rates above 17.5 percent.[8] We further discuss the overall interaction results below.

Models 3-6 examine how the effect varies in different time windows for the RIN measure. Models 3 and 4 show the results when the RIN measure is formed using patents over a two-year period, whereas Models 5 and 6 use a three-year window. These estimates are consistent with the baseline results in Models 1 and 2. For example, consistent with H1, a unit increase in the two-year RIN measure (Model 3) is associated with 0.143 additional high-growth firms per 10,000

[8] Obtained by solving the first-order condition from Model 2, $\frac{\partial HGE}{\partial RIN} = -3.076 + 0.175 EntrepreneurialCapital = 0$, for entrepreneurial capital.

establishments (β = 0.143; p = 0.000; 95% CI = [0.078, 0.208]), while a unit increase in the three-year RIN measure (Model 5) is associated with 0.085 additional high-growth firms (β = 0.085; p = 0.000; 95% CI = [0.039, 0.129]). Since the marginal effect of RINs diminishes as the patent window increases, this suggests that the local diffusion of *current* knowledge is more crucial in shaping high-growth entrepreneurship. The interaction regressions for the multi-year RINs (Models 4 and 6) are also consistent with the contemporaneous RIN interaction (Model 2): while higher entrepreneurial capital is, on average, associated with more high-growth entrepreneurship, the effects are too imprecise to conclude that they differ from zero with a high degree of confidence.

Interacting entrepreneurial capital with the RIN measures in Table 2 (Models 2, 4, and 6) isolates the average effect across the entire sample. This is informative, but it may also conceal important dynamics if the moderating effect is sensitive to different levels of regional entrepreneurial capital. To explore this possibility and gain deeper insights into the relationship between RIN and high-growth entrepreneurship, we estimate and plot how sensitive the effect of RIN on high-growth entrepreneurship is to different levels of our moderator, i.e., regional entrepreneurial capital. We present these estimates in Figure 4, where the values of entrepreneurial capital correspond to the sample mean, ±1 standard deviation (SD) and ±1.5 SD from the mean. Error bands, calculated using the delta method, show the 95% confidence interval for each point estimate.

