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Stock Returns and Geographic Innovation Index

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1. Introduction

Most research on stock returns has focused on market and firm-specific risk factors, as well as various capital market frictions. Very few studies, however, have explored the possibility that geographic frictions might also affect stock returns. Few financial economists have examined how an asset's location and innovation resources, to say nothing of its geographic context, might affect a firm's technological performance and, subsequently, its stock returns.

This is not surprising. According to the classical economic and finance paradigm, the value of a given set of risky cash flows should be unaffected by spatial frictions. This paradigm is based on the assumption that information or knowledge can flow or diffuse over space and time without physical restrictions, especially in this age of advanced information technology. However, Boasson et al (2005) find that the stock market value of pharmaceutical firms can be affected by certain geographic factors, even after controlling for Fama and French's (1998) firm-level financial decision variables. These findings lead us to pose an important question:

Is there a relation between stock returns and geographic sources of innovation?

Home bias literature in financial economics reports that international equity investment is basically concentrated in the home market of the investor (French and Poterba (1991), Tesar and Werner (1995) and Ahearne, Griever and Warnock (2004)). Many researchers have tried to explain this so-called "home bias puzzle". Some argue that this phenomenon is due to information asymmetry (i.e. investors know more about their home assets), whereas others argue that asymmetry should disappear when information is tradeable. However, Nieuwerburgh and Veldkamp (2007) argue that even when foreign information is no harder to learn, many investors will specialize in home assets, remain uninformed about foreign assets, and amplify their initial information asymmetry.

This paper does not attempt to explain the home bias puzzle, but to point out that the home bias phenomenon highlights the fact that geography seems to matter when it comes to asset pricing. If the learning of information is geographically immobile as suggested by Nieuwerburgh and Veldkamp (2007), we argue that a firm's knowledge assets are immobile as the physical spatial environment in which a firm can draw on competitive advantage is also immobile.

While the finance literature is virtually silent about the geographic innovation environment, the literature in economic geography, spatial economics, and regional science extensively documents the role of agglomeration and industry clusters in improving firm-level competitiveness (Audretsch & Feldman (1996), Porter (1998, 2000); Romer (1986), Boasson and MacPherson (2001), Boasson, Boasson, MacPherson, and Shin (2005)). Several of these works have explored the geographical aspects of knowledge externalities and the role of geographic proximity in mediating the processes of knowledge creation, transmission and appropriation. This stream of literature indicates that innovations, far from being scattered and randomly distributed, tend to cluster geographically (Anselin, Varga, & Acs, 2000a, 2000b; Boasson, Boasson, MacPherson, & Shin, 2005; Henderson, Jaffe, & Trajtenberg, 1998; Jaffe & Trajtenberg, 1996, 1999; Jaffe, Trajtenberg, & Henderson, 1993).

However, none of the previous researchers have attempted to link stock investment returns with the nature of the localized innovation environment. This paper intends to bridge this gap between these two streams of literature in connecting the dots between home-bias equity investment and the geographic innovation environment. Specifically, this paper focuses on the relation between stock returns and proximity to geographic innovation resources. We argue that geographic space matters because this space contains people, as well as natural and human resources. Transmission of knowledge assets is distance sensitive because tacit knowledge tends to be transmitted face-to-face. Thus, a firm located in a rich geographic innovation environment is likely to perform better than a firm located in a poor geographic innovation environment. We develop a geographic innovation index that captures the key geographic innovation resources. We classify corporate locations into high and low in accordance with our geographic innovation index. Our main finding is that investing in firms with close proximity to high index scores tends to yield a better risk-adjusted return than investments in companies located father away from geographic innovation resources.

The remainder of the paper is organized as follows: Section 2 describes our data, Section 3 explains our research method; Section 4 presents empirical results; Section 5 presents the survey results; and Section 6 concludes the study.

2. Data

We collected primary data through firm-level surveys in the summer of 2007. Our goal was to assess whether or not Chief Financial Officers (CFOs) felt that geographical proximity to local innovation or business support services played a significant role in their company's performance. We surveyed 225 pharmaceutical companies and received 97 responses, achieving a response rate of 43.1%. A pretest of the survey instrument revealed that we would need at least 90 responses to achieve 95% confidence for our parameter estimates. The parameters included 10 commonly recognized dimensions of innovation or business activity support that are widely known to be of extant or potential importance to the pharmaceutical industry. The final survey was conducted by a private market research consultancy, and was administered by telephone. Our research budget allowed for a total of 225 telephone interviews.

