Geographic Dispersion and Stock Returns*

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Abstract

This paper shows that stocks of truly local firms have returns that exceed the return on stocks of geographically dispersed firms by 70 basis points per month. By extracting state name counts from annual reports filed with the SEC on form 10–K, we distinguish firms with business operations in only a few states from firms with operations in multiple states. Our findings are consistent with the view that lower investor recognition for local firms results in higher stock returns to compensate investors for insufficient diversification.

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1 Introduction

It is well documented that both professional investment managers and individual investors display a strong preference for investing in local firms.[1] This finding is unexpected from the point of view of standard portfolio theory, and it has spurred a large literature on the causes and consequences of this local bias. Somewhat surprisingly, the asset-pricing implications of the local bias has received relatively little attention.[2] A possible reason for this omission is that the existing literature defines an investment as local if the investor is located geographically close to the firm's headquarter. According to this definition, all firms are local to some investors, and there is no cross-sectional variation in the degree of "localness" among firms. This paper constructs a novel measure that allows us characterize firms, rather than investments, as local. By distinguishing between truly local firms and firms that are geographically dispersed we are able to shed light on the asset pricing implications of the local bias.

We define a firm as local if its business activities are concentrated in a small geographic area. To measure the degree of geographic concentration, we extract state name counts from annual reports filed with the SEC on form 10-K. Based on the state name counts, firms are classified as geographically dispersed if a large number of states are mentioned in the annual report, and as local if only one or two states are mentioned. Using a large sample of U.S. publicly listed firms from the period 1994 through 2008, we document that the stock returns of truly local firms far exceed the stock returns for geographically dispersed firms.

To study the relationship between stock returns and the degree of geographic dispersion, we use both portfolio sorts and Fama-MacBeth cross-sectional regressions. Firms are sorted into portfolios of local firms and geographically dispersed firms using our state count measure. The portfolio of local firms has a Jensen's alpha of 48 basis points per month relative to a factor model that controls for risks related to the market, size, book-to-market ratio, momentum, and liquidity. The portfolio of geographically dispersed firms has a corresponding alpha of -22 basis points. This implies a 70 basis point difference in monthly risk adjusted returns between local firms and geographically dispersed firms. On an annual basis this corresponds to a return difference of 8.4%. Using Fama-MacBeth cross-sectional regressions, we find an effect of geographic dispersion that is similar both in terms of economic magnitude and statistical significance. The variation in average returns associated with firms' geographical dispersion is particularly pronounced for smaller firms, less liquid firms, and firms with high idiosyncratic volatility. But, the effect of geographic dispersion is not subsumed by these firm characteristics.

Our paper is closely related to a large and rapidly growing literature on how economic

[1]Coval and Moskowitz (1999) show that U.S. money managers are significantly more likely to invest in firms headquartered in the same city as the manager than in other firms.

[2]Exceptions are Pirinsky and Wang (2006), Hong, Kubik, and Stein (2008). and Gómez, Priestley, and Zapatero (2008).

decision making is influenced by firms' geographic location. Coval and Moskowitz (1999) show that U.S. money managers are significantly more likely to invest in firms headquartered in the same city as the manager than in other firms. Numerous subsequent studies have confirmed the strong preference for local firms and have suggested explanations that include informational advantages, familiarity, and social interactions.[3] A more recent branch of the literature has looked at the effects of geography from the firm's perspective and has found that geographic location also matters for corporate decision making.[4]

Given the strong evidence in favor of a relationship between geographic location and both investor decisions and corporate decisions, it seems natural to investigate how geography affects asset prices. Pirinsky and Wang (2006) show how the stock returns of firms headquartered in the same geographic area strongly comove with each other, and interpret their evidence as favoring the view that the trading pattern of local investors influences stock returns. Hong, Kubik, and Stein (2008) show that the local bias depresses the stock price through an "only game in town" effect.[5] Our paper contributes to this literature by providing evidence on the existence of a link between the geographical scope of a firm and its average stock returns.

Geographic dispersion has been shown to be important for a number of questions in economics.[6] However, we are the first to create a measure the geographical dispersion of a firm's operations that it is available for virtually the whole cross-section of publicly traded U.S. firms. Most other studies base their measures of dispersion on international data, small proprietary databases, or on information reported in Exhibit 21 of the 10-K statements, where firms break down financial variables by business segments (which sometimes are geographic segments). Although these sources provide data with less noise than our state counts, it can only be collected for a small subsection of listed U.S. corporations. Moreover, local firms are unlikely to be included in these datasets, precisely because they are local.

Theoretically, there are good reasons to expect the local bias to have implications for asset

[3]Coval and Moskowitz (2001), Hau (2001), Ivković and Weisbenner (2005), Ivković, Sialm, and Weisbenner (2008), and Teo (2009) conclude that local investors have an informational advantage. However, see Seasholes and Zhu (2010) for contradicting evidence. Huberman (2001) show that people tend to invest in the familiar. Social interaction among investors is shown to be important for investment decisions by Grinblatt and Keloharju (2001), Hong, Kubik, and Stein (2004), Hong, Kubik, and Stein (2005), Ivković and Weisbenner (2007), and Brown, Ivković, Weisbenner, and Smith (2008).

[4]See Kang and Kim (2008), Landier, Nair, and Wulf (2009), Becker, Ivković, and Weisbenner (2010), and Almazan, Motta, Titman, and Uysal (2010).

[5]Gómez, Priestley, and Zapatero (2008) show that a local risk factor has negative risk premium. This evidence is consistent with investors hedging local risk from relative wealth concerns. See Feng and Seasholes (2004), Loughran and Schultz (2005), Loughran (2007), Dorn, Huberman, and Sengmueller (2008), Bodnaruk (2009) for other related work.

[6]Landier, Nair, and Wulf (2009) show that the geographic dispersion of a firm affects its decision making. Gao, Ng, and Wang (2008) document that geographic dispersion affects firm value. There is also a large literature in economics that study why Silicon Valley-style geographic agglomeration exists. See for example Ellison and Glaeser (1997) and references therein. The international finance literature is also related, see for example Doukas and Travlos (1988) and Uysal, Kedia, and Panchapagesan (2008) for studies of M&As in an international context.

prices. Merton (1987) characterizes equilibrium stock returns when investors are not aware of all securities. In such informationally incomplete markets, stocks with lower investor recognition have higher expected returns to compensate investors that hold the stock for insufficient diversification. It is reasonable to expect that stocks of local firms will have a smaller investor base, and hence lower investor recognition, than stocks of geographically dispersed firms. It follows that local firms should have higher stock returns than geographically dispersed firms.

As investor recognition is not directly observable, the existing empirical literature has used proxies that includes cross-listings by non-U.S. firms (Foerster and Karolyi, 1999), trading volume (Gervais, Kaniel, and Mingelgrin, 2001; Kaniel, Ozoguz, and Starks, 2010), media attention (Fang and Peress, 2009), and a measure of the shadow cost of incomplete information (Bodnaruk and Östberg, 2008). In the international finance literature, Kang and Stulz (1997) and Dahlquist and Robertsson (2001) find some evidence that foreign firms that export, from Japan and Sweden respectively, are more likely to be held by foreign investors. The overall conclusion from this literature is that investor recognition matters for asset pricing.

To further explore predictions of the investor recognition hypothesis, we investigate how returns on stocks of local firms are related to the number of listed firms per capita in the state where the firms are headquartered. Following the evidence in Hong, Kubik, and Stein (2008), we conjecture that investors will be aware of most firms around them in areas where there are few publicly listed firms. On the other hand, in areas where there are a large number of firms, investors will have a hard time keeping up with all of them, and as a consequence they will only be aware of a subset of these firms. We find that local firms from states with a low firm-population density generate returns that are significantly lower than the return on local firms from states with high firm-population density. Controlling for potential differences in risk between firms from high-density states and firms from low-density states, the return on a portfolio of local firms from high-density states exceeds the return on a portfolio of local firms from low-density states by 58 basis points. This corresponds to a risk-adjusted annual difference in returns that exceeds 7%. We take this as evidence supporting the view that local firms earn higher returns due to the lack of investor recognition.

The rest of the paper is organized as follows. Section 2 describes our data selection procedure and explains how we construct our measure of geographic dispersion. Section 3 presents the main findings. In section 4 we provide possible explanations for the high returns on local firms as well as robustness tests. Section 5 concludes the paper.

2 Data

We use a sample of firms listed on the New York Stock Exchange (NYSE), the American Stock Exchange (AMEX), and NASDAQ. The data used to construct our measure of geographic dispersion is downloaded from the Electronic Data Gathering, Analysis, and Retrieval system (EDGAR) of the U.S. Securities and Exchange Commission (SEC). Stock returns, stock prices, and data on volume traded are from the Center for Research in Security Prices (CRSP). Accounting variables are from Compustat. The following sections describe our data selection procedure, explain how we construct our measure of geographic dispersion, and report summary statistics on both geographic dispersion and sample firms.

2.1 Geographic Dispersion

The degree of geographic dispersion of a firm's business operations is measured using data from 10-K filings. Form 10-K is an annual report required by the SEC that gives a comprehensive summary of a public company's performance and operations. Firms must file such a report with the SEC within 90 days of the end of their fiscal year. In addition to financial data, the annual report typically includes information on the evolution of the firm's operations during that year, details on its organizational structure, executive compensation, competition, and regulatory issues. The 10-K statement also gives information on the firm's properties, such as factories, warehouses, and sales offices. For example, firms may include sales at stores in different states, and/or list the manufacturing facilities they operate together with the city and state where they are located.