Table 2: Fixed Effects Regression Estimates

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Regional innovation network (RIN)	0.310**	-3.076				
	(0.154)	(2.147)				
Regional innovation network (RIN), 2yr			0.143***	-1.818		
			(0.032)	(1.225)		
Regional innovation network (RIN), 3yr					0.085***	-1.249
					(0.022)	(0.899)
Entrepreneurial capital	3.254***	2.912***	3.268***	2.962***	3.279***	3.009***
	(0.874)	(0.925)	(0.870)	(0.910)	(0.870)	(0.904)
Entrepreneurial capital * RIN		0.175				
		(0.113)				
Entrepreneurial capital * RIN, 2yr				0.103		
				(0.064)		
Entrepreneurial capital * RIN, 3yr						0.070
						(0.048)
Venture capital	0.325	0.319	0.326	0.322	0.324	0.321
	(0.306)	(0.305)	(0.306)	(0.305)	(0.306)	(0.304)
Business churn	-0.816	-0.826	-0.817	-0.837	-0.819	-0.842
	(0.631)	(0.628)	(0.630)	(0.629)	(0.631)	(0.629)
Net job creation rate	0.325*	0.313*	0.326*	0.313*	0.327*	0.312*
	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)	(0.163)
R&D investments	-0.062	-0.066	-0.062	-0.066	-0.062	-0.065
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
Net migration rate	-0.038***	-0.038***	-0.038***	-0.037***	-0.038***	-0.037***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Government size	-1.405	-1.434	-1.407	-1.468	-1.389	-1.497
	(2.671)	(2.649)	(2.676)	(2.659)	(2.679)	(2.672)
Tax freedom	8.026*	8.401*	7.995*	8.464*	7.991*	8.463*
	(4.411)	(4.443)	(4.415)	(4.434)	(4.418)	(4.421)
Labor market freedom	-1.496	-1.671	-1.549	-1.759	-1.552	-1.781
	(2.926)	(2.967)	(2.928)	(2.976)	(2.926)	(2.977)
Patent rate	0.594	0.534	0.595	0.528	0.608	0.540
	(0.370)	(0.371)	(0.372)	(0.370)	(0.372)	(0.372)
Innovation grants	0.941	0.937	0.919	0.938	0.932	0.957
	(1.919)	(1.921)	(1.924)	(1.925)	(1.921)	(1.921)
Cluster strength	-12.704**	-12.608**	-12.810**	-12.799**	-12.928**	-12.941**
	(5.271)	(5.258)	(5.256)	(5.254)	(5.253)	(5.260)
Creative class	0.302	0.298	0.249	0.225	0.228	0.179
	(2.956)	(2.967)	(2.950)	(2.962)	(2.952)	(2.959)
Agglomeration index	-2.645*	-2.680*	-2.631*	-2.657*	-2.630*	-2.648*
	(1.381)	(1.383)	(1.381)	(1.387)	(1.381)	(1.389)
Human capital	2.154*	2.076*	2.178*	2.098*	2.183*	2.108*
	(1.114)	(1.128)	(1.113)	(1.124)	(1.115)	(1.125)
Organizational share of patents	0.010	0.014	0.011	0.015	0.012	0.015
	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)	(0.039)
Large organization concentration	-5.017	-5.092	-5.059	-5.337	-5.041	-5.390
	(12.746)	(12.599)	(12.758)	(12.659)	(12.769)	(12.695)
Female CEO establishments	1.980**	1.907**	1.988**	1.895**	1.988**	1.886**
	(0.799)	(0.780)	(0.799)	(0.777)	(0.799)	(0.777)
N	4,296	4,296	4,296	4,296	4,296	4,296
Adj R-squared	0.747	0.747	0.747	0.747	0.747	0.747
Hausman test	177.78***	152.72***	179.47***	148.7***	180.09***	148.36***
Moran's I p-value	0.204	0.211	0.205	0.226	0.199	0.224
MSA fixed effects	yes	yes	yes	yes	yes	yes
Year fixed effects	yes	yes	yes	yes	yes	yes
p(RIN = RIN*Entrepreneurial capital = 0)		0.039		0.004		0.012

*DV = high-growth entrepreneurship. All models were estimated by OLS and include fixed MSA and year effects, as well as an intercept term. Standard errors are clustered at the state dimension. P-values denoted at bottom of the table from joint tests of significance of innovation network main effect and indicated interaction terms. Hausman specification test of FE vs RE specification. Moran's I p-value is from a test of residual spatial autocorrelation using an inverse distance weighting matrix. See Table 1 for variable descriptions. ***0.01; **0.05; *0.10.*

As depicted in Figure 4, the marginal effect of RINs on high-growth firms depends on the regional level of entrepreneurial capital. The positive slope indicates that as a region's entrepreneurial capital increases, RINs have a larger effect on high-growth firms, all else equal.[9] When the moderating effect is assessed at different levels of entrepreneurial capital rather than just the average across the entire sample, the marginal effect of RINs on high-growth firms is significantly higher in regions with above-average levels of entrepreneurial capital. This lends empirical support for H2.

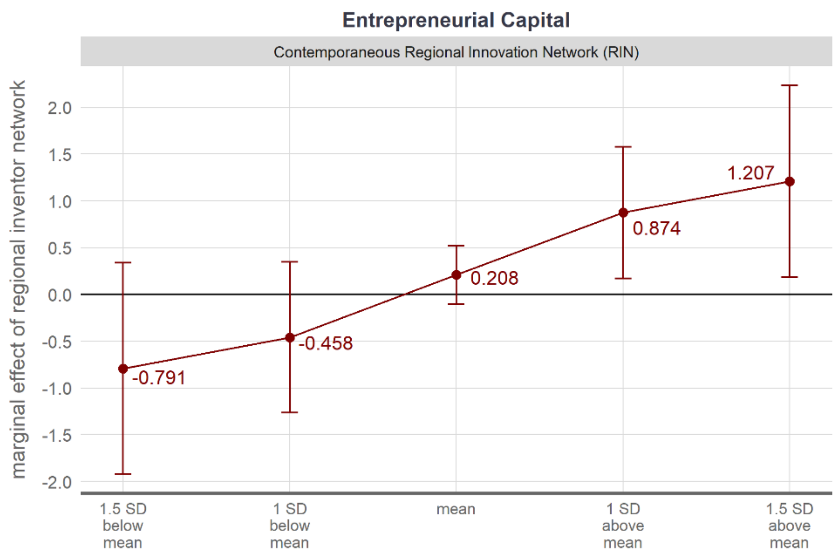

Figure 4: Marginal Effects of RIN by Entrepreneurial Capital Level

(Error bars represent 95% confidence intervals)