To test for non-response bias, we compared respondents versus non-respondents with respect to R&D spending, patent counts over the last 5 years, and global sales. T-tests failed to uncover statistically significant differences between respondents and non-participants across any of these variables. To test for spatial bias, chi-square tests were conducted to assess whether our sample over or under-represented spatially clustered firms. Again, no significant differences emerged.

In addition to our survey data collection, we extracted the pharmaceutical patent citation dataset from the patent citation database compiled by Jaffe and Trajtenberg (2002), which contains about 3 million U.S. patents granted between January 1963 and December 1999. There are over 16.5 million citations made to these patents between

1975 and 1999, more than 175,000 patent assignees, and over 4.3 million individual inventors' records.

To construct our dataset, a painstaking and time-consuming task was undertaken matching the citing and cited patents to patent assignee companies and originating companies and to the pharmaceutical companies available on Compustat files. For the patents cited by the pharmaceutical companies in our dataset, we matched a total of 42,849 observations across various industry sectors and across various counties, consisting of both private and public companies. From US Census, the National Science Foundation (NSF) Survey of Science and Engineering Resources and the Bureau of Economic Analysis (BEA) websites, we collected data on university research, industry R&D, testing labs, and business services. We collected data for university research in medicine, biology, chemistry and chemical engineering which are relevant for product innovation in drugs and medicines. The data for related and supporting industry inputs were collected from the County Business Patterns of the US Census Bureau database and then matched to the sales of the companies in the supporting and related industries from the Compustat database. The main related and supporting industries included in the study are biotechnological, chemical industries, specialized professional business services, and testing labs. From Compustat files, we collected data on publicly-traded pharmaceutical companies, and biotechnology companies. From CRSP, we collected data on stock returns. The data collected from all various sources were manually matched. Since the patent database does not contain information such as addresses at zip-code level for the patent assignees or organizations that own the citing and cited patents, we matched manually each patent citing firm and cited firm with its location down to the street address and zip-code level.

3. Variable Measurements and Research Models

We employed a 'geographic information systems' (GIS) approach, and geo-coded each firm's address with its longitude and latitude. We geo-coded each company by its headquarter location. The rationale for using the company headquarters location is that there is insufficient information related to each firm's R&D locations, subsidiaries or branches. In addition, it was impossible to attribute both returns and capital allocation to each of the subsidiaries or branches. Finally, R&D centers are normally very close to company headquarters and their locations do not make significant spatial differences.

We matched each firm with the geographic variables within a distance band of 100 miles from a firm's location. Within each 100 miles distance band, we calculated the fraction of the total market capitalization of all U.S. pharmaceutical companies that are within that band. In addition, we calculated the fraction of all related research expenditures of the universities that are within this distance of the company, the fraction of all industrial R&D, and the fraction of all value-added and sales of related and supporting industries.

After obtaining the measurements for each of our variables at this level, we followed the Fama and MacBeth (1973) procedure. Cross-sectional regressions were run for all the available firms in each year for the past 13 years from 1990 to 2002, and a series of t-tests were performed on the time-series of all the annual regression coefficients.

We conduct an industry cluster analysis for each industry in the sample in order to assemble a detailed picture of the location and performance of industries with a special focus on the linkages or externalities across industries that give rise to clusters. Specifically, industry clusters are measured via location quotients. The location quotient (LQ) is defined as:

$$LQ = \frac{L_{is} / T_s}{L_{inat} / T_{nat}} \qquad (1)$$

where L_{is} represents the value of sales, or R&D, or employment, or establishments in industry *i* in location *s*, T_s is the total value of sales, R&D, employment, and establishments in all industries in location *s*, L_{inat} represents the value of sales, R&D, employment, and establishments in industry *i* in the United States, and T_{nat} represents the value of sales, R&D, employment, and establishments in all industries in the United States. A location quotient greater than unity indicates a higher clustering in location *s* relative to the nation as a whole. Likewise, a location quotient less than unity indicates that an economic activity is relatively less concentrated (see Boasson (2002)).

In addition to industry clustering, we calculated variables to capture the role of related and supporting industries and the R&D environment, including: (1) value-added or sales of the chemical, and biotech industries, (2) sales in specialized professional business services (testing laboratories in this instance), (3) industrial R&D, (4) university R&D in fields that relate to pharmacology, and (5) competitor proximity measured by the firm value of the competitors within close geographic proximity.