Computerized parsing of all 10-Ks filed with the SEC during the period 1994 through 2008 allow a count of the number of times each 10-K mentions a U.S. state name. The structure of a 10-K filing is standardized, and the vast majority of 10-Ks are subdivided into the same set of sections. We count the occurrence of state names in sections "Item 1: Business", "Item 2: Properties", "Item 6: Consolidated Financial Data", and "Item 7: Management's Discussion and Analysis." In most of the analysis that follow, we simply measure geographic dispersion as the number of different states mentioned in these four sections. Firms that do not mention any U.S. state names in their 10-K are excluded from the analysis. Thus, geographic dispersion for firm i based on the 10-K for fiscal year t is an integer in $\{1, 2, \ldots, 50\}$.

The vast majority of firms file their annual report using SEC form 10-K. If a firm has not filed the 10-K within a fiscal year, or we cannot identify the right sections, we check if the firm has made an amended filing on form 10-K/A, and we use this filing to count states. If neither of these two forms are filed or contain the sections we are interested in, we repeat the procedure using forms 10-K405, 10-KSB, 10-KT, 10KSB, 10KSB40, 10KT405 and the amendments to these forms.[7] We only count states in one form in a given fiscal year. Overall, we read and attempt to count states in 118,242 forms.

[7] These forms are essentially 10-K statements for either (i) small firms, who are not required to give as many details as large firms (forms ending in SB), (ii) firms that, prior to 2003, had failed to file a Form 4 in time (forms ending in 405), or (iii) firms in transition (forms ending in KT).

Firms that file with the SEC using EDGAR are uniquely identified by the Central Index Key (CIK). The CIK is matched with data from CRSP and Compustat using the linkfile from the CRSP/Compustat Merged Database. We are able to match 91,460 forms with data from CRSP using this linkfile. Restricting firms to be listed on NYSE, AMEX, or NASDAQ with common equity (sharecodes 10 and 11) and only counting firms with a December-return on CRSP, leaves us with a sample of 66,628 firm-years for the sample period 1994 through 2008. The number of firms that satisfies the above sampling criteria fluctuates between a low of 934 in 1994 (when EDGAR filings were optional) to a high of 6,293 in 1998.

The state names most frequently mentioned in the 10-Ks are: California, Texas, New York, Florida and Georgia (in that order). The least common state names are Rhode Island, South Dakota and North Dakota. Delaware and Washington, particularly the former, are outliers in terms of number of counts per population of the state, as many companies are incorporated in Delaware, and Washington is also the name of the United States' capital. We present our results using the counts of the states without any adjustments, but we remark that all of our results are robust to the exclusion of Delaware and Washington as state names.

A prime example of a firm that is clearly geographically dispersed is Sears Holdings Corporation. It has a state count of 50 for all years in our sample period. In its 10-Ks, Sears always breaks down the number of Sears and Kmart stores by state. Other firms that, by our measure, operate in all 50 states are: Darden restaurants, the world's largest company-owned and operated restaurant company, GameStop Corp, a videogame retailer, and Genworth Financial Inc, a large retail financial firm. Well known firms with an average state count that exceeds 45 include: Barnes and Nobel, Applebees, Officemax, Zurich Reinsurance, Jo-Ann Stores, United Rentals, Regions Financial Corp, and Integrated Health Services.

2.2 Summary Statistics on Geographic Dispersion

Table 1 presents sample summary statistics for our measure of geographic dispersion. These results have interest on their own, as they are the first large sample evidence on the geographical scope of U.S. businesses. Panel A presents summary statistics for all firms in the sample. Focusing on the first row, the average number of U.S. state names mentioned in the annual report filed on form 10-K is 7.9. This average is computed using the time-series of July cross-sectional averages. In this 1994–2008 time-series, the minimum average is 7.1 states and the maximum average is 9.6 states. Based on average state counts, geographic dispersion seems to be stable over our sample period. The stability is confirmed by the graph in Panel A of Figure 1. This graph shows the monthly cross-sectional average geographic dispersion starting in May 1994 and ending in December 2008. At the start of the sample-period the average number of states is relatively high. This reflects the fact that prior to May 1996 filing via the EDGAR system was voluntary, and the firms that chose electronic filing were mostly large firms. Since

1997, when EDGAR filing was mandatory for all U.S. publicly traded firms, the average number of states mentioned in 10-Ks have increased steadily from around 7 states to around 8 states. Next we turn to the row labeled Median in Panel A of Table 1. Using the time-series of cross-sectional medians, the median firm in the median year mentions five states in its 10-K, indicating a distribution of state counts that is skewed to the right.

More importantly for our purposes, Table 1 shows that there is a significant variation in our measure of geographic dispersion. In particular, the cross-sectional standard deviation of the number of states is 7.7. Moreover, this cross-sectional variation does not change much over time. The minimum standard deviation is 6.9 while the maximum is 8.4. Focusing on the column labeled 20%, we observe that as many as 20% of the firms in our sample do business in three states or less. In the following, we will refer to firms below the 20th percentile as being "local." The last column of Panel A shows that for a typical year in our sample period, 80% of all firms do business in 11 states or less. We will refer to firms that do business in more states than the firm at the 80th percentile as being "geographically dispersed." Looking at the rows labeled Minimum and Maximum, we see that the 20th percentile varies between two and three states over the sample period while the 80th percentile varies between 10 and 14 states. Panel B of Figure 1 contains the full histogram of our geographical dispersion. As expected, it is heavily skewed to the right, with most firms clustered on single-digit state counts, but with a significant number of companies that operate in multiple states.

Panel B of Table 1 breaks down the averages from the first row of Panel A by the size of firms. As one would expect, big firms are more geographically dispersed, having almost twice as many state names mentioned in their 10-K statement as small firms. The difference is economically large: The average number of state names for small firms is 5.9 while the corresponding average for big firms is 10.5. To study how stock returns vary by geographic dispersion, we require a cross-sectional variation in dispersion that is independent of other firm characteristics known to be related to returns. Panel B documents, that even within size quintiles, there is a significant amount of variation in geographic dispersion. For small firms, the average 20th percentile is 2.1 states while the average 80th percentile is 8.5 states. The corresponding number of states for big firms are 3.5 and 15.3. For all three size groups, the lowest number of states mentioned in a 10-K is one state. The corresponding maximum number of states varies from an average of 48 states for small firms to an average of 50 states for large firms.

In sum, Table 1 documents significant cross-sectional variation in geographic dispersion. This geographic dispersion is stable over time and remains large even when breaking down the cross-section by size. Next, we further explore how geographic dispersion relates to firm size and other firm characteristics such as book-to-market ratio, liquidity, volatility and stock return momentum.

2.3 Geographic Dispersion and other Firm Characteristics

Previous research has found that, in the cross-section of firms, stock returns are related to a number of firm characteristics. We expect that our measure of geographic dispersion will be related to many of the same firm characteristics. For example, it seems likely that local firms will tend to be smaller and less liquid than geographically dispersed firms. Table 2 investigates this conjecture. Panel A documents how the averages of size (ME) measured using stock market capitalization, the book-to-market ratio (BEME), liquidity (AMI) measured as in Amihud (2002), liquidity measured using the proportional quoted bid-ask spread (SPR), and idiosyncratic volatility (VOL) varies between quintiles of geographic dispersion.

The first row in Panel A shows that the average 10-K state count for firms classified as local is 1.9. The corresponding average state count for firms classified as geographically dispersed is close to 20. As expected, local firms are smaller than dispersed firms. Moving from the first quintile of geographic dispersion (local firms) to the fifth quintile (dispersed firms), the average size (ME) more than doubles. As average stock returns are negatively related to size, the size effect would tend to cause higher returns for local firms. The book-to-market ratio is monotonically increasing as geographic dispersion increases. Although the difference in book-to-market ratios between local firms and dispersed firms is not large, holding other firm characteristics constant, the difference would tend to result in lower returns for local firms.

We study the relationship between liquidity and geographic dispersion using both the price-impact measure of Amihud (2002) and the proportional quoted bid-ask spread. We set the Amihud illiquidity measure to missing for firm i in month m if the number of days the stocks of firm i has traded in month m is below or equal to five. If the dollar volume traded for stock i is high during a month, but the price has moved only very little, the Amihud measure will be small and stock i is said to be liquid. A potential disadvantage of the Amihud measure is that it may be difficult to distinguish liquidity from volatility. We therefore use the bid-ask spread as an alternative measure of liquidity. Proportional quoted spread is computed as $100(P_A - P_B)/(0.5P_A + 0.5P_B)$, where P_A is the ask price and P_B is the bid price. Monthly firm-specific bid-ask spreads are computed as the average daily bid-ask spreads within the month. The fourth and fifth rows in Panel A show that the average liquidity of local firms is lower, using both price-impact and bid-ask spread, than the average liquidity of dispersed firms. To the extent that liquidity is priced and illiquid firms are more sensitive to priced liquidity-risk than liquid firms, the low liquidity of local firms would cause local firms to have higher average return than geographically dispersed firms.

Ang, Hodrick, Xing, and Zhang (2006) show that volatility can explain the cross-sectional variation in stock returns. We follow these authors and measure volatility as the standard deviation of the error term from a Fama and French (1993) time-series regression using daily data for one month. Ang, Hodrick, Xing, and Zhang (2006) find that firms with high volatility in month $t-1$ tend to experience low stock returns in the following months. Looking at the last row of Panel A of Table 2, local firms tend to be more volatile than dispersed firms. In isolation, this would tend to cause local firms to have lower average returns than dispersed firms. The last row of Panel A shows how average stock return momentum varies by geographic dispersion quintiles. We follow Fama and French (2008) and measure momentum as the cumulative return from month $t-12$ to $t-2$. Even though average past returns are higher for local firms than for dispersed firms, neither groups of firms display stock return momentum that is unusually high on average.