4.2 Robustness Analyses using Instrumental Variables

One concern with our main results is the potential endogeneity of the RIN measures. This section explores the robustness of the results presented in Table 2 using two alternative instrumental variables (IV) approaches. The alternative approaches rely on different identifying

[9] Appendix Figures A.3 and A.4 show the marginal effect plots when RINs are measured using a two-year and three-year patent window, respectively. Apart from a magnitude difference, both plots also show that the marginal effect of entrepreneurial capital on RINs is significantly different from zero (at the 5% level) in regions where the level of entrepreneurial capital is above the mean level.

assumptions, making them a useful sensitivity check to the OLS estimates that assume the RIN scores are exogenous.

The first IV strategy relies on external instruments to isolate exogenous variation in the RIN score so that the estimates have a causal interpretation. For an external instrument to be valid, it must be both strongly correlated with the RIN score and simultaneously be unrelated to high growth entrepreneurship so that it only affects high growth entrepreneurship indirectly through its effect on RINs. This second characteristic for instrument validity, known as the exclusion restriction, is inherently untestable.

We instrument for the RIN scores using RIN scores formed over a five-year period that are subsequently lagged 15 and 20 years. These are the longest lags permitted given the PatentsView data. To make the instrument construction concrete, the first year of our sample is 2003. One external instrument for the 2003 RIN score is the RIN score using all patents awarded during the five-year period 1983-1987 (15-year lag), and the second external instrument is the RIN score using all patents awarded during the five-year period 1978-1982 (20-year lag). Instruments for the RIN scores for 2004 through 2014 are adjusted accordingly. Lagged values of the RIN scores should be correlated with current RIN scores if there is a culture of collaboration within a region that persists over time. Considering that most patents and inventors are affiliated with organizations (rather than individual, unaffiliated inventors) and a culture of innovation is persistent within organizations (Fiordelisi et al., 2019), we believe there are plausible reasons to expect regions with strong inventor networks in the past to have strong networks in the present.

However, for the exclusion to be valid, it must also be the case that RIN scores from 15 and 20 years in the past are independent of *current* high-growth entrepreneurship. We argue that this is plausible for at least two reasons. First, most patents follow a pattern where citations peak within a few years of being awarded and then rapidly decline (Mehta et al., 2010). This implies that the knowledge associated with new patents is quickly dispersed. Second, as Wagner and Pavlik (2020) note, the median number of patents awarded to an individual is one, and only a small fraction of inventors (fewer than 2%) are awarded patents spanning two decades. Therefore, we believe it is plausible that *current* high growth entrepreneurship will be unrelated to *past* RINs because the current knowledge being generated, and the current individuals creating the knowledge, differ from the knowledge and networks of the past.

On the other hand, if *past* RINs are in fact correlated with *current* high growth entrepreneurship, then the exclusion restriction would be violated. We therefore supplement the IV analysis using external instruments with an IV approach using instruments generated from the dataset. This method relies on higher-order moment restrictions for identification (i.e., heteroskedasticity), so it can be used when external instruments are unavailable or as an additional robustness check (Lewbel, 2012), We form Lewbel instruments from three variables in our dataset: human capital, creative class, and the net migration rate.[10]

Table 3 provides a summary of the estimates from both IV approaches. Panel A reports estimates for our variables of interest using the external instruments, while Panel B reports the estimates using Lewbel's (2012) generated instruments.[11] Complete results for both approaches, including first-stage estimates, are reported in Appendix Tables B3 through B6.

