Geographic Momentum

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ABSTRACT

We document geographic momentum: a positive lead-lag stock return relation between neighboring firms operating in different sectors. Geographic momentum yields risk-adjusted returns of 5-6% per year, about half that observed for industry momentum. However, while industry momentum is strongest among thinly traded, small firms, and/or those with scant analyst following, geographic momentum is *unrelated* to these proxies for information processing. We propose an explanation linking this to the structure of the investment analyst business, which is organized by sector, rather than by geographic region.

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1 Introduction

Stock prices of firms with similar characteristics tend to move together. However, empirical studies document significant lead-lag relationships, indicating that, even among related firms, some stocks react to information before others. Indeed, the popular pairs trading strategy used by many quantitative hedge funds exploits, but apparently does not completely eliminate, this mispricing.

An important ingredient of any lead-lag strategy is categorization – i.e., sorting firms into groups based on one or more similar attributes. These attributes generally proxy for common sources of cash flow variation, and because investor clienteles tend to arise based on these attributes, they may also proxy for common sources of discount rate variation. In this paper, we explore the possibility that common clienteles create a type of echo chamber, whereby information is rapidly disseminated within groups, but less so outside them. Our main hypothesis is that scrutiny by a *common set of investors and analysts* facilitates the incorporation of information into prices, but that (even intense) scrutiny by non-overlapping sets of individuals lead to incomplete price reactions, and generates lead-lag effects.

We illustrate our intuition with a simple descriptive model where one firm announces its earnings early (at date 1), with two others announcing later (date 2). Earnings are generated by an industry factor, a location factor, and a firm-specific factor. As such, early earnings announcements provide information about factor realizations that can help predict the earnings of the late announcers. To keep our analysis simple, we assume the early announcer shares (only) an industry factor with one of the late announcers, and (only) a location factor with the other late announcer.

If markets are perfectly efficient, both late announcers' stock prices will fully respond to the earnings release of the early announcer. In other words, prices fully respond to realizations of both the industry factor and the geography factor. In the polar opposite case, late announcers' stock prices react only when they disclose earnings, i.e., late announcers fail to react when early announcers' earnings are released. Here, prices of the late announcers underreact to both the industry factor and the geography factor. The resulting lead-lag patterns give rise to momentum among industry or geographically sorted portfolios. Our focus is on an intermediate case, where only some firms underreact. The model's key source

of heterogeneity is the extent to which two firms are scrutinized by a common set of investors. More overlap hastens the incorporation of common information into prices, thereby weakening lead-lag effects, and reducing profits from a momentum strategy that exploit them.

Our empirical tests are guided by the structure of the institutional investment business. In particular, both sell-side and buy-side analysts are typically organized along industrial, rather than geographic, lines. As a result, our model predicts significant lead-lag effects within industry groups *only* for small stocks that are scrutinized by very few analysts, with little if any effect for large, heavily scrutinized firms with significant analyst overlap.

In contrast, for geographic peers in different sectors, analyst overlap tends to be minimal, even for firms scrutinized by a large number of industry-focused analysts. Among such firms, the model assumes limited awareness of and/or communication between their respective analysts, leading to lead-lag between geographic peers, irrespective of how many analysts follow each firm *individually*. In other words, even large firms will under react to pertinent geographic information.

To test these hypotheses, we run regressions that predict individual stock returns with the lagged returns of two portfolios: the stock's industry (non-local) peers and the stock's local (non-industry) neighbors. Both regressors are significant. We find that a 1% change in the prior month's returns of the industry portfolio forecasts a 20 basis point return the following month, consistent with Moskowitz and Grinblatt (1999)'s original documentation of industry momentum. The lagged returns of a firm's geographic peers also predict a stock's return, with magnitudes roughly one-half to one-third the magnitude generated in our industry-sorted regressions.

Consistent with most other anomalies, industry lead-lag decreases in firm size, with the largest firms exhibiting less than half the predictability of small firms. Likewise, the magnitude of the abnormal returns displays a strong decreasing relation with both trading volume and analyst coverage. These findings are consistent with our model: as the number of analysts following a firm increases, so too does the chance of overlap between one or more industry peers. Thus, industry lead-lag is expected (and is found) to be strongest for small firms with few analysts, and weaker or even absent among firms with high analyst following.

A starkly different picture emerges when examining lead-lags between geographic peers.

Rather, geographic lead-lag appears to be completely unrelated to proxies for the richness of the information environment, a key distinction not only with other lead-lag evidence, but also with most other asset pricing anomalies. For example, when attempting to predict a firm's one-month returns from the one-month lagged area returns of its geographic neighbors, we estimate a sensitivity of 0.072 ($t = 3.78$) for the quartile with lowest trading volume, and 0.100 ($t = 4.94$) for the quartile with the most. With analyst coverage, the quartiles with strongest area-level predictability are those with the third (0.071, $t = 3.75$) and fourth (0.066, $t = 2.51$) highest levels. Cuts on firm size produce similar patterns, with geographic lead-lag being significant and stable in every quartile.

These non-results are likewise consistent with our stylized model, combined with our observations about the structure of the analyst business. For, even among industry leaders headquartered nearby – e.g., Google and Genentech (both Bay Area), Target and General Mills (both Twin Cities), or Home Depot and Coca Cola (both Atlanta) – the lack of industry overlap means that few, if any analysts, will simultaneously cover both firms in the respective local pair. Thus, the recognition and/or transmission of area-level information is retarded just as much for large, heavily scrutinized large firms as it is for small, less scrutinized ones.

As an illustration, we calculate the returns of investment strategies that are implemented on a set of $20 \times 12 = 240$ city-industry portfolios, e.g., Denver-Manufacturing, Seattle-Health Care, Philadelphia-Telecommunications, and Boston-Utilities. Within every month, we rank each portfolio based on the average, one-month lagged returns of the eleven portfolios constructed in the same area, but outside the industry. The long-short hedge portfolio that buys (shorts) city/industry portfolios ranked in the top (bottom) 20% yields monthly profits of about 42 basis points per month, with a Fama-French (FF-3) alpha of 5.4% per year. Repeating this exercise, but focusing only on the top 20% of firms when ranked by market capitalization, we find profits of 43 basis points per month and a nearly identical FF-3 alpha of 5.6%.

Although our focus on geographically sorted lead-lags is novel, there is a large literature that explores non-synchronous return patterns. Atchison et al. (1987) was among the earliest to consider how these patterns generate serial correlation in portfolio returns. Lo and MacKinlay (1990) were the first to link lead-lags to the profitability of contrarian strategies, and to show that size is a determinant of lead-lag effects across securities, with large

firms leading small firms. Brennan et al. (1993), Badrinath et al. (1995) and Chordia and Swaminathan (2000) linked lead-lag return patterns to analyst coverage, institutional ownership and trading volume, respectively.[1] Relative to these earlier papers, our contribution is to more explicitly understand the channel linking the level of scrutiny to observed lead-lag relationships.

We are also not the first to suggest that lead-lag effects are generated by slow information diffusion. Hong et al. (2000), for example, finds that momentum – particularly when firms with negative returns are involved – weakens sharply with firm size and analyst coverage. This suggests that delayed awareness of, or reaction to, information is responsible for the sluggish price reaction observed in momentum. Other prominent examples include Cohen and Frazzini (2008), which examines the lead-lag relation between the stock returns of firms in a supply chain, and Cohen and Lou (2012), which documents underreaction between focused firms and conglomerates. We, however, are the first to explicitly tie the nature of the lead-lag relation to the *organization* of the analyst community, to examine how the lead-lag relation depends on investor scrutiny in alternative settings, and to document significant momentum within geographically-sorted portfolios.

Our paper is also related to the literature on limited attention, which provides a behavioral explanation for why stock prices may react sluggishly to public information (Hirshleifer et al. (2011)). Early work on this topic (Hirshleifer and Teoh (2003)) emphasizes how the information's presentation and/or timing chosen by firms can affect investors' abilities to process disclosures. Subsequent studies extend to consider events outside the firm using, for example, the day of the week (DellaVigna and Pollet (2009)) or number of competing news releases (Hirshleifer et al. (2009)) to measure 'information overload' by investors, during which underreaction is more severe. One contribution of our study is to provide an *institutional* rationale for limited attention, i.e., drawing on the structure of the investment analyst

[1] Numerous prior studies have examined lead-lag relationships in stock returns. Jegadeesh and Titman (1995) found that delayed reactions to common factors give rise to a size-related lead-lag effect in stock returns, while Mech (1993) and McQueen et al. (1996) showed that lead-lag effects can also be the result of non-synchronous trading or time-varying expected returns. Hou (2007) found that the lead-lag relationship between large and small firms found in the literature is predominantly an intra-industry phenomenon. Within the same industry, big firms lead small firms, and this effect is more important than the effect across industries. Hameed and Mian (2015) find intra-industry reversals in monthly returns that are consistently present over time, and prevalent across subgroups of stocks, including large and liquid stocks.

business to motivate why analysts and investors organize their information gathering efforts as they do.

Our focus on regional patterns in stock returns builds on Pirinsky and Wang (2006), which documents comovement (but not lead-lags) among firms headquartered in the same location, and on Korniotis and Kumar (2013), which examines the link between state-level economic variables and (future) stock returns of locally headquarters firms.[2] Our paper suggests that common variation in cash flows may also be important for neighboring firms, and that the market's awareness of these regional linkages may be incomplete.

Our paper is organized as follows. Section 2 begins with a simple model of underreaction. The key assumption is that when two firms are covered by a common analyst, common sources of information are incorporates quickly into prices, compared to two firms with non-overlapping analysts. The remainder of the paper is empirical, comparing lead-lag effects between industry peers (who are more likely to have common analysts) and firms headquartered nearby, but in different sectors (where analyst overlap is unlikely). In Section 3 we describe our sample, and in Section 4, we present our main results: significant lead-lags both at the industry and geographical level. How these sources of return predictability differ, one of our main interests, is described in Section 4.3. Specifically, while industry-level under-reaction is limited to small, thinly traded firms, area-level under-reaction persists even among large, highly scrutinized firms. Section 5 provides some alternative specifications and robustness checks. We conclude in Section 6.

2 Background and Theoretical Motivation

This section provides institutional details and a simple model that motivates our empirical analysis. Our characterization of the investment analyst business, discussed in subsection 2.1, describes prior research as well as stylized facts that demonstrate the high degree of sector concentration/focus observed among equity analysts. We then draw on these insights

[2] Other papers that examine the impact of location on asset prices and firm policies include Hong et al. (2008), Becker et al. (2011), John et al. (2011), Garcia and Norli (2012), Kumar et al. (2013), Tuzel and Zhang (2015) and Bernile et al. (2015b). Both papers emphasize that discount rates may be influenced by local factors, particularly when a firm's investors are geographically concentrated and undiversified.

in subsection 2.2 to develop a simple model that generates cross-serial correlation at both the regional and industry level.

2.1 Analyst specialization by industry

Sell-side equity analysts tend to specialize by industry. This is not particularly surprising given the evidence of industry factors generating both investment rates and profitability.[3] Academic research confirms the importance of industry affiliation in the day-to-day operations, evaluation, and career paths of analysts. Kadan et al. (2012) document, for example, that industry expertise is a key dimension that defines an analyst's skill. Being recognized by institutional clients as an "all star" depends on a ranking between analysts covering firms in a given sector (Stickel (1992), Clement (1999)).