The typical measure of spatial patterning in a distribution is captured by the spatial autocorrelation coefficient, which measures and tests whether a distribution is clustered or dispersed. One of the most common measures of spatial autocorrelation is the

Moran's *I* statistic. Since Moran's *I* incorporates distance measures and differences in attribute values across the entire point dataset, the calculations become extremely cumbersome with datasets of even moderate size.

To handle such a large scale calculation of Moran's *I*, a program was set up using GIS software and Excel macro to run tests for spatial autocorrelation. For this test, we need the pair of citations and the pair of addresses of citing firms and cited firms or patent citing firms and patent originating firms. The Moran's *I* statistic is used to evaluate the presence or absence of spatial autocorrelation or spatial dependence, as suggested by Rogerson (2001), Drennan and Saltzman (1998), and Boasson (2002). The Moran's *I* statistic is based on the covariance among designated associated locations (Fisher and Getis 1997). Moran's *I* is interpreted in a way similar to the correlation coefficient. Moran's *I* is computed as follows:

$$I = \frac{n\sum_{i}^{n}\sum_{j}^{n} w_{ij}(y_i - \bar{y})(y_j - \bar{y})}{\left(\sum_{i}^{n}\sum_{j}^{n} w_{ij}\right)\sum_{i}^{n}(y_i - \bar{y})^2} \tag{2}$$

where:

n = number of firms;

w_{ij} = a measure of the spatial proximity among firms;

y_i = patent i's citations received.

y_j = patent j's citations made to patent i.

Alternatively, if the variable of interest is first transformed into a *z*-score $\{z = (x - \bar{x})/s\}$, then a much simpler expression for Moran's *I* results:

$$I = \frac{n\sum_i \sum_j w_{ij} z_i z_j}{(n-1)\sum_i \sum_j w_{ij}} \tag{3}$$

According to Rogerson (2001), the conceptually important part of the formula is the numerator, which sums the products of z-scores in nearby regions. Pairs of regions where both regions exhibit above-average scores will contribute positive terms to the numerator, and these pairs will therefore contribute toward positive spatial autocorrelation.

To detect and evaluate whether the clustering of an industry occurs around a region or county, the local Moran's I statistic is employed as follows:

$$I_i = n(y_i - \bar{y})\sum_{j \neq i} w_{ij}(y_j - \bar{y}) \tag{4}$$

The sum of local Moran's I is equal to, up to a constant of proportionality, the global Moran; i.e., $\Sigma I_i = I$ (Rogerson, 2001).

We combine all the geographic variables to calculate an index of geographic sources of innovation for each location. We calculate this index by rank-order analysis, ranking each geographic variable and sum the scores of the rankings for each location. We coin this index as *GI* for geographic index for innovations. Mathematically, *GI* is calculated as follows:

$$GI_j = \sum_{i=1}^{N} rank_{ij} \tag{5}$$

where i represents the geography variable, and j represents the location score.

In order to examine the investment risk and returns between the high GI firms and low GI firms, we use the median GI in 1990 as the break point to divide the whole sample into two subgroups: a high GI group and a low GI group. The monthly holding period returns (HPR) were calculated as follows:

$$R_{it} = \frac{P_{it} + D_{it}}{P_{i,t-1}} - 1 \tag{6}$$

We then calculated the annualized monthly returns of various lengths of time using the following equation:

$$R_{iT} = \prod_{1}^{12}(1 + R_{it}) - 1 \tag{7}$$

We also multiplied the monthly returns to get the holding period return for various longer periods such as 5-year holding period returns, 10-year holding period returns, and the entire sample period holding period returns as follows:

$$R_{iT} = \prod_{1}^{T}(1 + R_{it}) - 1 \tag{8}$$

The caveat of comparing investment return performance with holding period returns (HPR) is that HPR is not risk-adjusted. To overcome this weakness, we applied the four-factor model as suggested by Carhart (1997) as follows:

$$R_{it} - R_{ft} = \alpha_i + \beta_{1i}(R_{mt} - R_{ft}) + \beta_{2i} SMB_t + \beta_{3i} HML_t + \beta_{4i} Mom_t + \varepsilon_{it} \tag{9}$$

where

$(R_{mt}-R_{ft})$ = market risk premium: the difference between market return R_{mt} and risk-free rate R_{ft}.

SMB_t = the return difference between a small cap portfolio and a large cap portfolio in month t,

HML_t = the return difference between a value (high BV/MV) portfolio and a growth (low BV/MV) portfolio in month t,

MOM_t = the return difference between a portfolio of past 12-month winners and a portfolio of past 12-month losers in month t.