[10] If ε is the residual from the first-stage regression of the endogenous RIN score on all exogenous variables (including fixed effects), Lewbel (2012) shows that a potentially valid instrument can be formed from the covariate Z using $(Z - \bar{Z})\varepsilon$. While any exogenous variable can be used to form a potentially valid instrument using Lewbel's method, a stronger covariance between Z and ε^2 will lead to a stronger instrument. We constructed the Lewbel instruments from human capital, creative class, and net migration rate because these covariates had the highest covariance (in absolute value) with the squared first-stage residual.
[11] In Models 2, 4, and 6 in Panel A, the instrument for the (RIN*entrepreneurial capital) interaction is the external lagged 15-year RIN score interacted with entrepreneurial capital. In Models 2, 4, and 6 in Panel B, the instrument for the (RIN*entrepreneurial capital) interaction is the human capital generated instrument interacted with entrepreneurial capital.

Table 3: IV Estimates

Variable	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6
Panel A: Results using External Instruments						
Regional innovation network (RIN)	0.328**	-2.816				
	(0.159)	(3.113)				
Regional innovation network (RIN), 2yr			0.093*	-1.503		
			(0.046)	(1.468)		
Regional innovation network (RIN), 3yr					0.049*	-1.055
					(0.025)	(0.986)
Entrepreneurial capital	3.253***	2.917***	3.273***	3.016***	3.280***	3.054***
	(0.868)	(0.979)	(0.870)	(0.933)	(0.871)	(0.919)
Entrepreneurial capital * RIN		0.167				
		(0.166)				
Entrepreneurial capital * RIN, 2yr				0.085		
				(0.079)		
Entrepreneurial capital * RIN, 3yr						0.059
						(0.053)
Robust Cragg-Donald	835.49	572.87	2689.58	2010.26	6515.94	4931.76
Sargan p-value	0.821	0.63	0.861	0.637	0.88	0.614
Panel B: Results using Lewbel (2012) Generated Instruments						
Regional innovation network (RIN)	0.381**	6.318				
	(0.159)	(6.635)				
Regional innovation network (RIN), 2yr			0.149***	3.481		
			(0.042)	(2.908)		
Regional innovation network (RIN), 3yr					0.082***	2.743
					(0.025)	(2.435)
Entrepreneurial capital	3.248***	3.853***	3.267***	3.790***	3.279***	3.820***
	(0.871)	(1.169)	(0.869)	(1.029)	(0.870)	(1.036)
Entrepreneurial capital * RIN		-0.308				
		(0.353)				
Entrepreneurial capital * RIN, 2yr				-0.175		
				(0.153)		
Entrepreneurial capital * RIN, 3yr						-0.141
						(0.129)
Robust Cragg-Donald	1533.67	77.89	9081.33	106.19	34379.97	128.46
Sargan p-value	0.577	0.158	0.958	0.961	0.273	0.551

*DV = high-growth entrepreneurship. All models were estimated by two-stage least squares assuming that the regional inventor network scores and interactions are endogenous. All models include an intercept term and fixed MSA and year effects that are not reported. Standard errors are clustered at the state dimension. Robust Cragg-Donald is a measure of instrument strength. The Sargan p-values is from the overidentifying restrictions test of instrument exogeneity See Table 1 for variable descriptions. Complete results for Panels A and B may be found in Appendix Tables B3 through B6. Control variables are omitted for brevity. ***0.01; **0.05; *0.10.*

Using Sargan's overidentifying restrictions test, we fail to reject the null hypothesis in every specification that the (extra) instruments are uncorrelated with the unexplained variation in high-growth entrepreneurship. We also report the robust Cragg-Donald statistics for instrument strength for each specification. Lee et al. (2022) show that the minimum first-stage F-statistic to ensure a test with a significance level of 0.05 is 104.7. The minimum F-statistics in panel A is 572.87 such that these estimates are well above the threshold of weak instruments. The same is true of the specifications in panel B excluding the RIN*Entrepreneurial Capital interaction (models 1, 3, 5). However, the F-statistics in the specifications containing interactions in panel B range from 77.89 to 128.46, suggesting that the IV estimates in panel B may be imprecisely estimated, particularly relative to the analogous IV estimates in panel A. Lewbel (2012, p. 67) notes that identification from data-generated instruments "is likely to provide less reliable estimates than identification based on standard exclusion restrictions", which is what we find for the interaction models. Thus, the IV estimates in panel A, which are based on external instruments (i.e., historical RIN) are more credible.