Figure 2 provides an indication of the importance of industry affiliation in the analyst community. The figure plots the percentage of firms (from 1993-2013) that are in an analyst's modal industry sector. For example, in 1995, the graph indicates that for the median analyst, about 83% of covered stocks were in the same industry. The interquartile range is also informative, indicating that on average, 75% of analysts spend two-thirds of their time on a single sector, with more than 25% being fully concentrated in one industry. A direct implication is that firms within the same industry tend to be covered largely by a common set of analysts. As we illustrate in the model below, this overlap in analyst coverage has an important effect on the lead-lag relation between the returns of individual stocks.

2.2 Industry and geographic momentum: a stylized model

We begin with a stylized model that explicitly links overlapping analyst coverage for a pair of stocks and lead-lag effects in their respective returns. The model assumes that in addition to firm specific shocks, there are two sources of potentially common variation – industry and regional factors. The workhorse assumption is a type of *industry focused limited attention*

[3] Schmalensee (1985)'s seminal study used cross-sectional data from the year 1975 to decompose the rates of return on assets into industry, firm, and market-specific factors. Industry factors were identified as the most important in generating differences in performance between firms. Though the findings and interpretation have been challenged – most prominently by Rumelt (1991) – subsequent work, e.g., McGahan and Porter (1997) continues to identify industry affiliation as a key source of variation between business units.

resulting from stock analysts' disproportionate focus on a small number of industry sectors. As our model illustrates, this focus implies that prices tend to more efficiently reflect common industry factors, especially for large, highly scrutinized firms. In contrast, the model predicts that prices may not immediately reflect regional shocks, but this mispricing will not depend on firm size or analyst coverage. The latter effect is exhibited as a lead-lag relation between neighboring firms operating in different industries.

2.2.1 Timing and Payoffs

The model has three dates, $t = 0, 1, 2$, and involves three firms $i \in \{1, 2, 3\}$. The interest rate is zero, and all investors are risk neutral. Each firm i realizes a liquidating dividend π_i at $t = 2$. The realization of the liquidating dividend depends on three factors: 1) an industry factor I, 2) a local factor L, and 3) a firm-specific factor ϵ.

There are two industries A and B, and two locations, X and Y. Firms 1 and 2 are in the same industry, and thus share industry shocks (I_A), but realize different values of the local shock, denoted L_X and L_Y, respectively. Firms 2 and 3, on the other hand, are both headquartered in location Y, but because they operate in different industries, are exposed, respectively, to I_A and I_B. Combining these assumptions, the realization of firm i's liquidating dividend at $t = 2$ is:

$$
\begin{aligned}
\pi_1 &= I_A + L_X + \epsilon_1 \\
\pi_2 &= I_A + L_Y + \epsilon_2 \\
\pi_3 &= I_B + L_Y + \epsilon_3.
\end{aligned}
\tag{1}
$$

Industry, area, and firm-specific shocks are all normally distributed, i.e., $(I_A, I_B) \sim N(0, \sigma_I^2 = \frac{1}{\tau_I})$, $(L_X, L_Y) \sim N(0, \sigma_L^2 = \frac{1}{\tau_L})$, and $(\epsilon_1, \epsilon_2, \epsilon_3) \sim N(0, \sigma_\epsilon^2 = \frac{1}{\tau_\epsilon})$. The covariance between all signals, both within and across groups, is zero.

The relevant timing is shown in the timeline below. Initially, at $t = 0$, the expected liquidating dividends for each firm, and thus prices, are zero, i.e., $P^1_{t=0} = P^2_{t=0} = P^3_{t=0} = 0$. At $t = 1$, firms 1 and 3 both announce earnings, information which can be used to update the stock price of firm 2. The model ends at $t = 2$, where the realization of π_2 is observed.

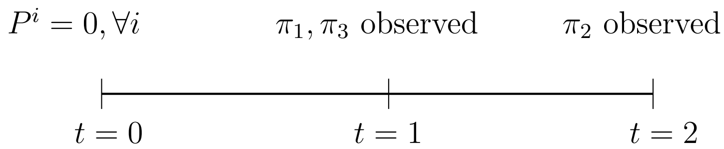

Figure 1: Timeline

2.2.2 Analyst reports

The model focuses on the stock price of firm 2, which shares an industry linkage (and only an industry linkage) with firm 1, and (only) a location linkage with firm 3. Analysts play an important role in the way stock prices are determined. Specifically, there exist a set of analysts indexed by $n \in \{1, 2, 3, ...N\}$ that cover stock 2, each of which may or may not also cover its industry peer (firm 1) or geographic neighbor (firm 3). Investors read analysts reports, and set the price of firm 2 as the expectation of π_2, conditional on the information produced by analysts that cover firm 2. Denoting the report produced by analyst n as r_n,

$$P^2_{t=1} = E[\pi_2|(r_1, r_2, r_3, ...r_N)]. \tag{2}$$

The model takes a stylized view of analyst reports. In reality, analysts and investors collect and analyze information from a wide variety of sources, many of which are specific to firm being covered (e.g., talking with management, surveying customers, etc.). However, because we are interested in cross-serial correlation *between* firms, rather than *within* them, we focus on information about other companies that analysts may view as relevant. In particular, analyst n may choose to report π_1, the profit of firm 2's industry peer, and/or π_3, the profit of firm 2's geographic neighbor. There are thus four possible reports each analyst can produce: $\{\pi_1, \pi_3\}, \{\pi_1\}, \{\pi_3\}, \{\}$.

The first would correspond to an analyst that followed both firms 1 and 3, in addition to firm 2 (the subject of his report). The second and third, respectively, correspond to analysts that cover only firm 2's industry peer (firm 1) and geographic neighbor (firm 3). In the last

case, the analyst covers neither firm 1 nor 3, and therefore reports neither's profits in his report.

Because investors of firm 2 read all available reports, they form expectations using the union of all information produced by the analyst community. Thus, from a pricing standpoint, it would make no difference whether all the information came from one analyst (e.g., $r_1 = \{\pi_1, \pi_3\}, r_2 = \{\}$), or whether the information is spread across analysts (e.g., $r_1 = \{\pi_1\}, r_2 = \{\pi_3\}$). The same intuition applies for more than two analysts, and for different values for the union of all reports. For example, the price formed with the set of reports ($r_1 = \{\pi_1\}, r_2 = \{\pi_1\}, r_3 = \{\pi_1\}, r_4 = \{\pi_1\}$) would be the same as that formed as with reports ($r_1 = \{\pi_1\}, r_2 = \{\}, r_3 = \{\}, r_4 = \{\}$).

2.2.3 Price and returns

Using the factor structure in Equation 1 as given, the stock price of firm 2 at $t = 1$ can take on four possible values:

$$P^2_{t=1} = \begin{cases} 0 & \text{if neither } \pi_1 \text{ nor } \pi_3 \text{ reported,} \\ \pi_1\left(\frac{\sigma_I^2}{\sigma_I^2+\sigma_L^2+\sigma_\epsilon^2}\right) & \text{if only } \pi_1 \text{ reported,} \\ \pi_3\left(\frac{\sigma_L^2}{\sigma_I^2+\sigma_L^2+\sigma_\epsilon^2}\right) & \text{if only } \pi_3 \text{ reported,} \\ \pi_1\left(\frac{\sigma_I^2}{\sigma_I^2+\sigma_L^2+\sigma_\epsilon^2}\right) + \pi_3\left(\frac{\sigma_L^2}{\sigma_I^2+\sigma_L^2+\sigma_\epsilon^2}\right) & \text{if both } \pi_1 \text{ and } \pi_3 \text{ reported.} \end{cases}$$

In the first case when neither π_1 nor π_3 is reported by the analyst community, no updating occurs, and $P^2_{t=1} = 0$. In the second case, only the industry signal is reported; here, $P^2_{t=1}$ is efficient with respect to industry information (π_1), but inefficient with respect to the geographical shock reflected by π_3. The third case is the converse, with $P^2_{t=1}$ capturing the impact of geographic, but not industry, information. The final case corresponds to the fully efficient case, where both industry and geographic shocks are appropriately incorporated into the stock price of firm 2.

We wish to characterize the conditional expected return of firm 2 from $t = 1$ to $t = 2$, using either the $t = 0$ to $t = 1$ return of firm 1 as the conditioning variable, $E[P^2_{t=2} - P^2_{t=1}|P^1_{t=1}]$, or the return of firm 3 over the same horizon, $E[P^2_{t=2} - P^2_{t=1}|P^3_{t=1}]$. The first

corresponds to cross-serial correlation between industry peers (industry momentum), and the second to cross-serial correlation between local neighbors that are in different industries (geographic momentum).

Calculating these quantities requires the probabilities for the prices given above. However, the fact that π_1 and π_3 are statistically independent allows us to take a notational shortcut. Rather than having to specify prices for each price realization (four probabilities), all that is needed is the probability of π_1 being reported, irrespective of whether π_3 is reported, and vice versa. Denote these, respectively, as $p_1(N)$ and $p_3(N)$. We will later be explicit about how $p_1(N)$ and $p_3(N)$ are expected to vary with the number of analysts N, as well as potentially with firm size, but for now we treat them as constant.

Industry momentum occurs when $cov(P^1_{t=1} - P^1_{t=0}, P^2_{t=2} - P^2_{t=1}) = cov(\pi_1, \pi_2 - P^2_{t=1}) > 0$. Expanding this using the factor structure given in Equation 1, we have

$$\begin{aligned}
cov(\pi_1 - 0, \pi_2 - P^2_{t=1}) &= cov(\pi_1, \pi_2) - cov(\pi_1, P^2_{t=1}) \\
&= \sigma^2_I - cov\Big(\pi_1, \frac{\sigma^2_I}{\sigma^2_I + \sigma^2_L + \sigma^2_\epsilon} p_1(N)\pi_1 + \frac{\sigma^2_L}{\sigma^2_I + \sigma^2_L + \sigma^2_\epsilon} p_3(N)\pi_3\Big) \\
&= \sigma^2_I(1 - p_1(N)).
\end{aligned}$$

Regional momentum takes a similar form:

$$\begin{aligned}
cov(\pi_3 - 0, \pi_2 - P^2_{t=1}) &= cov(\pi_3, \pi_2) - cov(\pi_3, P^2_{t=1}) \\
&= \sigma^2_L - cov\Big(\pi_3, \frac{\sigma^2_L}{\sigma^2_I + \sigma^2_L + \sigma^2_\epsilon} p_1(N)\pi_1 + \frac{\sigma^2_I}{\sigma^2_I + \sigma^2_L + \sigma^2_\epsilon} p_3(N)\pi_3\Big) \\
&= \sigma^2_L(1 - p_3(N)).
\end{aligned}$$

Proposition 1. *The magnitude of industry and regional momentum 1) decreases with the probability that the relevant signal is observed, p, and 2) increases with the variance of the shock, σ.*

For any mispricing (in expectation) to occur at $t = 1$, there must be some probability that investors of firm 2 ignore relevant information conveyed in the profits of its industry ($p_1 < 1$) and/or geographic peers ($p_3 < 1$). High values for these probabilities – i.e., when investors are more attentive – imply a more efficient stock price for firm 2 at $t = 1$, and accordingly,

less return predictability between $t = 1$ and $t = 2$. Moreover, shocks arising from a more volatile distribution are associated, in expectation, with stronger predictability. Intuitively, for a given probability that a signal is ignored $(1-p)$, shocks with higher volatility create a larger wedge between prices and fundamental value.

These observations will be useful when we compare the magnitudes of industry and geographic momentum in our empirical tests. We generally expect industry shocks to have more influence on cash flows than geographic shocks ($\sigma_I > \sigma_L$), but the probability that regional shocks are reported by analysts is probably less ($p_3 < p_1$). Consequently, it is an empirical question which effect dominates.