In the last Panel of Table 2, we run a regression with geographic dispersion as the dependent variable and other firm characteristics, year dummies, industry dummies, and U.S. census division dummies as independent variables. All firm characteristic measures are transformed using the natural logarithm. Each firm is allocated to one of 12 industries using Ken French's industry classification and SIC codes from CRSP. Each firm is also allocated to one of nine U.S. census divisions based on the location of the firm's headquarter. The headquarter location is from Compustat. Controlling for year, census division, and industry effects, the results from Panel B confirms that geographic dispersion is positively related to size and book-to-market ratio and negatively related to Amihud illiquidity and momentum. However, when controlling for other firm characteristics the marginal effect of the bid-ask spread and volatility is positive.

3 Results

The analysis presented in the previous section shows that geographic dispersion varies with firm characteristics known to explain some of the cross-sectional variation in stock returns. In this section, where we present results on the relationship between geographic dispersion and stock returns, it therefore becomes important to control for the potentially confounding effect of other firm characteristics. We follow two approaches commonly used in the literature to investigate the relationship between returns and firm characteristics. First, we sort firms and form portfolios based on geographic dispersion. Second, we perform cross-sectional regressions along the lines of Fama and MacBeth (1973).

3.1 Returns and Alphas on Portfolios Sorted on Geographic Dispersion

To investigate how stock returns are related to the degree of geographic dispersion, we start by forming five portfolios based on our state count measure. A firm that files a 10-K form on or before June of year t is eligible for inclusion in a portfolio starting in July of year t. The firm carries its state count up to and including June of next year. A firm gets added to the portfolio of local firms if its state count is below the 20th percentile in the June cross-section of state counts. Correspondingly, a firm gets added to the portfolio of dispersed firms if the state count exceeds the 80th percentile. Three more portfolios are formed using the 40th and the 60th percentile as breakpoints. To ensure that portfolios include a sufficient number of firms, portfolio formation starts in July 1994. The sample period ends in December 2008.

In this section we follow Fama and French (2008) and report results using both equally weighted and value weighted portfolio returns. The advantage of equally-weighted returns is that results will not be driven by a few very large stocks. However, when forming portfolios using geographic dispersion, which is negatively correlated with market capitalization, the portfolio of local firms may be unduly influenced by microcaps (defined by Fama and French (2008) as firms with market cap below the 20th NYSE percentile.) Since microcaps only account for about 3% of the aggregate market cap, equally-weighted returns may produce results that are unrepresentative of the market. Reporting results using both value-weights and equal-weights improves our understanding of the pervasiveness of the relationship between stock-returns and geographic dispersion.

Table 3 documents equally-weighted (EW) and value-weighted (VW) monthly return on the portfolios sorted on geographic dispersion. Focusing on the equally-weighted portfolio returns, local firms experienced an average monthly return of 1.18% per month during the sample period. Starting with local firms and moving from left to right along the first row in Table 3, the average returns are monotonically decreasing as firms get more and more geographically dispersed. The average equally-weighted monthly return for the quintile of the most dispersed firms is only 0.62% per month. The 56 basis point difference in average monthly equally-weighted returns between local and dispersed firms is economically large and statistically significant at conventional levels.

The second row shows a similar pattern for value-weighted returns. The return difference between the local portfolio and the dispersed portfolio is a statistically significant 40 basis points. The difference in return between the equally-weighted and value-weighted portfolios indicate that small local firms have higher returns than large local firms, but the effect of geographic dispersion is clearly also present for large firms. Notice that not only are the point estimates for the top and bottom quintiles statistically different, but they are monotonic along the five quantiles, both for equally- and value-weighted portfolios. The last row of the table shows that the average number of firms in each of the quintile portfolios varies between 757 and 1,084. The reason why the five portfolios does not contain the same number of firms is related to the fact that the quintile breakpoints are integers. Many firms are operating in two states—all of which get included in the portfolio of local firms.

The fact that the return difference between local firms and dispersed firms is related to size, as well as the earlier documented relationship between geographic dispersion and other firm characteristics, raises the question of whether the return-spread is compensation for exposure to other risk factors. To take this concern into account, we estimate the following regression model:

$$r_{pt} = \alpha_p + \beta_1(\text{Mkt} - \text{Rf})_t + \beta_2\text{SMB}_t + \beta_3\text{HML}_t + \beta_4\text{MOM}_t + \beta_5\text{LIQ}_t + e_t, \tag{1}$$

where r_{pt} is either the monthly return on a given portfolio, or the monthly return on a zero investment portfolio long local firms and short geographically dispersed firms. The market portfolio proxy Mkt-Rf, the size-factor SMB, the book-to-market factor HML, and the momentum factor MOM are all available from Ken French's web-site. The liquidity factor LIQ is the "traded" liquidity factor of Pástor and Stambaugh (2003), available from WRDS as a time-series updated to December 2008.

Panel A in Table 4 reports factor loadings and Jensen's alpha for equally-weighted portfolios formed using quintiles of geographic dispersion. Focusing on the first row of the table, the portfolio of local firms shows a large and statistically significant Jensen's alpha, 48 basis points with a heteroskedasticity consistent t-statistic of 2.66, relative to the five-factor model. The return on the local portfolio is closely related to the return on the size factor, reinforcing the earlier finding that local firms tend to be smaller firms. But, since the portfolio has a large alpha, the high return on local firms is not driven by the size effect. Moving down in the column labeled "Alpha," the abnormal returns are monotonically decreasing as portfolios contain more geographically dispersed firms, mimicking the change in raw returns documented in Table 3. For the quintile portfolio with the most dispersed firms the alpha is a statistically significant -22 basis points (t-statistic of -2.06). This portfolio is less sensitive to the size factor, but it shows much stronger sensitivities to the book-to-market factor and the liquidity factor.

The first row of Panel B in Table 4 reports the result from a regression with the equally-weighted zero-investment portfolio long local firms and short dispersed firms as the dependent variable. The monthly alpha on this portfolio is 70 basis point—corresponding to an annual abnormal return of 8.7%. The associated t-statistic is 4.45, implying an abnormal return statistically significant at all conventional levels. The return on the long-short portfolio is positively related to the size factor and negatively related to the other four factors. However, the factor loadings are unable to explain the large difference in returns between the portfolio of local firms and the portfolio of dispersed firms. The last row in Panel B constructs the long-short portfolio using value-weights. The monthly alpha on this portfolio is 50 basis points, with a t-statistic of 2.81. The smaller alpha on the value-weighted portfolio reinforces our previous finding that small local firms have larger abnormal returns than large local firms.

To investigate the effect of small firms further, Panel C of Table 4 reports results after dropping microcaps from all portfolios. This reduces the overall number of firms by approximately 60%. The reduction is largest in the portfolio of local firms where the average number of firms per month drops from 1,084 to 298. The original portfolio of dispersed firms contains only 300 microcaps—resulting in a new portfolio with 518 firms on average. As expected, dropping the smallest firms reduces the abnormal performance of the equally-weighted long-short portfolio. The alpha drops from 70 basis points using all firms to 32 basis points when excluding microcaps. With an associated t-statistic of 2.4, the abnormal performance remains statistically significant at conventional levels. Moving to the last row of the table, we observe that the alpha for the value-weighted long-short portfolio is practically unaffected by the microcaps. The alpha is 51 basis points with a t-statistic of 2.82.

The results reported in Table 4 show that local firms outperform geographically dispersed firms. The abnormal performance cannot be explained using standard characteristics based risk-factors. As an alternative to the above time-series analysis, the next section investigates to what extent geographic dispersion can explain the cross-sectional variation in stock returns while controlling for other firm characteristics known to explain returns.

3.2 Cross-Sectional Regressions

The analysis of this section is based on cross-sectional regressions similar to Fama and MacBeth (1973). In particular, for each month in the sample period, we run the following cross-sectional regression:

$$R_{it} - R_{ft} = c_0 + \sum_{m=1}^{M} c_{im} Z_{mit} + e_{it}$$

where R_{it} is return on stock i in month t, R_{ft} is the monthly yield on 30-day Treasury bills, Z_{mit} is one of the following M firm characteristics: geographic dispersion, the natural logarithm of our state name count (from the last June); size, the natural logarithm of the market capitalization in month $t-2$; the firm's book-to-market ratio, the natural logarithm of the book-to-market ratio measured as of last June; the stock's Amihud illiquidity, the natural logarithm of the Amihud (2002) illiquidity measure computed using daily returns and volume from month $t-2$; Bid-Ask spread, the natural logarithm of $(P_A - P_B)/(0.5P_A + 0.5P_B)$ where P_A is the ask price and P_B is the bid price, both measured in month $t-2$; idiosyncratic volatility, the natural logarithm of the standard deviation of the error term from a regression using the three-factor model of Fama and French (1993) and one-month worth of daily data; momentum, the buy-and-hold return for months $t-12$ through $t-2$; and the one-month lagged return.

Table 5 presents the time-series averages and associated t-statistics of the cross-sectional regression coefficients from the above model. Focusing first on the column labeled All Firms, we see that there is a strong negative relationship between geographic dispersion and future one-month stock returns. The average cross-sectional coefficient associated with the natural logarithm of geographic dispersion is -0.22. To compare this estimate with the findings in Tables 3 and 4, notice from the first row of Table 2 that the average state count in the portfolio of local firms is 1.9 while the average state count in the portfolio of geographically dispersed firms is 19.9. Taking the natural logarithm of these numbers, computing the difference, and multiplying with -0.22 shows that predicted monthly return of geographically dispersed firms is about 52 basis points lower than monthly predicted return for local firms, holding fixed other firm characteristics. Thus, the effect of geographic dispersion estimated via these Fama and MacBeth (1973) regressions has a similar magnitude as in our time-series analysis of Section 3.1.