The marginal effects of the RIN scores, both with and without interactions with entrepreneurial capital, are very close to the fixed effects results presented in Table 2. For example, Model 1 in Table 3 indicates that a one unit increase in the contemporaneous RIN score leads to 0.310 (p=0.049) additional high-growth firms (per 10,000 establishments) using OLS (Table 2), 0.328 (p=0.044) additional high-growth firms using IV with external instruments (Panel A), and 0.381 (p=0.021) additional firms using IV with data-generated instruments (Panel B). Given that each of these estimates relies on different identifying assumptions, the similarities between the OLS and IV approaches establish that our findings are not an artifact of a single empirical approach.

Our finding that RINs have a larger effect on high-growth firms in regions with more entrepreneurial capital is more sensitive to the instruments. We continue to find evidence in favor of H2 when employing historical RIN measures as instruments in panel A. However, the support for H2 is no longer statistically present in the specifications with data generated instruments (panel B in Table 3), but as we noted above these specifications are estimated imprecisely and likely suffer from weak instrumentation.

4.3 Exploratory Analyses

As noted in Section 3.5, we perform post-hoc analyses to explore the potential moderating effects of bottom-up and top-down entrepreneurship policies, and regional knowledge production. Bottom-up policies include regional pro-market institutions (i.e., government size, tax freedom, and labor market freedom). Top-down policies are measured by innovation grants. Regional knowledge production is proxied by patent rates. For brevity, we plot the (individual) marginal effect for each potential moderator in separate panels in Figure 5. Complete regression results, from which each figure is derived, are provided in Appendix Table B7. Given the similarities between the OLS and IV approaches, our exploratory models are estimated by OLS, and we use the contemporaneous RIN scores for this exercise.

Overall, we find little evidence that bottom-up or top-down entrepreneurship policies moderate the relationship between RINs and high-growth entrepreneurship. Notably, we find a lack of discernible effects for innovation grants. There is some evidence that stronger RINs are more effective in stimulating high-growth entrepreneurship in regions with very high patent rates, but the effect is economically small. The most notable effect from our exploratory analyses is associated with tax freedom. For regions with above average tax freedom (1 or 1.5 SD above the mean), there is evidence that innovation networks have a noticeably larger effect on high-growth entrepreneurship than in regions with average or below-average tax freedom.

5. Discussion

5.1 Contributions

Drawing on insights from geography of innovation and the KSTE, we develop a conceptual model to examine the role of RINs in high-growth entrepreneurship and how the effect of RINs can be contingent on regional entrepreneurial capital. We also explored other potential factors that could alter this relationship, notably, public policy and regional patent production. We used a host of empirical techniques to mitigate biases and better ascertain any effects we found. Our key findings are consistent with our conceptual model suggesting that RINs play an important (and nuanced) role in high-growth entrepreneurship. By doing so, we make several contributions to the literature.

First, we extend the KSTE in significant ways. The KSTE emerged as an important lens to understand regional growth by recognizing elements previously overlooked, including the role of entrepreneurs (Acs et al., 2009). Additionally, as noted by Acs and Plummer (2005, p. 440), it sought to correct previous assumptions that “spillovers are virtually automatic, costless, and unconstrained by spatial factors such as geographic distances.” However, the KSTE also introduced new puzzles, including how the knowledge filter can be penetrated (Qian & Jung, 2017). We join this conversation by bringing insights from the geography of innovation literature and its accumulated wisdom regarding the role of spatial factors. Particularly, we choose to examine the role of knowledge diffusion as a key factor for generating growth-enhancing spillovers. This is a contrast to the traditional focus of knowledge spillover studies on knowledge production alone. We note that a more complete understanding of the knowledge spillover