The data for these four factors were based on monthly returns obtained from the database on Fama and French Research Portfolios and Factors. We compared the alphas of the four-factor regressions between the high GI group and the low GI group to examine which group has a better risk-adjusted return performance.

In addition, we calculated Sharpe ratios to estimate the risk-adjusted returns over the whole sample period. Sharpe (1966) computed mean excess return and adjusted for the degree of total risk involved in the portfolio. The total risk for each stock return is estimated by the standard deviation of monthly returns for the whole sample period (1990-2002). The Sharpe ratio (SR) measures the return above the risk-free interest rate (excess return) divided by the total risk of the investment as follows:

$$SR_i = \frac{\mu_i - R_f}{\sigma_i} \tag{10}$$

where

σ_i = firm i's standard deviation of the monthly returns over the whole sample period;

μ_i = firm i's mean monthly returns over the whole sample period;

R_f = the mean risk-free monthly returns proxied by monthly Treasury bill rates.

4. Empirical Results

To examine the spatial distribution of patent citations, we plot the location of citing and cited firms on a map using ArcGIS program.

Figure 1.

Spatial distribution of patent citations.

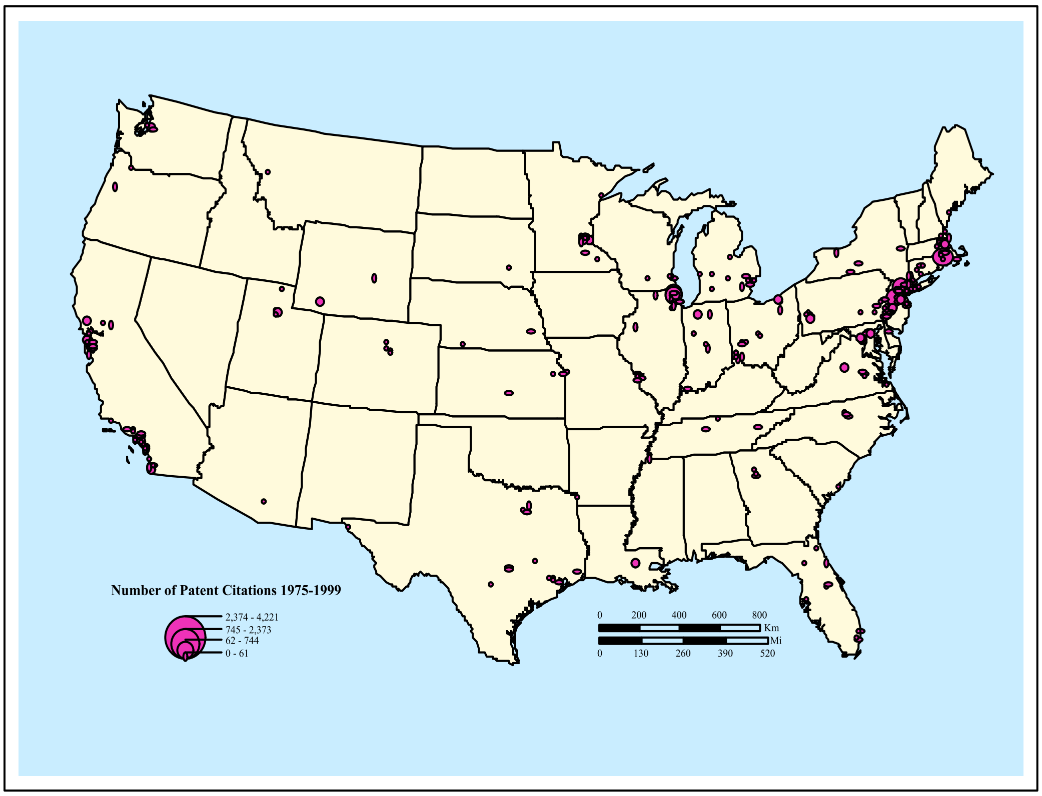

Figure 1 shows the spatial distribution of patent citations in the field of drugs and medicines within the United States. Each circle indicates the number of all citations to the patents owned by each patent assignee. The calculations involve 27,776 patent citations over the 1975-1999 period. Clearly, the results show a pattern of spatial clustering of patent citations. The clustering patterns of the patent citations show that most of the patent citations in the drugs and medicines sector are clustering in a few small areas of the United States. The largest spatial cluster of patent citations is in the New

York-New Jersey corridor, followed by clusters around Boston, Chicago, Los Angeles-San Diego, and San Francisco. This map shows that inventors tend to cite each other from nearby locations.