2.2.4 Varying the number of analysts N

To this point, we have taken $p_1(N)$ and $p_3(N)$ as given, so as to simplify the return predictability expressions. We now attempt to be more explicit about their relationship with the number of analysts (N) covering firm 2. In addition to comparing the average magnitudes observed for industry and geographic momentum, an important part of our empirical work will explore the impact of analyst coverage on both types of return predictability. As we now show, the number of analysts following a given stock has potential implications for any lead-lag relation its return may have with respect to industry and/or regional portfolios.

Recall that a report may take on four possible values: $\{\pi_1, \pi_3\}, \{\pi_1\}, \{\pi_3\}, \{\}$. Denote the probability of each, respectively, as x, y, z, and $1-x-y-z$. Let us assume that reports are written independently. Then, with N reports, the aggregate probability that π_1 is reported by at least one analyst, $p_1(N)$, is equal to $1-(1-x-y)^N$. Likewise, the analogous expression for π_3 is $1-(1-x-z)^N = p_3(N)$.

One of our key assumptions is that analysts are unlikely to cover firms operating in fundamentally different sectors, consistent with the patterns observed in Figure 2. Applied to the probabilities above, this implies that $x \approx z \approx 0$, which in turn implies that $p_1(N) \approx 1-(1-y)^N$ and that $p_3(N) \approx 0$.

Two empirical implications follow. First, *industry momentum should decline with analyst coverage.* The intuition is that because analysts tend to specialize by industry, a larger number of analysts increases the probability that π_1 is reported by at least one of them.

Consequently, the chance that investors of firm 2 will become aware of firm 1's earnings – allowing them to incorporate this information into prices – increases with N.

The expression allows us to be even more specific. Noting that $\frac{\partial p_1(N)}{\partial N} = -log(1-x-y)^N(1-x-y)^N \approx -log(1-y)^N(1-y)^N$, we can see that the relation between p_1 and N depends crucially on y. When the per-analyst probability of overlap (y) is high, even a small number of analysts will virtually ensure that π_1 is reported, i.e., $p_1 \approx 1$. On the other hand, for moderate or small probabilities of overlap, p_1 continues to increase even for relatively large N. For example, if $y = .15$, then $p_1(10) = 56\%$, but increases to 96% if 20 analysts are involved.

The second implication is that *geographical momentum should be relatively insensitive to analyst following.* If the probability that a given analyst covers both 2 and 3 is sufficiently small, then not only is p_3 similarly small, but is relatively insensitive to changes in N. As the mirror image to p_1, $\frac{\partial p_3(N)}{\partial N} = -log(1-x-z)^N(1-x-z)^N \approx 0$. For example, if $x + z = .01$, then with five analysts (beyond the 90^{th} percentile in the data), p_3 is still less than 5%, and for ten analysts (98^{th} percentile), the probability that π_3 is reported is less than 10%. The lack of sensitivity to N implies that geographical lead-lags may remain significant, even for firms covered by a large number of analysts.

The remainder of the paper is empirical. After first describing the data in the section immediately following, we document the presence of geographic lead-lag relationships, and benchmark them against lead-lags between industry peers. We then test both empirical implications above, asking how analyst following (or other proxies for investor scrutiny) impact the magnitude of these estimated lead-lags.

3 Data and Descriptive Statistics

Firm location. Our analysis pertains to stocks headquartered in, or immediately proximate to, the twenty largest urban centers in the United States. To construct our sample, we begin with the universe of domestic common stocks (codes 10 and 11) traded on the NYSE, NASDAQ, AMEX over the period 1970-2013. Then, we assign to each firm a location variable, based on the zip code (ZIP) corresponding to its headquarter location in the COMPUSTAT database. Because COMPUSTAT lists only the zip code of the firm's *current*

headquarters, we will misclassify firms that have relocated, such as Boeing, which moved its HQ from Seattle to Chicago in 2001. Though this introduces measurement error into our analysis, this works against us, i.e., the effects we estimate will be closer to zero than they would be absent headquarter misclassification.[4]

Headquarter locations are grouped by economic areas (EA), as defined by the Bureau of Economic Analysis. EAs are intended to capture local nodes of economic activity, and typically involve a main metropolitan area, along with smaller surrounding regions from which workers may commute. Examples of EAs include San Jose-San Francisco-Oakland (CA), Atlanta-Sandy Springs-Gainesville, (GA-AL) and Houston-Baytown-Huntsville (TX).[5]

Industry Classification. In addition to categorizing firms by headquarter location, we also group them by industry affiliation. Every month, we link each firm to a single Fama-French 12 industry, which groups firms by SIC designations. The industries are non-durables (1), durables (2), manufacturing (3), energy (4), chemicals (5), business equipment (6), telecommunications (7), utilities (8), shops (9), healthcare (10), finance (11), and other (12). We intentionally select such relatively broad groupings in order to reduce the extent of overlap between firms classified in different industries.

Summary Statistics. Table 1 presents summary statistics for our sample, broken down by decade. Panel A shows the results by city (EA), and Panel B by industry. Progressing from the left to right, we see a steady increase in the number of publicly traded firms, with an average (per city) of 73 in the 1970s to 178 in the 2000s. However, this growth is unequally distributed among both cities and industries.

As shown in Panel B, "old economy" industries have dwindled since the 1970s, with declines in the number of publicly traded firms observed for non-durables, durables, manufacturing, and utilities (chemicals is virtually flat). In contrast, rapid growth is observed in business equipment (341% increase in public companies from the 1970s to 2000s), telecommunications (+273%), healthcare (+585%) and finance (+629%). Many of these same patterns are reflected in Panel A, which indicates stagnation for traditional manufacturing hubs like Detroit, St. Louis, Cleveland and Indianapolis, and a burgeoning among technology centers

[4] In Section 5.1, we perform some robustness checks by showing that misclassifying a small percentage of locations does not affect our results.

[5] Further details on the definition and characteristics of EAs can be found at http://www.bea.gov/newsreleases/regional/rea/rea1104.htm.

like Boston, Denver, Seattle, and San Francisco.

The last four columns present average monthly returns by decade for cities (Panel A) and industries (Panel B). Across industries, we observe substantial heterogeneity with, for example, the energy sector having among the highest average return of any industry in the 1970s (2.64%) and again after 2000 (1.47%), the intermediate decades being dominated by telecommunications (2.14% in the 1980s) and business equipment (2.59% in the 1990s). To some extent, these industrial patterns are reflected geographically, e.g., Houston-based firms performed very well in the 1970s and 2000s. However, the data seem to indicate regional differences in stock returns beyond industrial clustering. For example, in the 1990s, monthly stock returns of Washington D.C.-based firms averaged almost one-half percent higher than those headquartered in Chicago (1.51% vs. 1.09%), despite neither area being heavily concentrated in a single industry. Similar geographical heterogeneity is observed in other decades, e.g., Minneapolis (1.30%) vs. Miami (0.79%) in the 2000s, Los Angeles (1.51%) vs. Atlanta (1.06%) in the 1970s, and St. Louis (1.60%) vs. Boston (0.99%) in the 1980s. Such regional differences are the foundation of our analysis.

4 Lead-lag effects: industry versus regional groups

This section describes our main empirical results. Subsection 4.1 uses Fama and MacBeth (1973) regressions to establish the presence of lead-lag effects, both between industry peers as well as between regional neighbors operating in different sectors. We then show how these lead-lags can be used to create profitable trading strategies in subsection 4.2. In the final subsection (4.3), we compare the cross-sectional patterns between industry and geographic momentum. Consistent with the model's predictions, we observe industry lead-lag effects most strongly among small, thinly traded companies, but regional predictability even (and equally) among large, heavily traded firms with substantial analyst coverage.

4.1 Fama-MacBeth regressions

4.1.1 Observations defined at the firm-month

Our benchmark specification predicts firm-level monthly stock returns using two predictors: (1) the lagged returns of a portfolio consisting of non-local industry peers, and (2) the lagged returns of a portfolio consisting of non-industry, local peers. The former portfolio is intended to capture lead-lag effects within industries (Moskowitz and Grinblatt (1999)), and the latter cross-industry lead-lag effects within cities.

We estimate the following stock-level predictive regression at the monthly level using the Fama and MacBeth (1973) methodology:

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin c,j,t} + \epsilon_{i,c,j,t+1}, \tag{3}$$

where $r_{i,c,j,t+1}$ is the month $t+1$ excess return of firm i, headquartered in city c, and operating in industry j. There are two predictor variables, both measured at time t. The first is $r_{c,\notin j,t}$, the equally-weighted, lagged return of firms headquartered in city c, but operating outside firm i's industry ($\notin j$). Coefficient β_1 thus estimates the lead-lag effect within cities, but across industrial sectors. The second predictor is $r_{\notin c,j,t}$, capturing the lagged returns of firm i's industry peers (j) located outside its city ($\notin c$). Thus, β_2 measures lead-lag effects between industry (but not local) peers.[6]

Table 2 shows the results of estimating (3), with successive panels corresponding to increasing horizons of the forecasting variables. In Panel A, both the industry and area portfolios are measured over the preceding month. For example, if the dependent variable is the July 2007 return of Coca-Cola (NYSE:KO), the city portfolio would include the June 2007 returns of such Atlanta peers as Home-Depot, and the industry portfolio would include the June 2007 return of non-local bottlers such as Pepsi-Cola, headquartered in New York

[6] A further restriction, which we impose for interpretational simplicity, is that industry portfolios are constructed excluding firms in *any* of the 20 cities we consider in our analysis. This ensures that for firms within a given industry j, β_2 is estimated against an identical portfolio of industry peers. Although we prefer this specification, we note that operationally, this restriction makes almost no difference in our estimates. If industry portfolios are instead constructed from firm i's industry neighbors using only those headquartered in the 19 other cities ($\notin c$), we obtain nearly identical estimated for β_1 and β_2.

City.

Starting with the first column of Panel A, we see that both β_1 and β_2 are significant, with lead-lags within cities being around one-third as strong as those within industry groups. A one percent increase in a firm's lagged industry portfolio is associated with a positive return of twenty basis points the following month (t=8.21), compared to seven basis points (t=5.64) for the same change in a firm's lagged city portfolio over the full sample. Both coefficients are highly significant.

Moving down the table, the horizon over which the forecasting variable is constructed increases. For example, in Panel B, Coca-Cola's July 2007 return would be predicted from Home-Depot's 3-month return from April to June 2007, as well as Pepsi's 3-month return over the same horizon. Results from six- and twelve-month horizons are shown in Panel C and D, respectively. Generally, expanding the horizon reduces forecasting ability, reflected in both smaller point estimates and, to a smaller extent, statistical significance. To more directly address this issue, we estimate panel regressions that predict the firm's current (month t) return using the prior 24 lags of both the city and industry portfolio returns. We then cumulate the coefficients for each horizon, (e.g., the coefficient on month $t-1$ returns, the sum of the coefficients on month $t-1$ and $t-2$, etc.) and plot these cumulated coefficients in Figure 3.[7]

The industry and geographic profiles provide an interesting comparison. In both cases, the one-month lagged return is an important predictor, but the additional lags of the geographic factor are comparatively much more important. For example, the one-month lag comprises approximately 50% of the entire 12-month lagged cumulative effect for the industry factor, but only about 20% for the city factor. In other words, realizations of the geographic factors are incorporated into stock prices much more slowly. There also seems to be some evidence that markets tend to somewhat over-react to industry factors, as indicated by a clear reversal after one year. In contrast, innovations in the geographic factors are fully captured by stock prices within 12 months, but show little to no sign of reversal.