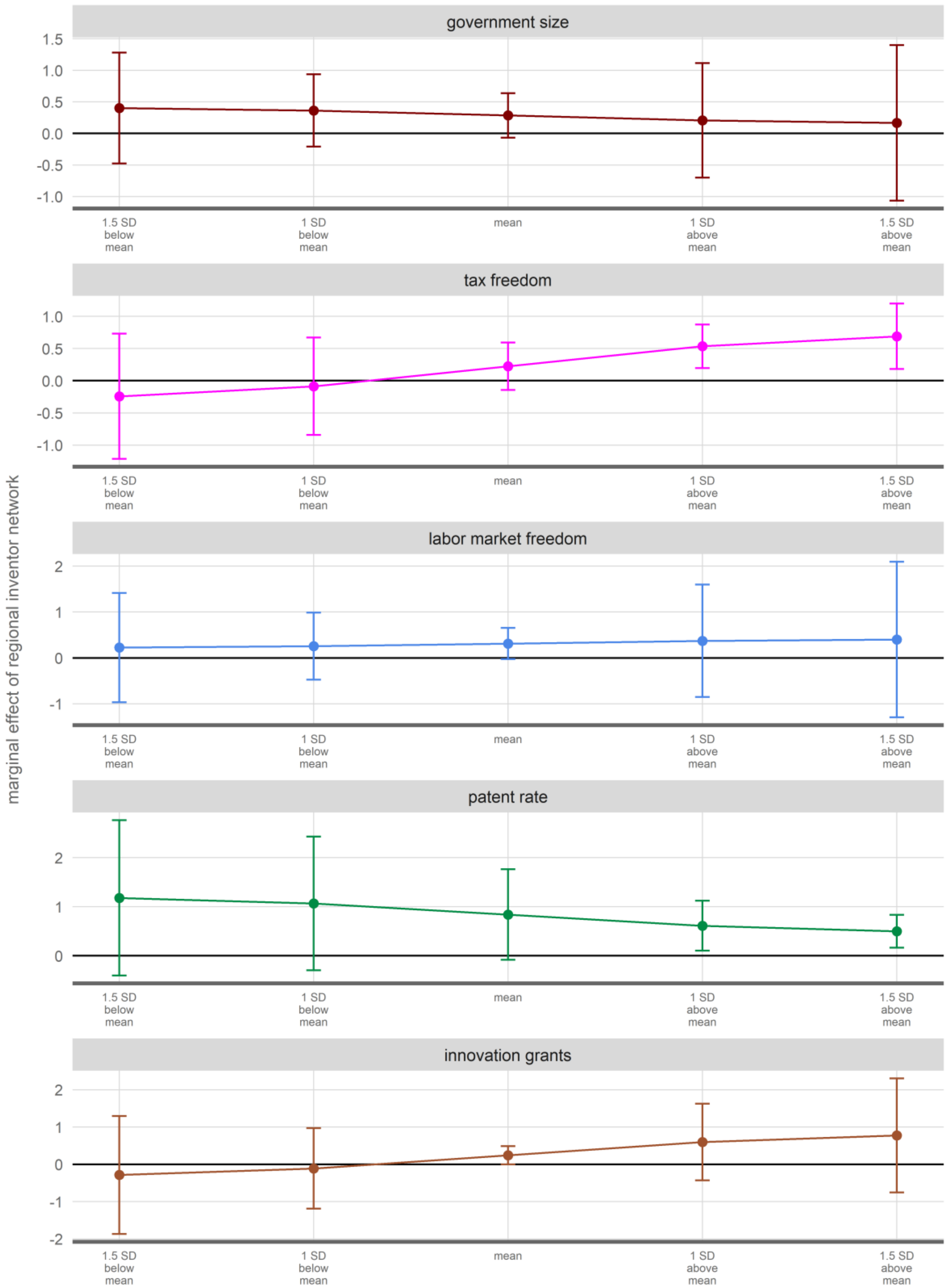

Figure 5: Marginal Effects of Regional Innovation Networks Conditioned by Moderating Variables

(*Error bars represent 95% confidence intervals*) phenomenon should include mechanisms that facilitate knowledge diffusion such as innovation networks. The implications of our findings are, thus, twofold: (1) we provide additional evidence about the insufficiency of knowledge production alone (Motoyama, 2014; Sleuwaegen & Ramboer, 2020; Yu & Fleming, 2022), and (2) we further validate knowledge diffusion as a mechanism to penetrate the growth-restraining knowledge filter (Qian & Jung, 2017). Accordingly, we suggest future studies using the KSTE approach to directly integrate knowledge diffusion as a key mechanism for addressing the knowledge filter puzzle.