The last three columns of Table 5 breaks down the cross-sections by market capitalization. We follow Fama and French (2008) and divide firms into microcaps, small firms, and large firms based on NYSE market capitalization breakpoints. As in previous sections, microcaps are defined as firms below the 20th NYSE size percentile. Small firms are firms between the 20th and the 50th percentile, while big firms are all firms above the 50th percentile. Consistent with the results from Table 4, we find that the effect of geographic dispersion is stronger for microcaps than for larger firms. The effect is weaker and not statistically significant for small firms, but for big firms it is both economically and statistically significant.[8]

Taken together, the results presented in Table 4 and Table 5 provide strong evidence in favor of concluding that local firms earn higher returns than geographically dispersed firms. The effect is robust to controlling for characteristics based risk factors in time-series regressions as well as to firm characteristics in cross-sectional regressions. The next section investigates potential explanations for the large return difference between local firms and geographically dispersed firms.

4 Explaining the Large Returns on Local Stocks

This section investigates investor recognition and limits-to-arbitrage, in the form of transaction costs, as potential causes for the return differential between local firms and dispersed firms.

4.1 Firm Density and Investor Recognition

Merton (1987) characterizes equilibrium stock returns when investors are not aware of all securities. In such informationally incomplete markets, stocks with lower investor recognition offer higher expected returns to compensate investors that hold the stock for insufficient diversification. To the extent that local stocks have lower investor recognition, the high average return

[8] This "U-shaped" cross-sectional effect of geographic dispersion is also evident from the alphas in Table 4. In Panel B of Table 4, the alpha from the equally-weighted zero-investment portfolio exceeds the alpha for the corresponding value-weighted portfolio. However, when dropping microcaps from the portfolios (Panel C in the same table), the alpha for equally-weighted portfolios is smaller than the alpha for the value-weighted portfolios. This also indicates that the effect of geographic dispersion is weaker for small firms than for big firms.

of local firms documented in the previous section is consistent with the investor recognition hypothesis. To investigate this hypothesis further, we study the returns on stocks in areas where there are a lot of listed firms, and compare these to returns on stocks from areas where there are few firms. Following the discussion and findings in Hong, Kubik, and Stein (2008), we conjecture that firms stand a higher chance of being ignored by investors in areas where the number of listed firms per capita is high.

For each state, we compute the ratio of the number of listed firms to the population of the state, which we loosely refer to as the state's firm density. We then group states into low, medium and high based on firm density. The group of states with low density is composed of all states with below median firm density. The remaining states are divided between medium-density states and high-density states to ensure that the number of listed firms in both state-groups are as close as possible. With this approach, the high-density states are Massachusetts, Connecticut, Colorado, New Jersey, Minnesota, and California. Using stocks headquartered in high-density states, we form quintile portfolios based on geographic dispersion as before. Similar portfolios are created using stocks headquartered in medium-density and low-density states.

Local stocks headquartered in states with low firm density should have higher investor recognition that local stocks headquartered in states with high firm density. According to the investor recognition hypothesis, the latter group of local stocks should have higher returns than the former group of local stocks. Panel A of Table 6 investigates this conjecture. The first vertical segment of the table uses all firms to form portfolios. The portfolio of local firms from states with low firm density has an alpha of 46 basis points with a t-statistic of 3.04. Moving to the next row, the portfolio of local firms from medium density states has an alpha of 78 basis points. For high density states, the local firm portfolio has an alpha of 1.04 (t-statistic of 4.19). The difference in abnormal returns between local firms in low density states and local firms in high density states is a statistically significant 58 basis points. Thus, local firms from states where there are many other listed local firms show average returns that are significantly higher than average returns for local firms in states where competition for attention is not as strong. The three remaining vertical segments of Panel A of Table 6 show that the effect of firm density is present in all size groups: microcaps, small firms, and big firms. Focusing on the last row of Panel A, the difference in alphas between portfolios from high density states and portfolios from low density states, ranges from 53 basis points for small firms to 84 basis points for big firms. Given that we are trying to reject the null hypothesis in favor of a one-sided alternative hypothesis, all alphas are statistically significant at conventional levels.

While Panel A focused on local firms only, Panel B of Table 6 reports alphas on portfolios long in local firms and short in geographically dispersed firms. Based on the investor recognition hypothesis, we would expect the difference between local firms and geographically dispersed firms to be smaller in states with fewer listed firms. The results reported in Panel B support this conjecture. Using all firms to form portfolios, the first vertical segment in Panel B shows an alpha of 47 basis points for the long-short portfolio in low density states. The corresponding portfolio for firms from high density states has an alpha of 83 basis points. The difference between these alphas is 36 basis points with an associated t-statistic of 1.72. For a one-sided test, this is statistically significant at a level below 5%. Looking at the three other segments of Panel B, the difference between low-density states and high-density states is present also among microcaps and big firms, but not for small firms. In sum, Table 6 presents evidence in favor of the importance of investor recognition for equilibrium stock returns.

4.2 Liquidity and Volatility

Our conclusion on the importance of the investor recognition hypothesis is similar to the main conclusion of Fang and Peress (2009). They find that firms with little media coverage have higher returns than comparable firms with high media coverage. Fang and Peress point out that some investors may recognize all securities, but that limits to arbitrage prevent them from taking advantage of the apparent mispricing between stocks. Consistent with this view, they document that the media-effect is stronger for low liquidity and high volatility firms. This section investigates if the effect of geographic dispersion is related to liquidity and volatility.

In order to investigate the importance of liquidity, we first sort firms into three portfolios based on the Amihud illiquidity measure. Then, within each liquidity portfolio, we sort firms into quintile portfolios based on their geographic dispersion. The same procedure is followed replacing Amihud illiquidity with bid-ask spread and volatility. Table 7 presents alphas for portfolios, within sorts on liquidity and volatility, that are long local firms and short geographically dispersed firms. Using all available firms to form portfolios, the first vertical segment of Panel A shows that the alpha for the long-short portfolio formed using the most liquid firms is 32 basis points. This alpha increases to 71 basis point for firms with medium liquidity and to 93 basis points for the least liquid firms. The difference in alphas for liquid and illiquid firms is 62 basis points with an associated t-statistic of 2.69. The fact that the alpha is monotonically increasing with reduced liquidity, and the economically and statistically significant difference in the alphas, seem to support the conclusions of Fang and Peress (2009) on the importance of liquidity for firms with low investor recognition.

However, when investigating the effect of Amihud liquidity within microcaps, and within the group of firms that are not microcaps, the effect of liquidity is dramatically reduced. First, when only using microcaps to form portfolios, the alphas on the portfolios long local firms and short geographically dispersed firms are economically and statistically significant. However, the alphas for liquid and illiquid firms are not statistically distinguishable from each other. The same conclusion applies to firms that are not microcaps. The implication of this finding is that most of the alpha-difference found when using all firms to form portfolios is driven by the difference in liquidity between microcaps and other firms. That is, we cannot separate the liquidity effect from the size effect that we have documented in earlier tables.

Panel B of Table 7 reports the result from a similar analysis using the bid-ask spread as a liquidity measure. For microcaps, there is an effect of liquidity. The alpha for the most liquid firms is 53 basis points smaller than the alpha for the least liquid firms. Using a one-sided test, the difference is statistically significant at below the 5% level. However, moving to the group of firms that are not microcaps, there is no effect of the bid-ask spread, as the alphas of the long-short portfolio is 36 basis points for highly liquid firms, but only 33 basis for stocks with high bid-ask spreads.

Panel C of Table 7 investigates the effect of volatility on the alphas on the portfolios long local firms and short geographically dispersed firms. The Merton (1987) model implies that investors require compensation for taking on the idiosyncratic risk that follows from holding less than perfectly diversified portfolios. Thus, local firms with high idiosyncratic risk should command higher expected returns than local firms with less idiosyncratic risk. We investigate this prediction by studying the alphas on long-short portfolios when portfolios are formed within groups of firms sorted based on idiosyncratic risk. Using all available firms to form portfolios, the difference in alphas for low-volatility firms and high-volatility firms is a statistically significant 87 basis points. This difference remains strong among microcaps (68 basis points with a t-statistic of 1.87) but is much weaker among non-microcaps (28 basis points with a t-statistic of 1.26).

Overall, Table 7 documents a strong effect of liquidity and volatility when using all firms to form portfolios. However, these effects are hard to distinguish from size effects. This does not imply that the effect of geographic dispersion is not stronger for illiquid firms with high volatility. It only implies that the effect is hard to separate from the size effect. However, it seems reasonable to conclude that size, liquidity, and volatility together influence the effect of geographic dispersion in much the same way as these variables modify the media-effect studied by Fang and Peress (2009). That is, arbitrageurs would find it harder to profit on the mispricing documented in this paper when firms are small, have low liquidity, and are volatile.

4.3 Industry and other measures of dispersion

Hou and Robinson (2006) conclude that industry concentration affects equilibrium stock returns. If industry membership is correlated with geographical dispersion, our findings could possibly be caused by industry membership rather than geographic dispersion. This section addresses this concern. We also investigate the robustness of our findings using alternative measures of geographic dispersion.