Columns 2 and 3 show the results separately for the first (1970-1990) and second half (1991-2013), respectively, of our sample period. Regardless of the predictive horizon, both the area- and industry-level predictors remain significant in both sub-samples. We note,

[7] These plots were originally presented by Jonathan Lewellen (our discussant) at the 2016 FRA conference.

however, that lead-lags between geographic peers appear to have weakened somewhat over the last two decades, whereas industry momentum has maintained relatively constant. As we will see shortly, industry momentum is driven primarily by smaller firms, whereas geographic momentum is relatively constant for firms across the size distribution. Thus, it is possible that the results in columns 2 and 3 reflect high, persistent limits to arbitrage for small firms (thus allowing industry-level mispricing to persist for decades), but gradually more efficient pricing over time for large, liquid firms.

4.1.2 Observations defined at the industry-city-month

An alternative way of testing for lead-lag relationships is to combine firms within the same industry and city into a single portfolio, rather then consider each firm separately. Doing so allows us to construct observations at the city-industry-month level, and then run a regression similar to equation 3, except that now the dependent variable is a portfolio return. Note that this aggregation reduces the number of observations to a little over 100,000, corresponding roughly to the product of the number of industries (12), the number of cities (20), and the number of months in our sample (527). We lose about 15,000 possible city-industry-month observations to cases when a potential city-industry-month group contains zero firms.

Table 3 shows the results. Compared to the firm-level results, city-industry portfolio regressions give similar estimates. Industry-level lead-lags are about 10% smaller across the board, while area-level lead-lags grow by about the same amount. Consequently, when we compare the respective magnitudes, the coefficients on the geographic portfolios varies between being about one-half (panel A) to two-thirds (panel D) the size of the industry coefficients.

It is also worth noting that despite reducing the number of observations by over an order of magnitude, the statistical significance is similar between Tables 2 and 3. This suggests that the reduction in statistical power – all else equal our estimated t-statistics should decrease by about $\sqrt{\frac{1{,}611{,}9731}{111{,}942}} \approx 3.8$ – is compensated for by portfolio returns measured with less noise. In any event, the results here confirm the firm-level analysis, and provide strong evidence that for at least some firms, area-level information is incorporated into stock prices with a delay.

4.2 Trading Profits

The results above lead themselves to a trading strategy that exploits cross-serially correlated returns between geographic neighbors. Every month, we rank each firm i not by its own lagged return (as we would in a simple momentum strategy), but by $r_{c,\notin j,t}$, the average lagged return of firms headquartered in the same region, but operating in different sectors. We use a one month horizon both for the sorting criterion (i.e., area-level stock returns are measured over a month) as well as the holding period (i.e., portfolios are reformed at the end of every month).

In Figure 4, we plot the value of a hypothetical dollar invested in each of three portfolios. The first, shown in blue, shows the evolution of a dollar invested in the market portfolio. Dividends are assumed to be reinvested. Against this benchmark, we also plot the 20% of firms with the highest lagged 1-month area returns (green), as well as the 20% of firms with the lowest lagged 1-month area returns (red). Note that the y-axis is displayed in natural logarithms. While the market portfolio grows by a (log) factor of over 4 during the four decades in our sample, bringing \$1 invested in the market to around \$70, \$1 invested in the lowest quintile barely exceeds \$20. On the other hand, a \$1 investment in the highest quintile performs almost an order of magnitude better, growing to approximately \$185 by 2013.

Table 4 makes these comparisons more formally. Starting with the first row, we see that the average monthly return for the quintile of firms surrounded by the poorest lagged returns is 74 basis points. Regressing the average returns of this portfolio against the market yields a statistically significant intercept of -26 basis points ($t = -3.21$), nearly identical to that obtained from a regression that also includes Fama and French (1993)'s size and value factors (-24 basis points, $t = -3.00$). The resulting Sharpe ratio is about 0.2, less than half what one would obtain by simply holding a market portfolio.

Proceeding down the table, we see that average returns increases steadily. The middle three groups appear fairly representative of the market as a whole, with similar average returns (CAPM alphas are small and insignificant for each group) and Sharpe ratios. However, outperformance is observed for the highest quintile, with raw monthly returns of 116 basis points, and statistically significant alphas relative to both the CAPM (t=3.19) and Fama-

French three factor model (t=3.03). The Sharpe ratio for this portfolio is 0.53. (See also nearly identical results in Appendix Table A1, which displays the results when portfolios are sorted into ten, rather than five, groups.)

Foreshadowing results in the following section, the most remarkable aspect of Table 4 is the apparent orthogonality to traditional risk factors. To see this, note that the difference in raw returns between the first and fifth quintiles (42 basis points, $t = 3.64$) is nearly identical to the intercept estimated from either a regression against the market (47 basis points, $t = 4.15$) or against the FF-3 factors (45 basis points, $t = 3.99$).[8]

Further evidence against a risk-based explanation can be inferred from the average portfolio characteristics within each quintile, shown in the far right-hand side of the table. Here, too, we observe no trends relevant for the pattern in average returns. Firm-specific volatility is highest among the quintile with the lowest returns, followed by the second-highest quintile, then the second-lowest, highest, and then median. Size is humped shaped, with average market capitalization being highest for the middle group; indeed, we find almost identical results for a trading strategy that focuses only on the largest 20% of firms in each period (see Appendix Table A2). Book-to-market ratios display the opposite patterns, dipping in the center. These results indicate that adjusting for characteristics rather than factor loadings as in Daniel and Titman (1997), tells the same story: a geographic momentum strategy is profitable, but appears unrelated to standard risk factors.

4.3 Richness of the information environment

In the last section, we presented evidence of significant lead-lag effects, both at the industry and geographic level. While underreaction to industry news has been recognized since Moskowitz and Grinblatt (1999), finding a significant lead-lags within regions *between* sectors suggests an additional source of information not (completely at least) appreciated by investors. In this section, we attempt to be more precise about the specific reasons why area-level return predictability might persist.

Returning to the stylized model described in Section 2, the key assumption is that infor-

[8] Adjusting for momentum (Carhart (1997)), not reported in the table, likewise makes almost no difference.

mation disseminates rapidly within industries, and less so within geographic regions. The mechanism we proposed is based on overlapping coverage between equity analysts, i.e., the extent to which two firms are commonly scrutinized by a common set of individuals. Our intuition is that when two firms share multiple analysts, common sources of information are more rapidly reflected in stock prices, compared to when two firms have little if any overlap. In these latter cases, lead-lag effects can persist, whereby some firms react early to information, and others react with a delay.

One of the model's important cross-sectional predictions is that at the industry level, returns are predictable only for firms with low analyst following. The intuition is that, with few analysts following a firm, the chance of overlap – even with industry peers – is small. In contrast, the model predicts that between geographic neighbors operating in different sectors, the magnitude of lead-lags is not expected to depend (much at least) on the number of analysts. As described in subsection 2.2.4, because the chance that any one analyst co-covers two (local) firms in different sectors is so small, then even with a large number of analysts, local neighbors in different sectors are unlikely to be commonly covered. Hence, whatever return predictability exists between local peers is expected to be relatively invariant to firm size, analyst coverage, trading volume, or other proxies for investor scrutiny.

To test this hypothesis, Table 5, Panel A presents the results of estimating Equation 3, but stratified by the number of analysts. The predictive horizon is one month, so that we are predicting the returns of firm i in month t, using the one-month lagged ($t-1$) returns of either its non-local, industry ($INDUSTRY$) or local, non-industry ($CITY$) peers. Note also that the cross-sectional filters apply only to the left-hand side of Equation 3. By holding the explanatory portfolios constant across columns, we can relate any mispricing (reflected in the coefficients) to the variables used to partition firms in consecutive columns.

Starting first with industry-level predictability, we see a strong, declining relation with analyst coverage. Stock returns of firms with either zero (column 1) or one (column 2) identifiable analyst are most sensitive to lagged industry returns, with significantly estimated coefficients of 0.268 ($t = 7.31$) and 0.272 ($t = 6.43$) respectively. The magnitude drops by almost half to 0.158 ($t = 4.77$) for firms with between two and nine analysts, and by over half again for firms with at the ten following analysts (0.064), the latter of which is marginally significant ($t = 1.83$). The last column tests for equality between the coefficient in the first

quartile (zero analysts) and that in the fourth (10 or more analysts), rejecting this at far better than the 1% level.

A different picture emerges for lead-lags at the regional level. Firms with zero analyst following actually have the *smallest* magnitude (0.057, t = 2.79) of any group, though this is not significantly different from that in any other column. The coefficient on the lagged area portfolio is fairly stable across columns, with sensitivities of 0.063 (t = 1.76), 0.071 (t = 3.75), and 0.066 (t = 2.51) for firms with progressively more analyst coverage. In contrast to the industry-level comparison, the final column indicates a p-value of 0.74, suggesting no statistically significant difference in area lead-lags for firms with low (column 1) and high (column 4) analyst coverage.

We next present cross-sectional results based on firm size (market capitalization) and trading volume.[9] There are three reasons we perform these additional sorts. First, both are strongly related to analyst coverage, but are available for the entire sample period. Second, even after 1980 (when I/B/E/S data begin), we lack a complete account of analysts that may follow and/or publish reports about specific firms. For example, buy-side analysts are not included in I/B/E/S (Cheng et al. (2006), Groysberg et al. (2013)). Finally, the I/B/E/S database is subject to alterations of recommendations, additions and deletions of records, and removal of analyst names (Ljungqvist et al. (2009)). Our hope therefore, is that size and trading volume capture cross-sectional variation for the general "scrutiny" of the investing community, even when data on analyst coverage is absent or unreliable.

Both Panels B and C reveal a strong, declining relation for industry momentum, similar to what we observed for analyst coverage. Industry lead-lags are very strong for the first three quartiles, with coefficients of 0.243 (t = 7.55), 0.232 (t = 7.61), and 0.189, (t = 6.94) respectively. In the fourth quartile however, the magnitude drops sharply. While still significant, the effect for the largest 25% of firms – representing 94% of the average total market capitalization – is less than half that observed in the first three groups (0.104, t = 4.36). As with Panel A, the difference in the industry coefficient between columns one and four is highly significant, as indicated in the final column.

Almost identical patterns are observed for trading volume (panel C). Within each month, we rank firms by total trading volume, and form quartiles. The least (most) heavily traded

[9] Sorting by alternative size proxies such as book value of assets or sales gives very similar results.

firms are presented on the left-hand (right-hand) side of the table. The point estimates are very similar for the first three groups, with magnitudes of about 0.2, and t-statistics above seven. However, the estimate drops by almost half to 0.128 (t=4.73) in column four, indicating that industry lead-lags are weaker when trading volume is higher. This difference, too, is significant at the 1% level.

Lead-lags at the regional level, however, show little relation to either firm size (Panel B) or trading volume (Panel C). With respect to firm size, the largest point estimate is 0.101 (t=4.11), corresponding to the smallest quartile when ranked by firm size. The second largest effect is the largest quartile (0.069, t=4.30), followed by the second (0.068, t=4.03) and third (0.047, t=2.93) groups. As indicated by the last column, the difference between the coefficient estimated for the quartile of largest firms (column 1) and smallest firms (column 4), is not statistically significant (p=0.197).

Likewise, geographic momentum appears to have no discernible relation to trading volume. The strongest effect is observed among the *most heavily* traded firms (0.100, $t = 4.94$), with the second strongest coming from the lowest quartile (0.072, t=3.78). This difference is not statistically significant (p=0.247). We observe significant, though weaker effects in the second (0.056, t=2.62) and third (0.055, t=2.93) quartiles.