Additionally, our study underscores the complexity of the relationship between RINs and high-growth entrepreneurship. The first is interdependencies with other variables. The KSTE notably positions entrepreneurs as the primary agents for knowledge spillover (Audretsch & Keilbach, 2008; Audretsch & Lehmann, 2005). An important finding from our study is that the effect of our main variable—RINs—is not homogenous but contingent on regional entrepreneurship capital. Accordingly, while innovations networks are a crucial ingredient, (Huggins & Thompson, 2015), they are not sufficient for producing high-growth entrepreneurship. Rather, a high level of regional entrepreneurship capital (Audretsch et al., 2008) is also required amplify the positive effect of RINs.

The second type of complexity that we uncover is temporal. Although we theorize that the effect of innovation networks on the emergence of high-growth firms is linked to the accessibility of entrepreneurs to cutting edge innovation and technology, there was no previous theory and evidence that could pinpoint a timeframe for these effects. That is, from the formation of knowledge ties to their application in high-growth entrepreneurship. Given this theoretical void, we gauge RINs across different times frames (e.g., 1-3 years), a strategy that allowed us to find that the effect of RINs on high-growth entrepreneurship is strongest for the contemporaneous networks but weakens as we extend the time window. This finding can spur more studies on the underexplored dynamic aspect of knowledge diffusion (Ejermo & Karlsson, 2006; Malecki, 2021). On the one hand, there are theoretical grounds to expect that the effects of networks may build slowly (Aldrich & Zimmer, 1986), and it may take time for a region to reach a network density large enough to facilitate high-growth entrepreneurship. However, our findings imply that contemporaneous networks are much more important in terms of the magnitude of the effects, which can inform future studies examining the temporal effects of innovation networks.

5.2 Practical Implications

Our study has implications for both entrepreneurs and policymakers. We first discuss two implications for entrepreneurs. First, entrepreneurs with high-growth aspirations should heed the location of their business by considering the strength of the local innovation network and the level of entrepreneurial capital. For entrepreneurs located in regions with a weak innovation network and low entrepreneurial capital, they should consider relocating to a region with a strong network and greater entrepreneurial capital to gain greater access to new ideas and technologies. This can provide access to novel capabilities and potential competitive advantages to fuel venture growth. Second, entrepreneurs should expand their network to include inventors and other entrepreneurs in their region for greater access to new knowledge and technologies that may spark innovative ideas. Although some entrepreneurs may be hesitant to share ideas, these conversations can refine their vision, generate new ideas, and lead to collaboration opportunities.

Our study also has implications for public policy. As explored in our post-hoc analysis, there are potential interdependence between RINs and the regional public policy environment for high-growth entrepreneurship. Specifically, we examined two aspects of the local policy environment as potential moderating factors of the relationship between RINS and high-growth entrepreneurship. First, we considered the potential moderating role of local pro-market institutions, which represent a bottom-up approach to regional entrepreneurship policy. Second, we consider the potential moderating role of government innovation grants, a top-down approach to entrepreneurship policy.

While existing research links innovation grants to an increased likelihood of recipient firms patenting their inventions and receiving private equity investments (Howell, 2017) and an increase the generation of high-tech startups in a region (Qian & Haynes, 2014), factors that are believed to foster nascent venture growth, we find no evidence to corroborate the top-down approach to regional high-growth entrepreneurship policy. That is, regions whereby firms receive large numbers of innovation grants do not produce more high-growth entrepreneurship, even when strong RINs are present. The fact that a positive relationship did not materialize in our analysis may reflect a misplaced focus when developing policies intended to encourage high-growth entrepreneurship. Previous research has noted an excessive focus on high-tech ventures by policymakers, which is misaligned with the fact that high-growth ventures are widely represented across sectors (Brown et al., 2017; Daunfeldt & Halvarsson, 2015). It may also reflect the possibility that innovation grants exhibit diminishing returns (Lanahan et al., 2021) and may encourage subsidy entrepreneurship, whereby entrepreneurs focus more on obtaining subsidies to sustain their ventures than pursuing commercialization and growth (Gustafsson et al., 2020).