Table 8 investigates the role of industry by creating portfolios within broad industry classifications.[9] In particular, for firms within each of the eight industries listed in Panel A of Table 8,

[9] In order to have a sufficient number of firms per month, we use eight broadly defined industries, closely aligned

we estimate (1) for the long-short equally weighted portfolio sorted on geographical dispersion. The estimated alpha from these eight time-series regressions is presented in the second column. The numbers are positive and large for all but one industry, for which the point estimate is virtually zero. Furthermore, a formal F-test of the equality of the eight alphas has a p-value of 11%. Thus, we cannot reject the hypothesis that the effect is the same for all industries. We conclude that the effect of geographic dispersion is not driven by one particular industry group.

In Panel B of Table 8 we conduct a further test as to whether our results are driven by industry effects. We repeat the portfolio formation in Section 3.1 with the difference that we replace a firm's stock return by that of its industry, using the Fama and French 38 industries classification to define industry membership. The local portfolio's alpha is 15 basis points, whereas that of the dispersed portfolio is -2 basis points. Comparing this to the estimates from Table 4, 48 and -22 basis points, we see that industry itself cannot explain our findings. A similar conclusion emerges from the long-short portfolio. The last row of Table 8 shows that the alpha of the portfolio obtained substituting a firm's return for that of its industry is 17 basis points, which is less than 25% of the point estimate of 70 basis points from Table 4.

Finally, we run Fama and MacBeth (1973) regressions similar to Table 5, but with added industry dummies created based on the Fama-French 38 industries classifications. Results are not reported, but the conclusion remain the same—industry fixed effects do not explain the significance of geographical dispersion as a determinant of stock returns.

Table 9 presents our results using alternative measures of geographical dispersion. The five rows in this table report the alphas of long-short portfolios, similar to Panel B of Table 4. We change the measure of geographical dispersion in each of the rows. In the first row we use the Herfindahl index to measure geographic dispersion.[10] An argument that favors such a measure is that it is continuous and it is widely used to summarize multi-dimensional information such as the state counts that are the core of our analysis. The Herfindahl index is more likely to classify a firm as local even when many states are mentioned in the 10–K but there is one state that receives a large number of counts. The results using the Herfindahl measure parallel those from Table 4. The alpha of the EW portfolio is 50 basis points, whereas that of the VW portfolio is 49 basis points, both highly significant by standard confidence levels.

Another interesting alternative measure of geographical dispersion uses the nine U.S. census divisions as the measure of location, rather than the fifty U.S. states. A firm that operates in Pennsylvania and California is arguably more geographically dispersed than one that operates in Virginia and North Carolina (both part of the South Atlantic division). Our next alternative geographical dispersion metric is constructed by associating firms with census divisions using the

to Fama and French twelve industries classification.

[10] We construct the Herfindahl index as follows. We create a vector $x \in \mathbb{R}^{50}$ that has as entry x_i the proportion of all state names mentioned in the 10–K statement that are associated with state i. The Herfindahl index is then defined as usual as $H = \sum_{i=1}^{50} x_i^2$.

state names mentioned in their 10-K statements. In other words, if a firm mentions Pennsylvania and California in their 10-K statement, the firm is said to do business in both the Mid-Atlantic division and the Pacific division. The second row of Table 9 reports the alpha-estimates for the long-short portfolios using both equal- and value-weights. The conclusions from our previous analysis carries through. The long-short portfolios have alphas above 50 basis points per month, both of which are economically large and statistically different from zero.

Finally, we investigate if firms' international presence affects our results. If international presence expands the investor base, it should lead to lower expected returns for international firms. However, the strong home bias of investors (French and Poterba, 1991), suggests that international presence only will have a small effect on the investor base. In other words, a company with operations in China and California may not reach more investors than a another similar firm with operations in California only. Nonetheless, it is possible that firms with global operations fail to list U.S. states in their 10-K because it is obvious that they are present in most states. Thus, international presence may cloud our results due to measurement error.

We check if our conclusions are robust to international presence by dropping firms that may have operations outside the U.S. In the third row of Table 9 we drop all firms that mention one or more country names in their 10-K statement. Using our state-count measure of geographic dispersion in the sample of non-international firms, the alpha on the equally-weighted portfolio is 51 basis points, whereas the value-weighted portfolio has an alpha of 84 basis points. The number of firms remaining in the sample, after dropping firms with some international presence, is significantly lower than for the full sample. Nonetheless, our results are still large in economic terms, and statistically different from zero. To retain more firms, the fourth row reports alphas on the long-short portfolio formed using firms that mention less than five countries in their 10-K statements. The alphas remain large in this subsample as well.

In our final robustness test, we check whether the international dispersion of a firm can have an effect similar to the effect of domestic dispersion. In the last row of Table 9, we report alphas when geographic dispersion is measured using country-name counts rather than state-name counts. In particular, we redo our previous analysis using the counts of 200 different countries, excluding the United States, instead of the earlier state-name counts. Both the equally-weighted and the value-weighted portfolios have alphas that are not distinguishable from zero at conventional levels of statistical significance. Based on the last three rows of Table 9, we conclude that our results are not driven by firms with international presence.

Overall, Tables 8 and 9 show that our main conclusion is not driven by any particular industry, that it is robust to using alternative measure of geographic dispersion, and that it is not driven by firms with international presence.

5 Conclusion

This is the first large sample study of the geographical dispersion of U.S. publicly traded firms. Our paper provides two key findings that shed new light on the pricing of local assets. First, we show that the geographical dispersion of a firm's business activities, measured by the number of states mentioned in a company's annual report, is related to average returns. Local firms, those that operate in two states or less, have average returns that are 70 basis points higher than firms whose operations transcend more than twenty states. Second, we show that stocks of local firms headquartered in states with few other publicly traded firms have lower returns than local stocks in states where the competition for investor attention is more intense.

We interpret our evidence as consistent with the predictions of the investor recognition hypothesis of Merton (1987). In Merton's informationally incomplete markets, stocks with lower investor recognition offer higher expected returns to compensate investors for insufficient diversification. To the extent that local stocks have lower investor recognition, the high average return of local firms is consistent with this prediction. Moreover, under the presumption that investor recognition is higher for firms located in states with few other firms, our second main finding is also consistent with the idea that investor recognition affects stock returns.

Our study shows how one can obtain an economically meaningful cross-sectional characterization of firms, in our case the geographical dispersion of operations, from the filings of 10-K forms on EDGAR. The use of textual analysis of business related information is a promising area for future research. Our study of geographic dispersion and stock returns is only one of many potential questions that can be addressed using this type of data in general—and using our geographic dispersion measure in particular.

References

Almazan, Andres, Adolfo De Motta, Sheridan Titman, and Vahap Uysal, 2010, Financial structure, acquisition opportunities, and firm locations, *Journal of Finance* 65, 529–563.

Amihud, Yakov, 2002, Illiquidity and stock returns: Cross-section and time-series effects, *Journal of Financial Markets* 5, 31–56.

Ang, Andrew, Robert J. Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259–299.

Becker, Bo, Zoran Ivković, and Scott Weisbenner, 2010, Local dividend clienteles, forthcoming *Journal of Finance*.

Bodnaruk, Andriy, 2009, Proximity always matters: local bias when the set of local companies changes, *Review of Finance* 13(4), 629–656.

———, and Per Östberg, 2008, Does investor recognition predict returns?, *Journal of Financial Economics* 91, 208–226.

Brown, Jeffrey R., Zoran Ivković, Scott Weisbenner, and Paul A. Smith, 2008, Neighbors matter: causal community effects and stock market participation, *Journal of Finance* 63(3), 1509–1531.

Coval, Joshua D., and Tobias J. Moskowitz, 1999, Home bias at home: Local equity preference in domestic portfolios, *Journal of Finance* 54, 2045–2073.

———, 2001, The geography of investment: informed trading and asset prices, *Journal of Political Economy* 109(4), 811–841.

Dahlquist, M, and G Robertsson, 2001, Direct foreign ownership, institutional investors, and firm characteristics, *Journal of Financial Economics* 59, 413–440.

Dorn, Daniel, Gur Huberman, and Paul Sengmueller, 2008, Correlated trading and returns, *Journal of Finance* 63, 885–920.

Doukas, John, and Nickolaos G. Travlos, 1988, The effect of corporate multinationalism on shareholders wealth: Evidence from international acquisitions, *Journal of Finance* 43, 1161–1175.

Ellison, Glen, and Edward L. Glaeser, 1997, Geographic consentration in u.s. manufacturing industries: A dartboard approach, *Journal of Political Economy* 105, 889–927.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 43, 3–56.

——— , 2008, Dissecting anomalies, *Journal of Finance* 63, 1653–1678.

Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Fang, Lily, and Jöel Peress, 2009, Media coverange and the cross-section of stock returns, *Journal of Finance* 64(5), 2023–2052.

Feng, Lei, and Mark S. Seasholes, 2004, Correlated trading and location, *Journal of Finance* 59(5), 2117–2144.

Foerster, Stephen R., and G. Andrew Karolyi, 1999, The effects of market segmentation and investor recognition on asset prices: Evidence from foreign stocks listing in the united states, *Journal of Finance* 54(3), 981–1013.

French, Kenneth, and James Poterba, 1991, International diversification and international equity markets, *American Economic Review* 81(2), 222–226.

Gao, Wenlian, Lilian Ng, and Qinghai Wang, 2008, Does geographic dispersion affect firm valuation?, *Journal of Corporate Finance* 14(5), 674–687.

Gervais, Simon, Ron Kaniel, and Richard R. Mingelgrin, 2001, The high-volume return premium, *Journal of Finance* 56, 877–919.