Table 1.
Spatial Autocorrelation of Patent Citations – Moran's I (1975-1999)

Summary Moran's *I* Statistics	**All patent citations for all firms**	**Excluding Self Citations for all firms**
Moran's *I*	0.143	0.400
z-Normal *I*	7.256	20.220
Var. Normal *I*	0.000	0.000
z-Random *I*	8.944	21.575
Var. Random *I*	0.000	0.000
Mean citations per neighbor	9.477	6.163
St.Dev	147.797	59.375
# of neighbors	2542	2542
Median distance (miles)	20.975	20.975
Mean distance (miles)	23.336	23.336

Table 1 shows the statistical results of Moran's *I* for testing the spatial-autocorrelations of patent citations made to patent assignees in the field of drugs and medicines. The calculations involve 2,542 neighbor pairs between citing and cited patent assignees. For all patent citations including self-cites, the mean citation is 9.5 per neighbor pair. Moran's *I* statistics indicate that there is a positive spatial autocorrelation and the statistical result is significant as indicated by z-normal *I* of 7.26. For patent citations excluding self-cites, the mean citation is 6.2 per neighbor pair. Moran's *I* statistics indicate that there is a positive spatial autocorrelation and the statistical result is significant as indicated by z-normal *I* of 20.22. In other words, a patent citation is more likely made to a patent owned by a close-by assignee. This is strong evidence that knowledge flows are geographically concentrated.

Table 2.
Risk-adjusted Stock Returns between High-GI Firms and Low-GI Firms

	Mean		Standard Deviation		Mean DIF	t-Stat	Wilcoxin-Z
	High GI	Low GI	High GI	Low GI	High-Low		
Jensen's Alpha	0.022	0.017	0.016	0.022	0.005	0.990	-1.790
Sharpe Ratio	0.138	0.079	0.039	0.037	0.059	5.931	-4.975
Annualized HPR Returns (in percentage) :							
Average R [illegible]	0.454	0.246	0.241	0.223	0.208	3.219	-3.289
Average R [illegible]	0.453	0.313	0.219	0.168	0.140	2.762	-2.502
R [illegible]	0.961	0.063	0.944	0.899	0.896	2.460	-2.621
R [illegible]	1.426	0.744	1.601	1.483	0.681	1.151	-1.576
R [illegible]	0.893	0.161	1.327	0.841	0.532	1.229	-0.931
R [illegible]	1.389	0.588	1.630	1.421	0.801	1.470	-1.085
R [illegible]	2.808	0.782	3.638	2.179	2.027	2.063	-1.912
R [illegible]	2.730	1.370	5.811	4.331	1.381	0.877	-1.795
R [illegible]	2.134	1.948	2.689	7.432	0.186	0.104	-2.168
R [illegible]	1.840	0.116	2.482	1.287	1.724	3.474	-3.999
R [illegible]	0.579	-0.470	1.610	0.770	1.049	3.418	-3.720
R [illegible]	1.807	-0.087	3.103	0.880	1.895	3.466	-3.124
R [illegible]	8.205	0.883	8.080	2.570	7.322	3.185	-2.835

Table 2 presents the investment returns performance comparison between the high GI firms and the low GI firms. We use the median of the geographic index in the first sample year 1990 (GI1990) as a breakpoint to divide the sample into two sub-groups: the high and low groups. This table presents the t-test and Wilcoxon non-paramentric test comparisons of alphas for the risk-adjusted monthly returns using the four-factor model and the Sharpe ratios. The results indicate that the high GI firms outperform the low GI firms as indicated by the Sharpe ratios and the regression alphas from the four-factor model (the results are statistically significant). Table 2 also shows the results of various holding period returns using equations (6) through (8). No matter how we reconfigure the holding period returns or which periods we use, the high GI firms' stock returns consistently outperform the low GI firms. The results are statistically significant for most of the testing periods.

Section 5: Survey Results

The parameter values shown in Table 3 are mean scores across 7-point scales with respect to the importance of proximity to a list of geographic innovation externalities (where 1 = no importance whatsoever; 7 = critically important). Firms were asked to give impressionistic responses regarding the contribution of spatial proximity to these assets with respect to their innovation and financial performance, and thus we have a qualitative dataset that was established via direct observation.