Meanwhile, we find some evidence supportive of the bottom-up approach. Specifically, regions with greater tax freedom, which facilitates entrepreneurial experimentation and lowers the financial burden of starting and growing a business (Bennett, 2021b), produce more high-growth entrepreneurship when strong RINs are present. This suggests a synergistic relationship between strong RINs and tax freedom in facilitating high-growth entrepreneurship. Policymakers in regions with strong RINs can therefore enhance the potential for producing high-growth entrepreneurship by increasing tax freedom. However, our results also imply that increasing tax freedom is not conducive for high-growth entrepreneurship in regions with weak RINs. This suggests that there is not a one-size-fits all recipe for supporting regional high-growth entrepreneurship, as the success of a policy (e.g., increasing tax freedom) depends on locational characteristics (e.g., strong innovation network). This finding is consonant with recent entrepreneurship studies highlighting the need to consider contextual factors when assessing the efficacy of public policies (e.g., Lucas & Boudreaux, 2020), which advances our understanding of regional pro-market institutions' role in fostering high-growth entrepreneurship (Fotopoulos, 2022; Sleuwaegen & Ramboer, 2020).

5.3 Limitations & Further Studies

As with all studies, ours has several limitations that we believe provide opportunities for future research. First, we focus on the role of RINs in enabling high-growth entrepreneurship, but several studies suggest that knowledge diffusion is increasingly less geographically constrained (Malecki, 2010). In preliminary analyses, we also considered the effect of inter-RINs using the external social proximity measure of the connectedness between a region's inventors to all other inventors in the U.S. (Breschi & Lenzi, 2016). Including this factor in our model did not affect our main findings, and we found little evidence that having a greater connectivity to innovators in other regions is significantly associated with high-growth entrepreneurship.[12] While this is consistent with the perspective that geographic proximity and inter-personal linkages

[12] Because of space limitations and to preserve the focus of our paper on RINs, we do not report these results, but they are available upon request.

matter for knowledge spillovers, more research is needed to better understand how inter-RINs influence the knowledge spillover and venture creation processes (Ejermo & Karlsson, 2006). For example, delving further into the potential substitutionary or complementary roles of inter-RINs and intra-RINs could shine additional light on how networks facilitate the spillover of new knowledge into high-growth ventures. It would also be useful to study whether certain types and variety of knowledge creation are more amenable to collaboration and spillover across geographic space (Miguelez & Moreno, 2018).

Next, our findings are based on the measurement of RIN strength as the average geodesic distance between all inventor pairs in a region (Breschi & Lenzi, 2016), which aligns with our theory development by capturing both direct and indirect ties that serve as a key mechanism for knowledge diffusion (Singh, 2005). We did not test the sensitivity of our results to alternative network connectivity measures such as e.g., small-world clusters (Fleming et al., 2007), high betweenness centrality, high degree centrality, or component analysis (Balconi et al., 2004). Our measure of RIN also does not distinguish between intra-firm and inter-firm networks (Baum et al., 2010), or strategic alliances (Hohberger et al., 2015). Furthermore, we are unable to establish ties between inventors in the patent data and the high-growth firms captured in our regionally aggregated measure because we do not have access to the names of the entrepreneurs. Future research that re-examines or extends our theoretical model using some of these measures or network types would be worthwhile.

It is also conceivable that there are unobservable, time-varying factors that correlate with both RINs and high-growth entrepreneurship. The omission of such factors from our model would violate the exogeneity assumption, biasing our results. It is also possible that high-growth firms influence a region's innovation network, resulting in a simultaneity bias. While these issues are plausible, we believe they are not major problems for several reasons. First, we account for numerous time-varying factors, time-invariant unobservable regional effects, and time fixed effects. Second, estimates from our IV regression are very similar to our main results. Third, our models have high explanatory power, accounting for three-fourths of the within variation in high-growth entrepreneurship. Next, we measure high-growth entrepreneurship at the beginning of their growth period because future growth will not have an influence on contemporaneous network development. Finally, our results are qualitatively similar when we measure innovation networks with a longer lag period.

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