Figure 5 provides a visual summary of the results in Table 5. For all three cross-sectional cuts, the magnitude of the industry coefficient (red bars) declines, with the most pronounced decline coinciding with the highest quartiles. In contrast, the blue bars – representing the geographic coefficients – display no clear relation with the sorting variables. Taken together, the results in this section provide broad support for the model's predictions. While predictability at the industry level is – when it occurs – generally larger than that at the regional level, it is mainly restricted among small firms, and those with low analyst coverage and trading volume. Predictability at the regional level, though smaller on average, seems to apply equally well to firms of differing sizes, trading volumes, and analyst coverage.

5 Robustness and Extensions

In this section, we present the results of a number of robustness checks and specification alternatives to our main results. The first two subsections address the possibility that our

measure of a firm's headquarters may be an imperfect proxy for its location, and therefore, its sensitivity to local factors. Subsection 5.1 quantifies the potential impact of mis-measured headquarter locations, which may arise when firms relocate, and subsection 5.2 expands beyond headquarters to consider, e.g., the location of a companies' operations, manufacturing, etc. Finally, we present our main predictability results under several alternative specifications in subsection 5.3.

5.1 Misclassified headquarter locations

Our measure of firm location is its headquarters, as inferred by the ADDZIP variable in COMPUSTAT, which reports the zip code of the firm's *most recent* headquarters. Consequently and unfortunately, in most cases, we do not observe when a firm changes headquarters, resulting in a type of look-ahead bias. For example, General Dynamics moved from St. Louis to the Washington D.C. area in 1992, but the ADDZIP variable takes a value of 22042, corresponding to Falls Church, Virginia (near Washington D.C.), both for years prior to its move (pre-1992), as well as afterward (1992 and beyond).

Comprehensive data on firm headquarter changes is conspicuously absent in the finance literature, but audit studies indicate that they are fairly uncommon. Pirinsky and Wang (2006), for example, use news data to track headquarter changes from 1992-1997. Excluding firms that moved as a result of mergers or other major restructuring, as well as those moving within the same MSA, the authors estimate that between 2-3% of firms moved during this five year period, or about 0.5% per year. If we assume that all firms have this rate of relocation, then over 40 years, we expect to for about $0.995^{43} \approx 80.6\%$ of firms to still be correctly classified in 2013, the last year of our sample. However, because the location reported in 2013 would be correct, on average, half the time (as for General Dynamics post-1992), we should expect error rates by firm-year in the range of perhaps $0.5 * (100\% - 80.6\%) = 9.7\%$. Even this, however, is probably conservative. Because our panel is disproportionately represented by large firms with long histories, and because large firms are less likely to move than small ones (as Pirinsky and Wang (2006) also shows), the percentage of misclassification is likely even lower. Most importantly, bad location data biases against our findings.

Because we have some uncertainty about the true misclassification rate, Table 6 presents

our one-month predictive regressions under various scenarios. In the first panel, 1% of the headquarter locations are scrambled randomly, followed by successively higher percentages in each panel. For misclassification rates of 1% and 5%, the impact on the area coefficient is trivial, and are only slightly affected by misclassifications of 10%. For 20%, the magnitude is cut by one-third, although it remains statistically significant for the full sample (but not for the latter half). With half the locations assigned incorrectly (Panel E), the result vanishes entirely.

Given Pirinsky and Wang (2006)'s estimates, along with our intuition about the composition of firms throughout the sample, our best guess is an error rate in the 5-10% rate over all firm-years in the panel. If so, this suggests that the reported estimates in our prior tables are not meaningfully affected by misclassifications. On the other hand, if we are wrong by a factor of (10-20%), then our reported results should be grossed up by about 30% to account for measurement error.

5.2 Location beyond a firm's headquarters

Throughout the paper, we have identified a firm's location using its headquarters. While this is both simple and observable for every firm in the sample, it ignores clear differences in the extent to which a firm's facilities, customer base, or labor force are concentrated in a particular geographic region. For example, at one end of the spectrum are retail firms with a national (or even global) presence, e.g., Wal-Mart, Home Depot, Whole Foods, and Costco which have highly dispersed stores, customers, and workers. At the other extreme are companies with most or all their operations conducted at a single location. DTE Energy, a Michigan-based utility company mentioning only Michigan and Indiana in its annual reports, and AutoDesk (mentioning only California) are at other other extreme.

The question we explore in this section is whether regional predictability is stronger for more regionally concentrated firms (e.g., AutoDesk) compared to one with a more disperse presence (e.g., Whole Foods). To obtain a more general measure of a firm's geographical presence, Garcia and Norli (2012) utilize a text-based parsing algorithm that counts the number of unique state names mentioned in the annual reports of publicly traded firms from

1994-2008.[10]

As Garcia and Norli (2012) describe, state names are often listed when describing/discussing the locations of stores, manufacturing facilities, or other operations. We follow their approach, after downloading the relevant dataset from Diego Garcia's website. For each firm we calculate the time-series average of state names over the available time period (1994-2008), and apply this measure to all years (including before 1994 or after 2008) in which data are available.[11]

Table 7 presents the results of our one-month Fama-MacBeth predictive regressions, when sorted by the above/below median level of geographic concentration. The first two columns correspond to the entire sample, with columns 3 and 4 (5 and 6) to small (large) firms.[12] Firms above the median list nine states on average, compared to three states for firms below it. Note that because we use the same cutoff (5.46 states) for each of the sub-samples, the corresponding sub-sample averages are similar, but need not be identical to the aggregate sample.

In all cases, the point estimates for the more regionally concentrated firms are somewhat larger compared to their less concentrated counterparts. Small firms are associated with the biggest differential, with highly concentrated firms being twice as sensitive to lagged area returns (0.102, t=3.07) compared to firms that mention more states in their annual reports (0.052, t = 1.92). Although this difference is not statistically significant at conventional levels, we have experimented with other specifications and find stronger results. For example, a Fama-MacBeth regression (one month horizon) that interacts the number of states mentioned with the lagged city portfolio returns yields a p-value less than 3%. Given these suggestive results using a fairly coarse measure of regional concentration, we hypothesize

[10] Other papers adopting a similar approach to measuring firm location include Bernile et al. (2015b), Addoum et al. (2015), and Bernile et al. (2015a).

[11] Because Garcia and Norli (2012) data are available only for 15 years of our 43 year panel, an extrapolative approach is required in order to apply the concentration measure to our entire sample period. Taking the time-series average of state names for each state, unfortunately, ignores dynamics. However, it is unusual for firms to become dramatically more or less concentrated over time, leading us to believe that the ranking obtained from 1994-2008 provides a good proxy for its ranking across all years. For example, the median time-series standard deviation of state counts for firms in Garcia and Norli (2012) sample is 1.34, suggesting little aggregate time-variation of geographical concentration.

[12] Note that the sample size is reduced by about 500,000 firm-month observations, corresponding to firms not in the Garcia-Norli database.

that more refined measures – using establishment data from the U.S. Census would seem promising – would give even stronger results.

5.3 Alternative regression specifications

5.3.1 Panel regressions with time fixed effects

Our main empirical tests use Fama-MacBeth cross-sectional regressions. By construction, this procedure sweeps out any common "time effect" through a date-specfic intercept applied to each cross-sectional regression. However, as discussed in Petersen (2009), three potential problems remain. First, Fama and MacBeth's procedure does not address serial correlation in residuals. Second, although a unique intercept for each ($year \times month$) controls for a *uniform* effect across stocks, it is possible for subsamples to be more or less sensitive to a given shocks. For example, in September 2001, airline stocks suffered far worse than did, say, stocks of food or defense firms. Third and finally, Fama-MacBeth regressions give equal weight to each cross-sectional regression when calculating the standard error of β_1 (the sensitivity to lagged area returns), thus ignoring the fact that some periods contain more information than others.

Table 8 shows the results of re-estimating equation 3, but with date fixed effects, and residuals double-clustered by firm and date (Petersen (2009)). When comparing these to the area-level lead lags to the Fama-MacBeth estimates shown in Table 2, we observe similar point estimates, but weaker statistical significance. As an example, the full sample coefficient (t-statistic) for our one-month predictive regression is 0.063 (3.66) in panel regressions, and 0.073 (5.64) with Fama-MacBeth. Results are also slightly stronger at the 3-month and 6-month predictive horizon, and nearly identical at the 12-month window. Note, however, that although weaker, geographic lead-lags remain significant at all horizons.

Industry momentum also weakens from a significance perspective. In the double-clustered panel estimation for example, industry lead-lags are profitable only at relatively short horizons (within three months), and all but disappears in the second half of the sample. In Fama-MacBeth regressions however, the anomaly continues to work after 1990 (though with a smaller magnitude), and remains profitable through twelve months after the sort date.

We have experimented with various specifications, in an attempt to better understand

which of the three factors mentioned at the beginning of this section are most responsible for the weakened results. It turns out that firm-clustering is relatively insignificant; the standard errors reported in Table 8 are almost identical if this cluster is removed. Rather, the additional clustering by time is most responsible for the differences. This exercise thus indicates that accounting for remaining cross-sectional correlation within time may be relevant, and likewise suggests that our panel-generated estimates are considerably more conservative than Fama-MacBeth's methodology.

5.3.2 Delayed portfolio formation

In this section we examine the time it takes the information in one firm's stock price to be incorporated in the stock prices of its industry and location peers. Specifically, we examine whether there is still predictability when we skip a month between when the past returns are measured, and when the strategy is implemented. If information is transmitted relatively quickly, we expect that predictability should be largely eliminated.

Table 9 reports Fama-MacBeth regressions that are identical to the one-month predictive regressions reported in first column of Table 3, save for the one-month skip. As the table reveals, area- and industry-level lead-lags are weaker, but they remain statistically significant. The impact of delayed portfolio formation is most severe when the predictor variables are measured over short horizons. For example, the coefficient on the area-level predictor drops from 0.073 to 0.037 (t=3.06), and that on the industry-level predictor drops from 0.199 to 0.118 (t=4.59). At longer horizons, the impact of delayed portfolio formation is less pronounced. For example, when month $t-13$ to $t-1$ returns are used to forecast stock returns beginning at month t, the coefficient on the area portfolio is nearly identical (0.011, t=3.43) to that estimated without the one-month skip (i.e., month $t-12$ to t returns are used as predictors). Industry momentum suffers a similarly modest decline, dropping from 0.025 to 0.019 (t=3.52).

Together, these results suggest that prices remain inefficient for at least a month after portfolio formation, suggestive a fairly long delay in processing industry or area-specific information.

5.3.3 Value-Weighted Portfolios

In the main results of Table 8 we construct the local and industry portfolios by equally weighting firms within each group, similar to Pirinsky and Wang (2006). As a robustness check, in Table 10 we re-estimate our one-month Fama-MacBeth predictive regression using value-weighted local and industry portfolios. Whereas both industry and geographic momentum remain statistically significant, the magnitudes are 30-40% smaller, depending on the horizon. In retrospect, this result is intuitive. If the goal is to measure local economic fundamentals using portfolio returns, an equally-weighted basket is more likely to be informative, compared to one that puts disproportionate weight on a few large firms (e.g., Dallas's ExxonMobil, Seattle's Amazon, etc.), especially given that they are less likely to be regionally concentrated.

6 Conclusions

Analyzing lead-lag effects between related securities provides a useful way to gauge the efficiency of financial markets. Prior research has identified a number of ways to identify "similar" firms including relationships between companies in the same industry, between customers and suppliers, and between focused firms and conglomerates. Such classifications play an important role in the trading strategies of quantitative hedge funds, which exploit lead-lag effects between related stocks, bonds, options, and other derivatives. The underlying rationale is that although similar firms are exposed to common fundamental shocks, there may still exist variation in the rate at which this information is reflected in prices. Naturally, stocks with the highest (lowest) informational efficiency react the quickest (slowest).