The responses for spatially clustered firms are reported in column C. For corporate innovation, the clustered firms (C-column) rated on a higher scale than non-clustered firms (NC-column) for the importance of proximity to these geographic innovation externalities to their innovation efforts for almost every geographic innovation driver. In terms of financial performance, the clustered firms also give higher rating values than do the non-clustered firms. For clustered firms, innovation performance appears to be heavily influenced by proximity to rivals (a competition density effect), the availability of skilled labor (reflecting urbanization or agglomeration economies), and proximity to biotechnology companies (i.e. sources of new or innovative ideas). Notice that clustered firms rank the importance of these factors more strongly than non-clustered firms ($p = 0.05$ or less with T-tests). Broadly similar results can be seen with respect to financial performance. Overall, our qualitative results lend support to the general proposition that proximity to local technological or infrastructural resources contributes to the innovation and/or financial performance of pharmaceutical companies.

Table 3.
Survey Results

Factor	Innovation			Financial Performance		
	C	NC	All	C	NC	All
N	56	41	97	56	41	97
University research facilities	4.9	2.9	3.9	4.1	2.7	3.4 *
Teaching hospitals	4.8	2.8	3.8	3.8	2.9	3.3 *
Biotechnology companies	5.3	3.1	4.2	3.2	3.1	3.1 *
Suppliers	3.8	3.2	3.5	3.1	2.8	2.9
Testing laboratories/clinical trial firms	4.1	3.2	3.6	3.3	3.1	3.2
Competitors	5.9	3.3	5.1	4.8	3.2	4 *
Skilled labor	6.1	4.4	5.2	6.2	4.7	5.4 *
Collaborators	2.7	2.2	3.4	2.1	2	2.5
Business services	3.1	2.8	2.9	3.6	3.1	3.3
Airports/transportation infrastructure	4.9	4.2	4.5	4.7	3.9	4.3

* Statistically significant t-test differences at p = 0.05 or less for both indicators (i.e. innovation and financial performance).

Table 4 shows the effects of geographic proximity to innovations. The companies located in high GI locations or clusters tend to be more innovated than firms located in low GI or non-clustered locations. Moreover, the clustered firms achieve better financial performance than non-clustered firms. These results are statistically significant at 1 percent level.

Table 4.
Geographic Proximity to Innovations

Geographic Proximity to Innovation Resources						
	Clustered	Non-Clustered	Mean-Diff		t-Stat	Wilcoxin-Z
Mean	4.560	3.210	1.350	***	5.117	-2.805
Std. Dev	1.125	0.656				
Financial Performance						
	Clustered	Non-Clustered	Mean-Diff		t-Stat	Wilcoxin-Z
Mean	3.890	3.150	0.74	***	3.959	-2.805
Std. Dev	1.136	0.721				

Table 5.
Effect of Innovations on Financial Performance

	Clustered	Non-Clustered	All firms
Intercept	0.198	-0.189	-0.040
	0.199	-0.457	-0.041
Coeff	0.802	0.945	0.800
t-Stat	3.793	8.204	3.774
Adj R^2	0.598	0.880	0.595

Table 5 shows that our survey results confirm our hypothesis that innovations are positively correlated with the firm's financial performance across all firms and for both clustered and non-clustered firms. The results are statistically significant at the 1 percent level.

6. Conclusions

In conclusion, our empirical results clearly indicate that investment in companies with greater proximity to geographic innovation resources tend to produce a better risk-adjusted stock market returns.

Spatial clusters tend to exist for corporate innovations as evidenced by patent citations. In other words, a patent citation is more likely made to a patent assignee located within relatively close geographic proximity. Corporate innovation as proxied by citation-weighted patent stock is positively correlated with external geographic clustering of innovation resources.

The citation-weighted patent stock for the firms that are endowed with greater geographic clustering of innovation resources has a greater positive impact upon a firm's risk-adjusted stock returns. When this was confirmed, we turned to our final question: can a firm with high geographic innovation endowments reap a better return in terms of higher stock market firm value for their investments in knowledge and innovation activity? We hypothesized that the citation-weighted patents that are associated with the higher value for the combined geographic sources of innovation are likely to have a greater positive impact upon the stock market valuation of the firm. In other words, a firm with high geographic innovation endowments may achieve better economic value in terms of higher firm value for their knowledge and innovation outputs as proxied by citation-weighted patent stocks. The empirical findings confirmed this hypothesis, indicating that the citation-weighted patent stock for the firms that are endowed with greater geographic innovation resources has a greater positive impact upon the stock market valuation as measured by risk-adjusted returns. The interplay between geography and invention strongly influences a firm's stock market valuation, which ultimately translates into better risk-adjusted stock returns.

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