Gómez, Juan-Pedro, Richard Priestley, and Fernando Zapatero, 2008, The effect of relative wealth concerns on the cross-section of stock returns, Discussion paper Marshall School of Business, USC.

Grinblatt, Mark, and Matti Keloharju, 2001, How distance, language, and culture influence stockholdings and trades, *Journal of Finance* 56(3), 1053–1073.

Hau, Harald, 2001, Location matters: An examination of trading profits, *Journal of Finance* 56, 1959–1983.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2004, Social interaction and stock-market participation, *Journal of Finance* 59, 137–163.

——— , 2005, Thy neighbor's portfolio: word-of-mouth effects in the holdings and trades of money managers, *Journal of Finance* 60, 2801–2824.

——— , 2008, The only game in town: Stock-price consequences of local bias, *Journal of Financial Economics* 90(1), 20–37.

Hou, Kewei, and David T. Robinson, 2006, Industry concentration and average stock returns, *Journal of Finance* 61, 1927–1956.

Huberman, Gur, 2001, Familiarity breeds investment, *Review of Financial Studies* 14, 659–680.

Ivković, Zoran, Clemens Sialm, and Scott Weisbenner, 2008, Portfolio concentration and the performance of individual investors, *Journal of Financial and Quantitative Analysis* 43(3), 613–656.

Ivković, Zoran, and Scott Weisbenner, 2005, Local does as local is: information content of the geography of individual investors' common stock investments, *Journal of Finance* 60(1), 267–306.

——— , 2007, Information diffusion effects in individual investors' common stock purchases: covet thy neighbors' investment choices, *Review of Financial Studies* 20(4), 1327–1357.

Kang, JK, and RM Stulz, 1997, Why is there a home bias? An analysis of foreign portfolio equity ownership in Japan, *Journal of Financial Economics* 46, 3–28.

Kang, Jun-Koo, and Jin-Mo Kim, 2008, The geography of block acquisitions, *Journal of Finance* 63, 2817–2858.

Kaniel, Ron, Arzu Ozoguz, and Laura T Starks, 2010, The high volume return premium: Cross country evidence, *Journal of Financial Economics* p. forthcoming.

Landier, Augustin, Vinay B. Nair, and Julie Wulf, 2009, Trade-offs in staying close: Corporate decision making and geographic dispersion, *Review of Financial Studies* 22(3), 1119–1148.

Loughran, Tim, 2007, Geographic dissemination of information, *Journal of Corporate Finance* 13, 675–694.

——— , and Paul Schultz, 2005, Liquidity: Urban versus rural firms, *Journal of Financial Economics* 78, 341–374.

Merton, Robert C., 1987, A simple model of capital market equilibrium with incomplete information, *Journal of Finance* 42(3), 483–510.

Pástor, Ľuboš, and R. F. Stambaugh, 2003, Liquidity risk and expected stock returns, *Journal of Political Economy* 111, 642–685.

Pirinsky, Christo A, and Qinghai Wang, 2006, Does corporate headquarters location matter for stock returns?, *Journal of Finance* 61, 1991–2015.

Seasholes, Mark S., and Ning Zhu, 2010, Individual investors and local bias, forthcoming *Journal of Finance*.

Teo, Melvyn, 2009, The geography of hedge funds, *Review of Financial Studies* 22, 3531–3561.

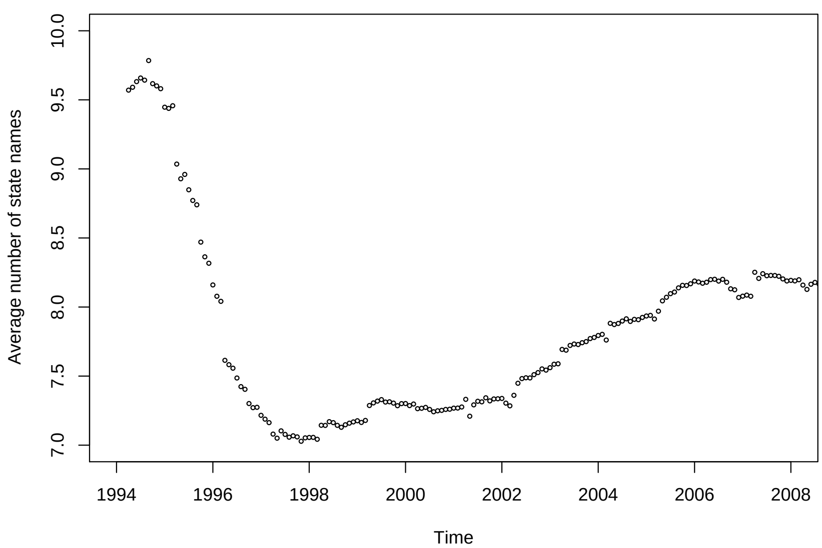
Uysal, Vahap B., Simi Kedia, and Venkatesh Panchapagesan, 2008, Geography and acquirer returns, *Journal of Financial Intermediation* 17, 256–275.

White, Halbert, 1980, A heteroskedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity, *Econometrica* 48, 817–838.

Figure 1
Geographic Dispersion

Geographic Dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10-K with the SEC. Panel A plots cross-sectional average geographic dispersion for each month in the period May 1994 through December 2008. Panel B shows a histogram of geographic dispersion across all firm-years.

A. Mean Geographical Dispersion



B. Histogram of Geographical Dispersion

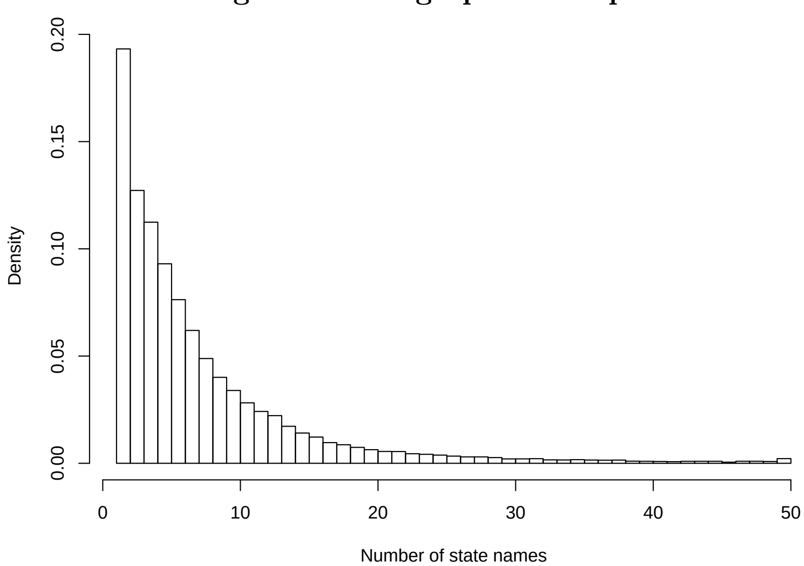


Table 1
Summary Statistics on Geographic Dispersion

Geographic Dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. Geographic Dispersion for year t is the counts from the last annual report filed prior to July of year t. Using the column labeled Median as an example, summary statistics in Panel A are computed as follows. First, the median is computed for each July cross-section in the sample period 1994–2008. This gives a time-series of annual medians. Second, using the time-series of medians, the rows in Panel A report the average, the median, the minimum, and the maximum. Panel B breaks down the 4,509 observations from the first row in Panel A by market capitalization (firm size). The sample period is 1994 through 2008.

	Number	Geographic Dispersion								
	of Firms	Mean	Std.	Min	Max	20%	40%	Med	60%	80%
A. Summary Statistics on Geographic Dispersion for All firms										
Average	4,509	7.9	7.7	1	50	2.6	4.3	5.5	6.8	11.3
Median	4,557	7.8	7.7	1	50	3	4	5	7	11
Minimum	934	7.1	6.9	1	50	2	4	5	6	10
Maximum	6,293	9.6	8.4	1	50	3	6	8	9	14
B. Average Geographic Dispersion by Firm Size										
Small	1,503	5.9	5.1	1	48	2.1	3.2	4.3	5.3	8.5
Medium	1,503	7.3	6.9	1	49	2.5	4.4	5.4	6.5	10.5
Big	1,503	10.5	9.4	1	50	3.5	6.0	7.6	9.3	15.3

Table 2
Geographic Dispersion and Other Firm Characteristics

Geographic Dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. Geographic Dispersion for year t is the number of U.S. states mentioned in the last annual report filed prior to July of year t. Size (the market value of common equity) and the Book-to-Market Ratio is computed as described in Fama and French (1993). Amihud Illiquidity is the price-impact liquidity measure of Amihud (2002). Bid-Ask Spread is the proportional quoted spread measured as: $100(P_A - P_B)/(0.5P_A + 0.5P_B)$, where P_A is the ask price and P_B is the bid price. Volatility is computed as the standard deviation of the error term from a regression using the three-factor model of Fama and French (1993) on one-month worth of daily data. Momentum is the buy-and-hold return for months $t-12$ through $t-2$. In Panel A, all variables are measured as of July each year and the Panel reports time-series averages of cross-sectional averages. Panel B report results from a pooled time-series cross-sectional regression. All variables in the regression are measured in natural logs. For the momentum variable, the natural log is computed from 1+Momentum. YEARS indicates the presence of dummy variables for each year. DIVS indicates the presence of dummy variables for each of nine U.S. census divisions. INDS indicates the presence of dummy variables for each of twelve industries from Ken French's website. Parentheses contain t-statistics computed from the heteroscedasticity consistent standard errors of White (1980). The sample period is July 1994 through December 2008.