This paper contributes to this literature by identifying geography – using firm headquarters – as a source of fundamental value. We show that under a variety of empirical specifications, regionally-sorted portfolios generate trading profits that are a third to half as large as those using industry sorts. Note that in addition to documenting an apparent pricing inefficiency, these results point to the presence of locally-derived fundamentals that have a meaningful impact on neighboring firms, even those in vastly different lines of business.

Our most important contribution is a non-result. When we analyze lead-lags between

industry peers, trading profits decline sharply for highly scrutinized firms – specifically large firms, those with significant trading volume, or with high analyst following.[13] In contrast, we observe no relation between trading profits and the same variables among regionally sorted portfolios. In addition to being relatively unusual among asset pricing anomalies, this finding suggests that a regional trading strategy might be profitably deployed even with large amounts of capital.

The mechanism we propose is a refinement of limited attention. Our intuition is that when an investor simultaneously monitors two stocks, he/she is more likely to recognize common relevant sources of information, and through simultaneous trading, reduce lead-lag effects. *Within an industry,* it is the largest firms who are more likely to have more analysts in common with other industrial peers, making it difficult to use industry-based information to predict the returns of large firms. On the other hand, *within a geographic region*, the chance of overlap between neighboring firms in different sector is very small, even among (large or heavily traded) firms with substantial analyst followings individually. As we illustrate in a simple model, industry-focused analysts permit regional lead-lags among virtually all firms (which we observe), but industry lead-lags only for those with the least scrutiny (which we also observe).

It should be stressed that our analysis, which suggests that the organization of the analyst community affects the co-movement of securities, takes that organization as given. Of course, the organizational structure of the analyst community is endogenous, taking into account the synergies associated with analyzing a closely related group of firms, as well as constraints on information processing (Peng and Xiong (2006)). While we cannot conclude that our analysis indicates that analysts should engage in the collection of costly information by location as well as industry, our analysis does indicate that location-based return information, which is virtually free, can be used to supplement the industry information of stock market analysts. One implication, in light of our findings, is a potential role for *regionally focused* analysts in the investment community. Given the trend toward urbanization, and the increased importance of spillovers and other city-level dynamics (Moretti (2012)), an institutional shift toward recognizing these factors seem worth exploring.

[13] Likewise, Cohen and Frazzini (2008) find that predictability between firms with economic linkages declines with proxies for informational efficiency.

References

Addoum, Jawad M., Alok Kumar, and Kelvin Law, 2015, Slow diffusion of state-level information and return predictability, Working Paper .

Atchison, Michael D., Kirt C. Butler, and Richard R. Simonds, 1987, Nonsynchronous security trading and market index autocorrelation, The Journal of Finance 42(1), 111–118.

Badrinath, S.G., Jayant R. Kale, and Thomas H. Noe, 1995, Of shepherds, sheep, and the cross-autocorrelations in equity returns, The Review of Financial Studies 8(2), 401–430.

Becker, Bo, Zoran Ivkovic, and Scott Weisbenner, 2011, Local dividend clienteles, The Journal of Finance 66(2), 655–683.

Bernile, Gennaro, Stefanos Delikouras, George M. Korniotis, and Alok Kumar, 2015a, Geography of firms and propagation of local economic shocks, Working Paper .

Bernile, Gennaro, Alok Kumar, and Johan Sulaeman, 2015b, Home away from home: Geography of information and local investors, The Review of Financial Studies 28(7), 2009–2049.

Brennan, Michael J., Narasimhan Jegadeesh, and Bhaskaran Swaminathan, 1993, Investment analysis and the adjustment of stock prices to common information, The Review of Financial Studies 6(4), 799–824.

Carhart, Mark M., 1997, On persistence in mutual fund performance, The Journal of Finance 52(1), 57–82.

Cheng, Yingmei, Mark H. Liu, and Jun Qian, 2006, Buy-side analysts, sell-side analysts, and investment decisions of money managers, Journal of Financial and Quantitative Analysis 41(1), 51–83.

Chordia, Tarun, and Bhaskaran Swaminathan, 2000, Trading volume and cross-autocorrelations in stock returns, The Journal of Finance 55(2), 913–935.

Clement, Michael B., 1999, Analyst forecast accuracy: do ability, resources, and portfolio complexity matter?, Journal of Accounting and Economics 27, 285–303.

Cohen, Lauren, and Andrea Frazzini, 2008, Economic links and predictable returns, The Journal of Finance 63(4), 1977–2011.

Cohen, Lauren, and Dong Lou, 2012, Complicated firms, Journal of Financial Economics 104, 383–400.

Daniel, Kent, and Sheridan Titman, 1997, Evidence on the characteristics of cross sectional variation in stock returns, The Journal of Finance 52(1), 1–33.

DellaVigna, Stefano, and Joshua M. Pollet, 2009, Investor inattention and friday earnings announcements, The Journal of Finance 64(2), 709–749.

Fama, Eugene, and Kenneth French, 1992, The cross-section of expected stock returns, The Journal of Finance 47, 427–465.

Fama, Eugene F., and Kenneth R. French, 1993, Common risk factors in the returns on stocks and bonds, Journal of Financial Economics 33(1), 3–56.

Fama, Eugene F., and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, Journal of Political Economy 81(3), 607–636.

Garcia, Diego, and Oyvind Norli, 2012, Geographic dispersion and stock returns, Journal of Financial Economics 106, 547–565.

Groysberg, Boris, Paul Healy, George Serafeim, and Devin Shanthikumar, 2013, The stock selection and performance of buy-side analysts, Management Science 59(5), 1062–1075.

Hameed, Allaudeen, and G. Mujtaba Mian, 2015, Industries and stock return reversals, Journal of Financial and Quantitative Analysis 50(1-2), 89–117.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh, 2009, Driven to distraction: Extraneous events and underreaction to earnings news, The Journal of Finance 64(5), 2289–2325.

Hirshleifer, David, Sonya Seongyeon Lim, and Siew Hong Teoh, 2011, Limited investor attention and stock market misreactions to accounting information, Review of Asset Pricing Studies 1(1), 35–73.

Hirshleifer, David, and Siew Hong Teoh, 2003, Limited attention, information disclosure, and financial reporting, Journal of Accounting and Economics 36, 337–386.

Hong, Harrison, Jeffrey D. Kubik, and Jeremy C. Stein, 2008, The only game in town: Stock-price consequences of local bias, Journal of Financial Economics 90, 20–37.

Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, The Journal of Finance 55(1), 265–295.

Hou, Kewei, 2007, Industry information diffusion and the lead-lag effect in stock returns, The Review of Financial Studies 20(4), 1113–1138.

Jegadeesh, Narasimhan, and Sheridan Titman, 1995, Overreaction, delayed reaction, and contrarian profits, The Review of Financial Studies 8(4), 973–993.

John, Kose, Anzhela Knyazeva, and Diana Knyazeva, 2011, Does geography matter? firm location and corporate payout policy, Journal of Financial Economics 101, 533–551.

Kadan, Ohad, Leonardo Madureira, Rong Wang, and Tzachi Zach, 2012, Analysts' industry expertise, Journal of Accounting and Economics 54(2-3), 95–120.

Korniotis, George M., and Alok Kumar, 2013, State-level business cycles and local return predictability, The Journal of Finance 68(3), 1037–1096.

Kumar, Alok, Jeremy K. Page, and Oliver G. Spalt, 2013, Investor sentiment and return comovements: Evidence from stock splits and headquarters changes, Review of Finance 17, 921–953.

Ljungqvist, Alexander, Christopher Malloy, and Felicia Marston, 2009, Rewriting history, The Journal of Finance 64(4), 1935–1960.

Lo, Andrew W., and A. Craig MacKinlay, 1990, When are contrarian profits due to stock market overreaction?, The Review of Financial Studies 3(2), 175–205.

McGahan, Anita M., and Michael E. Porter, 1997, How much does industry matter, really?, Strategic Management Journal 18(S1), 15–30.

McQueen, Grant, Michael Pinegar, and Steven Thorley, 1996, Delayed reaction to good news and the cross-autocorrelation of portfolio returns, The Journal of Finance 51(3), 889–919.

Mech, Timothy S., 1993, Portfolio return autocorrelation, Journal of Financial Economics 34(3), 307–344.

Moretti, Enrico, 2012, The New Geography of Jobs (Houghton Mifflin Harcourt).

Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do industries explain momentum?, The Journal of Finance 54(4), 1249–1290.

Peng, Lin, and Wei Xiong, 2006, Investor attention, overconfidence, and category learning, Journal of Financial Economics 80(3), 563–602.

Petersen, Mitchell A., 2009, Estimating standard errors in finance panel data sets: Comparing approaches, The Review of Financial Studies 22(1), 435–480.

Pirinsky, Christo, and Qinghai Wang, 2006, Does corporate headquarters location matter for stock returns?, The Journal of Finance 61(4), 1991–2015.

Rumelt, Richard P., 1991, How much does industry matter?, Strategic Management Journal 12(3), 167–185.

Schmalensee, Richard, 1985, Do markets differ much?, The American Economic Review 75(3), 341–351.

Stickel, Scott E., 1992, Reputation and performance among security analysts, The Journal of Finance 47(5), 1811–1836.

Tuzel, Selale, and Miao Ben Zhang, 2015, Local risk, local factors and asset prices, Working Paper .

PANEL A: CITIES								
	Average # of firms				*Average return (volatility)*			
	1970-1979	*1980-1989*	*1990-1999*	*2000-2013*	*1970-1979*	*1980-1989*	*1990-1999*	*2000-2013*
Atlanta	44	90	163	140	1.06% (13.76%)	1.39% (15.78%)	1.41% (18.28%)	0.89% (18.67%)
Boston	100	210	355	303	1.44% (14.87%)	0.99% (15.10%)	1.75% (18.46%)	1.01% (18.96%)
Chicago	122	173	298	296	1.12% (12.64%)	1.49% (13.50%)	1.09% (14.73%)	0.85% (13.42%)
Cleveland	58	72	93	68	1.10% (13.51%)	1.32% (13.71%)	1.15% (16.85%)	1.31% (15.39%)
Dallas	89	183	243	174	1.60% (14.75%)	0.77% (17.13%)	1.16% (20.10%)	1.14% (18.65%)
Denver	32	122	141	108	2.12% (17.29%)	-0.10% (22.48%)	1.40% (22.00%)	0.96% (19.81%)
Detroit	58	73	92	70	1.22% (13.49%)	1.26% (14.10%)	1.28% (17.15%)	1.07% (19.15%)
Houston	77	144	206	193	1.89% (13.67%)	0.60% (18.98%)	1.04% (19.28%)	1.55% (19.30%)
Indianapolis	17	29	51	40	1.10% (11.76%)	1.12% (13.21%)	1.30% (14.36%)	1.08% (15.62%)
Los Angeles	127	287	403	291	1.51% (16.90%)	1.07% (18.58%)	1.23% (23.89%)	0.93% (21.22%)
Miami	46	113	170	102	1.22% (17.10%)	0.83% (20.02%)	1.15% (24.93%)	0.79% (22.30%)
Minneapolis	45	108	181	114	1.49% (13.91%)	1.27% (16.43%)	1.42% (18.14%)	1.30% (18.07%)
New York	372	674	856	666	1.26% (15.13%)	1.14% (18.07%)	1.27% (20.39%)	0.92% (18.37%)
Orlando	13	33	39	26	1.54% (18.77%)	0.81% (16.60%)	1.80% (24.94%)	0.86% (22.19%)
Philadelphia	74	127	227	240	1.31% (14.07%)	1.38% (15.46%)	1.42% (18.02%)	0.89% (15.38%)
Phoenix	24	48	71	55	1.51% (16.37%)	0.52% (19.90%)	1.48% (21.10%)	1.16% (20.15%)
San Francisco	54	172	338	356	1.61% (14.93%)	0.75% (17.07%)	2.31% (22.94%)	0.86% (18.67%)
Seattle	14	37	63	69	1.90% (15.36%)	1.15% (15.69%)	1.81% (19.98%)	0.94% (22.34%)
St. Louis	31	42	61	49	1.04% (12.27%)	1.60% (15.15%)	1.22% (14.20%)	1.45% (18.71%)
Washington, DC	55	132	214	191	1.27% (15.45%)	1.04% (16.78%)	1.51% (19.32%)	1.17% (20.64%)

Table 1: Descriptive statistics. Panel A: Average number of firms, cross-sectional mean and volatility of monthly stock returns for the twenty largest U.S. cities, by decade. Panel B: Average number of firms, cross-sectional mean and volatility of monthly stock returns for the twelve Fama and French (1992) industries, by decade. Monthly data, 1970-2013.

PANEL B: INDUSTRIES

	Average # of firms				*Average return (volatility)*			
	1970-1979	*1980-1989*	*1990-1999*	*2000-2013*	*1970-1979*	*1980-1989*	*1990-1999*	*2000-2013*
Consumer Non Durables	166	178	211	135	1.07% (14.07%)	1.62% (15.03%)	0.65% (19.18%)	1.22% (16.45%)
Consumer Durables	66	79	87	55	1.16% (13.86%)	1.20% (16.70%)	0.97% (19.64%)	0.88% (21.03%)
Manufacturing	278	347	357	236	1.43% (14.52%)	1.21% (16.45%)	1.09% (18.29%)	1.36% (17.70%)
Energy	64	172	147	123	2.64% (15.22%)	-0.11% (21.83%)	0.89% (18.68%)	1.47% (17.21%)
Chemicals	63	80	92	68	1.13% (12.89%)	1.35% (14.32%)	0.98% (16.52%)	1.18% (17.70%)
Business Equipment	152	469	736	671	2.01% (18.17%)	0.69% (19.54%)	2.59% (25.35%)	0.80% (24.53%)
Telecoms	26	57	114	97	1.39% (14.00%)	2.14% (16.88%)	2.24% (23.24%)	0.28% (25.38%)
Utilities	61	76	74	55	0.92% (7.45%)	1.62% (8.10%)	1.13% (8.26%)	1.14% (9.64%)
Wholesale and Retail	187	320	414	274	1.10% (14.77%)	1.04% (17.52%)	0.89% (21.23%)	1.17% (18.78%)
Healthcare	55	182	412	377	1.41% (15.64%)	1.13% (20.05%)	1.51% (22.49%)	1.51% (24.92%)
Finance	148	492	1,085	1,079	1.10% (13.80%)	1.02% (13.44%)	1.23% (13.54%)	0.87% (11.32%)
Others	187	414	536	382	1.37% (16.12%)	1.07% (18.65%)	1.10% (22.92%)	0.85% (20.23%)

PANEL A: 1-month predictors

	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.073***	.092***	.057***
	(5.64)	(4.82)	(3.26)
$\beta_{INDUSTRY}$	.199***	.185***	.212***
	(8.21)	(6.42)	(5.56)
Avg R^2	1.03%	0.79%	1.24%
Observations	1,611,973	553,127	1,058,846
# time clusters	527	251	276

PANEL B: 3-months cumulative predictors

	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.035***	.047***	.024**
	(4.90)	(4.56)	(2.51)
$\beta_{INDUSTRY}$	.087***	.091***	.084***
	(7.27)	(5.60)	(4.79)
Avg R^2	1.03%	0.92%	1.13%
Observations	1,583,404	539,563	1,043,841
# time clusters	525	249	276

PANEL C: 6-months cumulative predictors

	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.023***	.028***	.018**
	(4.37)	(3.66)	(2.57)
$\beta_{INDUSTRY}$	.043***	.041***	.046***
	(5.43)	(4.02)	(3.77)
Avg R^2	1.03%	0.89%	1.15%
Observations	1,541,127	519,667	1,021,460
# time clusters	522	246	276

PANEL D: 12-months cumulative predictors

	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.013***	.019***	.008*
	(3.83)	(3.49)	(1.96)
$\beta_{INDUSTRY}$	.025***	.029***	.021***
	(5.13)	(5.09)	(2.80)
Avg R^2	1.09%	0.94%	1.21%
Observations	1,458,783	481,729	977,054
# time clusters	516	240	276

Table 2: Predictability of individual stock returns by area and industry porfolios (Fama-MacBeth). This table reports the coefficients of the Fama-MacBeth predictive regression

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin C,j,t} + \epsilon_{i,c,j,t+1}$$

where $r_{i,c,j,t+1}$ is the stock return of firm i, in city c, industry j, $r_{c,\notin j,t}$ is the equally-weighted lagged return of firms located in city c, outside industry j (city portfolio), and $r_{\notin C,j,t}$ is the equally-weighted lagged return of firms in the same industry j, but outside of the 20 cities (industry portfolio). The predictors are the 1-month (Panel A), and cumulative 3-months (Panel B), 6-months (Panel C) and 12-months (Panel D) lagged city and industry portfolio returns. Column 1: 1970-2013 (full sample). Column 2: 1970-1990. Column 3: 1991-2013. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West standard errors (5 lags). Monthly data.

PANEL A: 1-month predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.082***	.081***	.082***
	(5.90)	(3.69)	(4.82)
$\beta_{INDUSTRY}$	.173***	.166***	.179***
	(8.56)	(5.93)	(6.19)
Avg R^2	3.72%	3.12%	4.27%
Observations	111,942	52,001	59,941
# time clusters	527	251	276

PANEL B: 3-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.043***	.051***	.036***
	(4.82)	(3.81)	(3.04)
$\beta_{INDUSTRY}$	.078***	.082***	.074***
	(7.66)	(4.99)	(5.96)
Avg R^2	3.81%	3.79%	3.82%
Observations	109,063	50,160	58,903
# time clusters	525	249	276

PANEL C: 6-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.026***	.031***	.021***
	(4.73)	(3.79)	(2.93)
$\beta_{INDUSTRY}$	.038***	.039***	.038***
	(5.71)	(3.82)	(4.23)
Avg R^2	3.70%	3.68%	3.71%
Observations	106,037	48,137	57,900
# time clusters	522	246	276

PANEL D: 12-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.014***	.021***	.008
	(3.85)	(4.02)	(1.38)
$\beta_{INDUSTRY}$	.022***	.028***	.018***
	(5.15)	(5.02)	(2.72)
Avg R^2	3.84%	3.92%	3.77%
Observations	100,174	44,277	55,897
# time clusters	516	240	276

Table 3: Predictability of city-industry portfolios (Fama-MacBeth). This table reports the coefficients of the Fama-MacBeth predictive regression

$$r_{j,c,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin C,j,t} + \epsilon_{i,c,j,t+1}$$

where $r_{j,c,t+1}$ is the return of industry j, in city c, $r_{c,\notin j,t}$ is the equally-weighted lagged return of firms located in city c, outside industry j (city portfolio), and $r_{\notin C,j,t}$ is the equally-weighted lagged return of firms in the same industry j, but outside of the 20 cities (industry portfolio). The predictors are the 1-month (Panel A), and cumulative 3-months (Panel B), 6-months (Panel C) and 12-months (Panel D) lagged city and industry portfolio returns. Column 1: 1970-2013 (full sample). Column 2: 1970-1990. Column 3: 1991-2013. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West standard errors (5 lags). Monthly data.

Momentum Trading Strategy - Quintiles

	returns						portfolio characteristics			
	Mean (%)	*CAPM α*	*t-stat*	*FF-3 α*	*t-stat*	*Sharpe Ratio*	*Volatility (%)*	*Mkt share (%)*	*Size*	*B/M*
lowest city return	0.736	-0.257	-3.213	-0.242	-2.997	0.207	5.291	0.181	15.313	0.597
	0.876	-0.077	-1.117	-0.037	-0.525	0.318	4.985	0.212	15.682	0.567
	1.026	0.108	1.425	0.126	1.576	0.452	4.660	0.218	15.777	0.564
	0.949	-0.009	-0.098	-0.001	-0.019	0.366	5.030	0.206	15.625	0.571
highest city return	1.157	0.212	3.193	0.211	3.026	0.526	4.862	0.180	15.264	0.590
5-1 spread	0.421 [3.64]	0.469	[4.148]	0.453	[3.988]		2.628			

Table 4: Area Momentum Trading Strategy. This table reports the performance of a trading strategy that exploits return continuation at the geographic level. Every month, we rank each firm i by the equally-weighted lagged return of firms headquartered in the same city, outside its industry. We then construct quintile value-weighted portfolios of the sorted firms, and hold them for one month. Portfolios are rebalanced every month. Displayed are mean returns, CAPM α, FF-3 α of each quintile portfolio. *Volatility* is the monthly standard deviation of the portfolio returns, *Mkt share* is the proportional market share of the individual portfolios, *Size* is the natural logarithm of the market value of the portfolios (in thousands), *B/M* is the book-to-market ratio of the portfolios. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West (5 lags) standard errors. Monthly data, 1971-2013.

PANEL A: Number of analysts

	(0)	*(1)*	*(2-9)*	(≥ 10)	High/Low Diff
$\boldsymbol{\beta_{CITY}}$	.057***	.063*	.071***	.066**	
	(2.79)	(1.76)	(3.75)	(2.51)	[0.7375]
$\boldsymbol{\beta_{INDUSTRY}}$	.268***	.272***	.158***	.064*	
	(7.31)	(6.43)	(4.77)	(1.83)	[0.00***]
Avg R^2	1.09%	1.63%	1.39%	3.00%	
Observations	561,460	127,602	401,220	172,803	
# time clusters	336	336	336	336	

PANEL B: Firm Size

	(1)	*(2)*	*(3)*	*(4)*	Big/Small Diff
$\boldsymbol{\beta_{CITY}}$	.101***	.068***	.047***	.069***	
	(4.11)	(4.03)	(2.93)	(4.30)	[0.1974]
$\boldsymbol{\beta_{INDUSTRY}}$	.243***	.232***	.189***	.102***	
	(7.55)	(7.61)	(6.94)	(4.30)	[0.00***]
Avg R^2	0.83%	1.50%	1.88%	2.52%	
Observations	400,088	403,689	404,079	404,117	
# time clusters	527	527	527	527	

PANEL C: Trading Volume

	(1)	*(2)*	*(3)*	*(4)*	High/Low Diff
$\boldsymbol{\beta_{CITY}}$	.072***	.056***	.055***	.100***	
	(3.78)	(2.62)	(2.93)	(4.94)	[0.2469]
$\boldsymbol{\beta_{INDUSTRY}}$	.216***	.212***	.209***	.128***	
	(8.90)	(7.65)	(7.66)	(4.73)	[0.0035***]
Avg R^2	0.96%	1.21%	1.35%	1.99%	
Observations	380,839	380,929	381,466	381,322	
# time clusters	527	527	527	527	

Table 5: Predictive regressions with cross-sectional cuts (Fama-MacBeth). This table reports the coefficients of the Fama-MacBeth predictive regression

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin C,j,t} + \epsilon_{i,c,j,t+1}$$

conditioning on the number of analysts following a firm post-1985 (Panel A) and quartiles based on firm size (Panel B) and trading volume (Panel C). $r_{i,c,j,t+1}$ is the stock return of firm i, in city c, industry j, $r_{c,\notin j,t}$ is the equally-weighted lagged return of firms located in city c, outside industry j (city portfolio), and $r_{\notin C,j,t}$ is the equally-weighted lagged return of firms in the same industry j, but outside of the 20 cities (industry portfolio). Quartiles are estimated within every month. Quartile 1 is the smallest quartile. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West (5 lags) standard errors. Monthly data, 1970-2013.