A. Averages by Geographic Dispersion Quintiles

	Local	2	3	4	Dispersed
Geographic Dispersion	1.9	3.8	5.7	8.8	19.9
Size (ME)	1,732	1,640	1,862	2,645	3,963
Book-to-Market Ratio (BEME)	0.689	0.688	0.707	0.760	0.767
Amihud illiquidity (AMI)	0.028	0.021	0.012	0.014	0.006
Bid-Ask Spread (SPR)	0.030	0.028	0.026	0.023	0.018
Volatility (VOL)	0.031	0.032	0.031	0.028	0.025
Momentum (MOM)	0.150	0.119	0.108	0.107	0.110

B. Regression with Geographic Dispersion as the Dependent Variable

ME	BEME	AMI	SPR	VOL	MOM	YEARS	DIVS	INDS	AR^2	N
1.03	0.90	−0.31	0.43	0.33	−0.91	Yes	Yes	Yes	0.17	51,902
(25.03)	(24.01)	(−10.72)	(6.15)	(5.99)	(−16.59)					

Table 3
Average Return on Portfolios Sorted by Geographic Dispersion

The table reports average portfolio returns in percent. Geographic dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. Five portfolios are formed based on geographic dispersion. A firm that files a 10–K form on or before June of year t is eligible for inclusion in a portfolio starting in July of year t. The firm carries its state count up to and including June of next year. A firm gets added to the portfolio of local firms if its state count is below the 20th percentile in the cross-section of state counts. Correspondingly, a firm gets added to the portfolio of dispersed firms if the state count exceeds the 80th percentile. Three more portfolios are formed using the 40th and the 60th percentile as breakpoints. The sample period is July 1994 through December 2008.

	Local	2	3	4	Dispersed	Local − Dispersed
EW returns	1.18	0.97	0.87	0.83	0.62	0.56 (2.73)
VW returns	0.89	0.78	0.74	0.58	0.49	0.40 (2.06)
Average number of firms	1,084	830	784	757	818	

Table 4
Jensen's Alpha for Portfolios Sorted on Geographic Dispersion

Geographic dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. Five portfolios are formed based on geographic dispersion. A firm that files a 10–K form on or before June of year t is eligible for inclusion in a portfolio starting in July of year t. The firm carries its state count up to and including June of next year. A firm gets added to the portfolio of local firms if its state count is below the 20th percentile in the cross-section of state counts. Correspondingly, a firm gets added to the portfolio of dispersed firms if the state count exceeds the 80th percentile. Three more portfolios are formed using the 40th and the 60th percentile as breakpoints. The regression model is:

$$r_{pt} = \alpha_p + \beta_1(\mathrm{Mkt} - \mathrm{Rf})_t + \beta_2\mathrm{SMB}_t + \beta_3\mathrm{HML}_t + \beta_4\mathrm{MOM}_t + \beta_5\mathrm{LIQ}_t + e_t$$

where r_{pt} is either a portfolio excess return (Panel A) or the return on a zero investment portfolio long local firms and short geographically dispersed firms (Panels B and C). The market portfolio Mkt-Rf, the size-factor SMB, the book-to-market factor HML, and the momentum factor MOM are downloaded from Ken French's website. The liquidity factor LIQ is the "traded" liquidity factor of Pástor and Stambaugh (2003). The coefficients are estimated using OLS. The column labeled T reports the number of monthly observations. The column labeled AR^2 contains the adjusted R-squared. The numbers in parentheses are t-statistics computed from the heteroscedasticity consistent standard errors of White (1980). Portfolio returns are measured in percent. The sample period is July 1994 through December 2008.

Portfolio	Alpha	Mkt−Rf	SMB	HML	MOM	LIQ	T	AR^2
A. Portfolios Formed Based on Geographic Dispersion Quintiles (EW returns)								
Local	0.48 (2.66)	0.85 (16.55)	0.94 (12.19)	0.08 (1.06)	−0.10 (−1.32)	0.00 (0.10)	174	0.88
2	0.25 (1.16)	0.94 (16.12)	1.00 (10.84)	0.05 (0.65)	−0.17 (−1.76)	0.05 (0.99)	174	0.88
3	0.09 (0.51)	0.95 (18.95)	0.97 (13.31)	0.15 (2.37)	−0.11 (−1.54)	0.07 (1.68)	174	0.90
4	0.01 (0.06)	0.99 (24.68)	0.86 (16.51)	0.30 (6.10)	−0.05 (−0.99)	0.06 (1.88)	174	0.93
Dispersed	−0.22 (−2.06)	0.94 (27.58)	0.67 (14.78)	0.51 (10.14)	0.03 (0.61)	0.07 (2.12)	174	0.94
B. Portfolios Long in Local Firms and Short in Dispersed Firms Using All Firms								
EW returns	0.70 (4.45)	−0.09 (−2.02)	0.27 (3.80)	−0.44 (−6.56)	−0.13 (−2.36)	−0.06 (−1.49)	174	0.50
VW returns	0.50 (2.81)	0.05 (1.01)	0.02 (0.38)	−0.35 (−5.19)	−0.13 (−2.48)	−0.02 (−0.34)	174	0.24
C. Portfolios Long in Local Firms and Short in Dispersed Firms Dropping Micro-Caps								
EW returns	0.32 (2.40)	0.05 (1.17)	0.22 (3.68)	−0.43 (−7.68)	−0.17 (−4.27)	−0.02 (−0.59)	174	0.58
VW returns	0.51 (2.82)	0.06 (1.02)	−0.01 (−0.12)	−0.36 (−5.18)	−0.13 (−2.58)	−0.02 (−0.29)	174	0.23

Table 5
Time-series averages of Cross-sectional Regression Coefficients

The table reports time-series averages of cross-sectional regression coefficients from the following model:

$$R_{it} - R_{ft} = c_0 + \sum_{m=1}^{M} c_{im} Z_{mit} + e_{it}$$

where R_{it} is return on stock i in month t, R_{ft} is the monthly yield on 30-day Treasury bills, Z_{mit} is one of M firm characteristics: Geographic dispersion, the natural logarithm of the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. Each monthly cross-sectional regression uses the state count from last June. Size, the natural logarithm of the market capitalization in month $t-2$. Book-to-market ratio, the natural logarithm of the book-to-market ratio measured as of last June. Amihud illiquidity, the natural logarithm of the Amihud (2002) illiquidity measure computed using daily returns and volume from month $t-2$. Bid-Ask spread, the natural logarithm of $(P_A - P_B)/(0.5P_A + 0.5P_B)$ where P_A is the ask price and P_B is the bid price, both measured in month $t-2$. Volatility, the natural logarithm of the standard deviation of the error term from a regression using the three-factor model of Fama and French (1993) on one-month worth of daily data. Momentum, the buy-and-hold return for months $t-12$ through $t-2$. One-Month Lagged Return, return for month $t-1$. Each coefficient time-series average is multiplied with 100. Microcaps are all firms below the NYSE 20th size decile. Small firms are larger than the firm and the 20th NYSE decile and smaller than or equally sized to the firm at 50th NYSE decile. Big firms are all firms larger than the firm at the 50th NYSE decile. Parentheses contain t-statistics computed from the standard errors of the time-series. The sample period is July 1994 through December 2008.

		Cross-Sections Grouped by Size		
Independent Variable	All Firms	Microcaps	Small	Big
Geographic dispersion	−0.22 (−4.05)	−0.32 (−4.21)	−0.07 (−1.07)	−0.11 (−2.45)
Size	−0.52 (−3.33)	−1.21 (−4.55)	−0.33 (−1.68)	−0.21 (−1.57)
Book-to-market ratio	0.32 (3.38)	0.30 (2.03)	0.23 (2.16)	0.18 (1.91)
Amihud illiquidity	−0.32 (−2.98)	−0.41 (−3.45)	−0.05 (−0.42)	−0.16 (−1.54)
Bid-Ask spread	0.11 (0.90)	0.03 (0.17)	−0.26 (−1.76)	−0.01 (−0.13)
Volatility	−0.16 (−0.63)	−0.13 (−0.46)	−0.30 (−1.14)	−0.32 (−1.32)
Momentum	0.43 (2.14)	0.71 (3.38)	0.21 (0.95)	0.49 (1.51)
One-Month Lagged Return	−4.02 (−5.57)	−4.58 (−5.56)	−1.58 (−1.99)	−1.56 (−1.70)
Intercept	3.45 (2.05)	5.22 (2.48)	1.00 (0.50)	−0.27 (−0.14)
Avg. cross-sectional obs.	3,671	2,111	765	795
Number of cross-sections	174	174	174	174
Avg. R^2	0.05	0.05	0.06	0.09

Table 6
Jensen's Alpha for Equally-Weighted Portfolios Formed using Firms Headquartered in States with Low, Medium, and High Firm Density

U.S. states are ranked according to the ratio of firms headquartered in the state to total population in the state. Low firm density states, medium firm density states, and high firm density states are formed using breakpoints that ensure that the number of firms in each group is approximately the same. The high firm density states are: California, Minnesota, New Jersey, Colorado, Connecticut, and Massachusetts. Geographic dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. A firm is local if it is among the 20% least geographically dispersed firms. A firm is Dispersed if it is among the 20% most geographically dispersed firms. The regression model is:

$$r_{pt} = \alpha_p + \beta_1(\text{Mkt} - \text{Rf})_t + \beta_2\text{SMB}_t + \beta_3\text{HML}_t + \beta_4\text{MOM}_t + \beta_5\text{LIQ}_t + e_t.$$

In Panel A, r_{pt} for $p \in \{\text{Low}, \text{Medium}, \text{High}\}$ are portfolios of all local firms headquartered in a state that has Low, Medium, and High Firm densities. In Panel B, the portfolios are long local firms and short geographically dispersed firms. All portfolio returns are equally weighted. The market portfolio Mkt-Rf, the size-factor SMB, the book-to-market factor HML, and the momentum factor MOM are downloaded from Ken French's web-site. The liquidity factor LIQ is the "traded" liquidity factor of Pástor and Stambaugh (2003). The coefficients are estimated using OLS. The numbers in parentheses are t-statistics computed from the heteroscedasticity consistent standard errors of White (1980). The sample period is July 1994 through December 2008, but, months where the geographic dispersion portfolio contains less than 15 firms are dropped from the time-series.

	All Firms				Microcaps				Small				Big			
	Alpha		T	AR^2	Alpha		T	AR^2	Alpha		T	AR^2	Alpha		T	AR^2
A. Portfolios of Local Firms by U.S. State Firm Density																
Low Firm Density States	0.46	(3.04)	174	0.85	0.65	(2.98)	162	0.73	0.25	(1.03)	162	0.78	0.03	(0.18)	174	0.83
Medium Firm Density States	0.78	(4.25)	174	0.86	0.93	(3.63)	174	0.75	0.29	(1.93)	174	0.91	0.47	(3.78)	174	0.92
High Firm Density States	1.04	(4.19)	174	0.85	1.25	(3.62)	162	0.77	0.78	(3.75)	162	0.91	0.87	(3.77)	174	0.86
High Density − Low Density	0.58	(2.64)	174	0.63	0.60	(2.05)	162	0.53	0.53	(1.67)	162	0.52	0.84	(2.85)	174	0.56
B. Portfolios Long Local Firms and Short Dispersed Firms by U.S. State Firm Density																
Low Firm Density States	0.47	(2.83)	174	0.28	0.72	(3.39)	150	0.38	0.29	(1.08)	162	0.09	−0.07	(−0.38)	174	0.06
Medium Firm Density States	0.67	(4.60)	174	0.40	0.89	(5.26)	162	0.31	0.36	(1.93)	174	0.19	0.30	(1.96)	174	0.17
High Firm Density States	0.83	(3.57)	174	0.51	1.42	(4.12)	150	0.38	0.22	(0.74)	162	0.52	0.65	(2.77)	174	0.49
High Density − Low Density	0.36	(1.72)	174	0.41	0.70	(1.86)	150	0.29	−0.07	(−0.18)	162	0.27	0.72	(2.65)	174	0.37

Table 7
Jensen's Alpha for Equally-Weighted Double Sorted Portfolios Long in Local Firms and Short in Geographically Dispersed Firms

Geographic dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. A firm is local if it is among the 20% least geographically dispersed firms. A firm is Dispersed if it is among the 20% most geographically dispersed firms. The regression model is:

$$r_{Lt} - r_{Dt} = \alpha_p + \beta_1(\text{Mkt} - \text{Rf})_t + \beta_2\text{SMB}_t + \beta_3\text{HML}_t + \beta_4\text{MOM}_t + \beta_5\text{LIQ}_t + e_t$$

where $r_{Lt} - r_{Dt}$ is a zero investment portfolio long local firms and short geographically dispersed firms. Portfolio returns are equally weighted. The market portfolio Mkt-Rf, the size-factor SMB, the book-to-market factor HML, and the momentum factor MOM are downloaded from Ken French's web-site. The liquidity factor LIB is the "traded" liquidity factor of Pástor and Stambaugh (2003). The coefficients are estimated using OLS. The numbers in parentheses are t-statistics computed from the heteroscedasticity consistent standard errors of White (1980). The sample period is July 1994 through December 2008, but, months where the geographic dispersion portfolio contains less than 15 firms are dropped from the time-series.

	All Firms			Microcaps			All but Microcaps		
Portfolio	Alpha	T	AR^2	Alpha	T	AR^2	Alpha	T	AR^2
A. Amihud Illiquidity									
Liquid	0.32 (1.80)	174	0.62	0.86 (3.56)	163	0.38	0.50 (2.35)	174	0.49
Medium	0.71 (3.96)	174	0.39	0.98 (4.99)	162	0.20	0.22 (1.04)	174	0.52
Illiquid	0.93 (5.41)	162	0.28	1.04 (4.07)	162	0.20	0.29 (1.78)	174	0.32
Illiquid−Liquid	0.62 (2.69)	162	0.46	0.18 (0.52)	162	0.08	−0.21 (−0.98)	174	0.29
B. Bid-Ask Spread									
Small	0.33 (1.96)	174	0.62	0.59 (3.24)	173	0.23	0.36 (1.81)	174	0.58
Medium	0.71 (3.25)	174	0.21	0.93 (4.19)	162	0.24	0.22 (1.19)	174	0.50
Large	1.13 (5.68)	162	0.40	1.23 (4.84)	162	0.28	0.33 (1.57)	174	0.16
Large−Small	0.83 (3.62)	162	0.25	0.53 (1.73)	162	0.05	−0.03 (−0.10)	174	0.31
C. Volatility									
Low	0.40 (3.46)	174	0.35	0.41 (2.62)	174	0.32	0.27 (2.57)	174	0.20
Medium	0.63 (3.80)	174	0.41	1.11 (5.32)	162	0.35	0.29 (1.65)	174	0.24
High	1.25 (5.25)	162	0.40	1.22 (3.68)	151	0.30	0.55 (2.37)	174	0.47
High−Low	0.87 (3.54)	162	0.31	0.68 (1.87)	151	0.31	0.28 (1.26)	174	0.38

Table 8
Jensen's Alpha for Portfolios Long in Local Firms and Short in Geographically Dispersed Firms by Industries and using EW returns

Geographic dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. A firm is local if it is among the 20% least geographically dispersed firms. A firm is Dispersed if it is among the 20% most geographically dispersed firms. The regression model is:

$$r_{Lt} - r_{Dt} = \alpha_p + \beta_1(\text{Mkt} - \text{Rf})_t + \beta_2\text{SMB}_t + \beta_3\text{HML}_t + \beta_4\text{MOM}_t + \beta_5\text{LIQ}_t + e_t$$

where $r_{Lt} - r_{Dt}$ is a zero investment portfolio long local firms and short geographically dispersed firms. The market portfolio Mkt-Rf, the size-factor SMB, the book-to-market factor HML, and the momentum factor MOM are downloaded from Ken French's web-site. The liquidity factor LIQ is the "traded" liquidity factor of Pástor and Stambaugh (2003). The coefficients are estimated using OLS. The numbers in parentheses are t-statistics computed from the heteroscedasticity consistent standard errors of White (1980). The sample period is July 1994 through December 2008, but, months where the geographic dispersion portfolio contains less than 15 firms are dropped from the time-series.

	Alpha	T	AR^2
A. Double Sorts Using 8 Industries and Quintiles of Geographic Dispersion			
Consumer Durables and Non-Durables	−0.09 (−0.36)	174	0.07
Manufacturing	0.55 (2.07)	174	0.23
Energy and Chemicals	0.54 (1.67)	174	0.03
Business Equipment, Telecom and Utilities	0.66 (2.53)	174	0.52
Wholesale and Retail	0.82 (3.30)	174	0.09
Health	0.86 (2.21)	173	0.34
Finance	0.62 (3.61)	174	0.27
Other	0.85 (3.22)	174	0.30
F-test of equal alphas	1.68 [0.11]	8×173	
B. Individual Stock Returns Replaced with Industry Portfolio Returns			
Local	0.15 (1.00)	174	0.92
Dispersed	−0.02 (−0.15)	174	0.92
Local − Dispersed	0.17 (3.55)	174	0.43

Table 9
Jensen's Alpha for Portfolios Long in Local Firms and Short in Geographically Dispersed Firms Using Alternative Measures of Geographic Dispersion

Geographic dispersion is measured as the number of U.S. states mentioned in the annual report filed on form 10–K with the SEC. A firm is local if it is among the 20% least geographically dispersed firms. A firm is Dispersed if it is among the 20% most geographically dispersed firms. The regression model is:

$$r_{Lt} - r_{Dt} = \alpha_p + \beta_1 (\mathrm{Mkt} - \mathrm{Rf})_t + \beta_2 \mathrm{SMB}_t + \beta_3 \mathrm{HML}_t + \beta_4 \mathrm{MOM}_t + \beta_5 \mathrm{LIQ}_t + e_t$$

where $r_{Lt} - r_{Dt}$ is a zero investment portfolio long local firms and short geographically dispersed firms. The market portfolio Mkt-Rf, the size-factor SMB, the book-to-market factor HML, and the momentum factor MOM are downloaded from Ken French's web-site. The liquidity factor LIQ is the "traded" liquidity factor of Pástor and Stambaugh (2003). The coefficients are estimated using OLS. The numbers in parentheses are t-statistics computed from the heteroscedasticity consistent standard errors of White (1980). The sample period is July 1994 through December 2008, but, months where the geographic dispersion portfolio contains less than 15 firms are dropped from the time-series.

	EW Returns				VW Returns			
Measure of Geographic Dispersion	Alpha		T	AR^2	Alpha		T	AR^2
1 − Herfindahl	0.50	(3.75)	174	0.39	0.49	(2.87)	174	0.31
U.S. Divisions	0.52	(5.71)	174	0.35	0.55	(3.60)	174	0.09
Dropping Firms when Present in:								
One or More Countries	0.51	(2.07)	144	0.14	0.84	(2.28)	144	-0.02
Five or More Countries	0.65	(4.11)	174	0.42	0.44	(1.83)	174	0.34
Country Names	−0.12	(−0.80)	174	0.57	−0.25	(−1.27)	174	0.19