PANEL A: 1% misclassified HQ locations			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.073***	.090***	.057***
	(5.61)	(4.66)	(3.34)
$\beta_{INDUSTRY}$	.199***	.185***	.212***
	(8.21)	(6.41)	(5.57)
Avg R^2	1.03%	0.79%	1.24%
Observations	1,611,973	553,127	1,058,846
# time clusters	527	251	276

PANEL B: 5% misclassified HQ locations			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.064***	.076***	.054***
	(5.28)	(4.09)	(3.40)
$\beta_{INDUSTRY}$	.199***	.184***	.212***
	(8.20)	(6.35)	(5.58)
Avg R^2	1.02%	0.78%	1.23%
Observations	1,611,973	553,127	1,058,846
# time clusters	527	251	276

PANEL C: 10% misclassified HQ locations			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.057***	.062***	.052***
	(4.71)	(3.56)	(3.13)
$\beta_{INDUSTRY}$	.199**	.185***	.212***
	(8.21)	(6.37)	(5.58)
Avg R^2	1.01%	0.76%	1.23%
Observations	1,611,973	553,127	1,058,846
# time clusters	527	251	276

PANEL D: 20% misclassified HQ locations			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.037***	.050***	.026*
	(3.34)	(2.97)	(1.75)
$\beta_{INDUSTRY}$	.198***	.185***	.211***
	(8.21)	(6.37)	(5.58)
Avg R^2	0.99%	0.76%	1.21%
Observations	1,611,973	553,127	1,058,846
# time clusters	527	251	276

PANEL E: 50% misclassified HQ locations			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	-.003	.008	-.014
	(-0.28)	(0.56)	(-0.76)
$\beta_{INDUSTRY}$	.197***	.186***	.208***
	(8.29)	(6.35)	(5.64)
Avg R^2	0.97%	0.72%	1.20%
Observations	1,611,973	553,127	1,058,846
# time clusters	527	251	276

Table 6: Misclassified locations. This table reports the coefficients of the Fama-MacBeth predictive regression

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin C,j,t} + \epsilon_{i,c,j,t+1}$$

where $r_{i,c,j,t+1}$ is the stock return of firm i, in city c, industry j, $r_{c,\notin j,t}$ is the equally-weighted lagged return of firms located in city c, outside industry j (city portfolio), and $r_{\notin C,j,t}$ is the equally-weighted lagged return of firms in the same industry j, but outside of the 20 cities (industry portfolio). In every panel, the predictors are the 1-month lagged "random" city and industry portfolio returns. 1% of the locations are randomized in Panel A, 5% in Panel B, 10% in Panel C, 20% in Panel D, 50% in Panel E. Column 1: 1970-2013 (full sample). Column 2: 1970-1990. Column 3: 1991-2013. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West standard errors (5 lags). Monthly data.

	Full Sample		Small Firms		Large Firms	
	Low	*High*	*Low*	*High*	*Low*	*High*
$\boldsymbol{\beta_{CITY}}$	.056***	.083***	.052*	.102***	.059**	.076***
	(3.57)	(3.93)	(1.92)	(3.07)	(2.61)	(3.72)
$\boldsymbol{\beta_{INDUSTRY}}$	.161***	.198***	.190***	.233***	.132***	.143***
	(7.40)	(7.66)	(6.30)	(7.14)	(5.66)	(5.28)
Avg R^2	1.38%	1.20%	1.53%	1.32%	2.26%	2.33%
Observations	526,278	528,599	188,966	307,598	337,312	221,001
# time clusters	527	527	527	527	527	527
avg. # of states	9	3	8	3	10	4

Table 7: Geographic Concentration. This table reports the coefficients of the Fama-MacBeth predictive regression

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin C,j,t} + \epsilon_{i,c,j,t+1}$$

conditioning on geographic concentration. $r_{i,c,j,t+1}$ is the stock return of firm i, in city c, industry j, $r_{c,\notin j,t}$ is the equally-weighted lagged return of firms located in city c, outside industry j (city portfolio), and $r_{\notin C,j,t}$ is the equally-weighted lagged return of firms in the same industry j, but outside of the 20 cities (industry portfolio). Geographic concentration is defined as in Garcia and Norli (2012), based on the number of states mentioned in the 10K. The first column of every block ("Low") indicates the least geographic concentrated firms. The second column of every block ("High") indicates the most geographic concentrated firms. Columns 3-4 (5-6) report the geographic concentration results for small (large) firms. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West standard errors (5 lags). Monthly data, 1970-2013.

PANEL A: 1-month predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.063***	.101***	.048**
	(3.66)	(4.62)	(2.11)
$\beta_{INDUSTRY}$	.155**	.175***	.147*
	(2.30)	(5.65)	(1.71)
Adj R^2	10.47%	14.27%	8.96%
Adj R^2 *w/o time fixed effect*	0.58%	0.87%	0.46%
Observations	1,611,973	553,127	1,058,846
# time clusters	527	251	276
# firm clusters	12,998	5,978	10,519

PANEL B: 3-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.027***	.047***	.019
	(2.86)	(3.54)	(1.42)
$\beta_{INDUSTRY}$	.065*	.076***	.062
	(1.80)	(4.42)	(1.30)
Adj R^2	10.45%	14.38%	8.92%
Adj R^2 *w/o time fixed effect*	0.10%	0.18%	0.06%
Observations	1,583,404	539,563	1,043,841
# time clusters	525	249	276
# firm clusters	12,930	5,942	10,459

PANEL C: 6-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.018***	.025***	.015*
	(2.87)	(3.23)	(1.67)
$\beta_{INDUSTRY}$	.026	.032***	.023
	(1.24)	(3.21)	(0.85)
Adj R^2	10.36%	14.31%	8.86%
Adj R^2 *w/o time fixed effect*	0.00%	0.05%	0.00%
Observations	1,541,127	519,667	1,021,460
# time clusters	522	246	276
# firm clusters	12,821	5,828	10,375

PANEL D: 12-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.014***	.016***	.011**
	(4.11)	(3.51)	(2.51)
$\beta_{INDUSTRY}$	.014	.022***	.011
	(1.41)	(3.42)	(0.82)
Adj R^2	10.27%	14.46%	8.76%
Adj R^2 *w/o time fixed effect*	0.00%	0.03%	0.00%
Observations	1,458,783	481,729	977,054
# time clusters	516	240	276
# firm clusters	12,480	5,571	10,132

Table 8: Predictability of individual stock returns by area and industry portfolios (pooled OLS). This table reports the coefficients of the panel predictive regression with fixed effects

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin C,j,t} + \epsilon_{i,c,j,t+1}$$

where $r_{i,c,j,t+1}$ is the stock return of firm i, in city c, industry j, $r_{c,\notin j,t}$ is the equally-weighted lagged return of firms located in city c, outside industry j (city portfolio), and $r_{\notin C,j,t}$ is the equally-weighted lagged return of firms in the same industry j, but outside of the 20 cities (industry portfolio). The predictors are the 1-month (Panel A), and cumulative 3-months (Panel B), 6-months (Panel C) and 12-months (Panel D) lagged city and industry portfolio returns. Column 1: 1970-2013 (full sample). Column 2: 1970-1990. Column 3: 1991-2013. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered on both time and firm dimensions following Petersen (2009). Monthly data.

	1-month return	*3-months return*	*6-months return*	*12-months return*
$\boldsymbol{\beta_{CITY}}$	.037***	.025***	.017***	.011***
	(3.06)	(3.15)	(3.49)	(3.43)
$\boldsymbol{\beta_{INDUSTRY}}$	.118***	.062***	.025***	.019***
	(4.59)	(4.68)	(2.75)	(3.52)
Avg R^2	0.97%	0.98%	0.97%	1.06%
Observations	1,598,268	1,569,804	1,527,731	1,445,822
# time clusters	526	524	521	515

Table 9: Predictability of individual stock returns by area and industry portfolios skipping 1-month (Fama-MacBeth). This table reports the coefficients of the Fama-MacBeth predictive regression

$$r_{i,c,j,t+2} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin C,j,t} + \epsilon_{i,c,j,t+2}$$

where $r_{i,c,j,t+2}$ is the stock return of firm i, in city c, industry j, $r_{c,\notin j,t}$ is the equally-weighted lagged return of firms located in city c, outside industry j (city portfolio), and $r_{\notin C,j,t}$ is the equally-weighted lagged return of firms in the same industry j, but outside of the 20 cities (industry portfolio). The predictors are the 1-month (column 1), and cumulative 3-months (column 2), 6-months (column 3) and 12-months (column 4) lagged city and industry portfolio returns. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West standard errors (5 lags). Monthly data, 1970-2013.

PANEL A: 1-month predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.036***	.041***	.032**
	(3.97)	(3.34)	(2.38)
$\beta_{INDUSTRY}$	.145***	.177***	.117***
	(7.55)	(7.24)	(4.07)
Avg R^2	0.76%	0.61%	0.89%
Observations	1,611,973	553,127	1,058,846
# time clusters	527	251	276

PANEL B: 3-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.019***	.018**	.021***
	(4.01)	(2.43)	(3.28)
$\beta_{INDUSTRY}$	.059***	.063***	.055***
	(5.53)	(4.70)	(3.39)
Avg R^2	0.80%	0.73%	0.86%
Observations	1,583,404	539,563	1,043,841
# time clusters	525	249	276

PANEL C: 6-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.016***	.018***	.015***
	(4.04)	(2.80)	(2.91)
$\beta_{INDUSTRY}$	.033***	.034***	.032***
	(4.74)	(3.77)	(3.07)
Avg R^2	0.83%	0.70%	0.94%
Observations	1,541,127	519,667	1,021,460
# time clusters	522	246	276

PANEL D: 12-months cumulative predictors			
	full sample	*1970-1990*	*1991-2013*
β_{CITY}	.006**	.011***	.002
	(2.28)	(2.63)	(0.51)
$\beta_{INDUSTRY}$	.025***	.027***	.023***
	(5.45)	(5.85)	(3.08)
Avg R^2	0.93%	0.79%	1.05%
Observations	1,458,783	481,729	977,054
# time clusters	516	240	276

Table 10: Predictability of individual stock returns by area and industry portfolios (value-weighted portfolios). This table reports the coefficients of the Fama-MacBeth predictive regression

$$r_{i,c,j,t+1} = \alpha + \beta_1 r_{c,\notin j,t} + \beta_2 r_{\notin C,j,t} + \epsilon_{i,c,j,t+1}$$

where $r_{i,c,j,t+1}$ is the stock return of firm i, in city c, industry j, $r_{c,\notin j,t}$ is the value-weighted lagged return of firms located in city c, outside industry j (city portfolio), and $r_{\notin C,j,t}$ is the value-weighted lagged return of firms in the same industry j, but outside of the 20 cities (industry portfolio). The predictors are the 1-month (Panel A), and cumulative 3-months (Panel B), 6-months (Panel C) and 12-months (Panel D) lagged city and industry portfolio returns. Column 1: 1970-2013 (full sample). Column 2: 1970-1990. Column 3: 1991-2013. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West standard errors (5 lags). Monthly data.

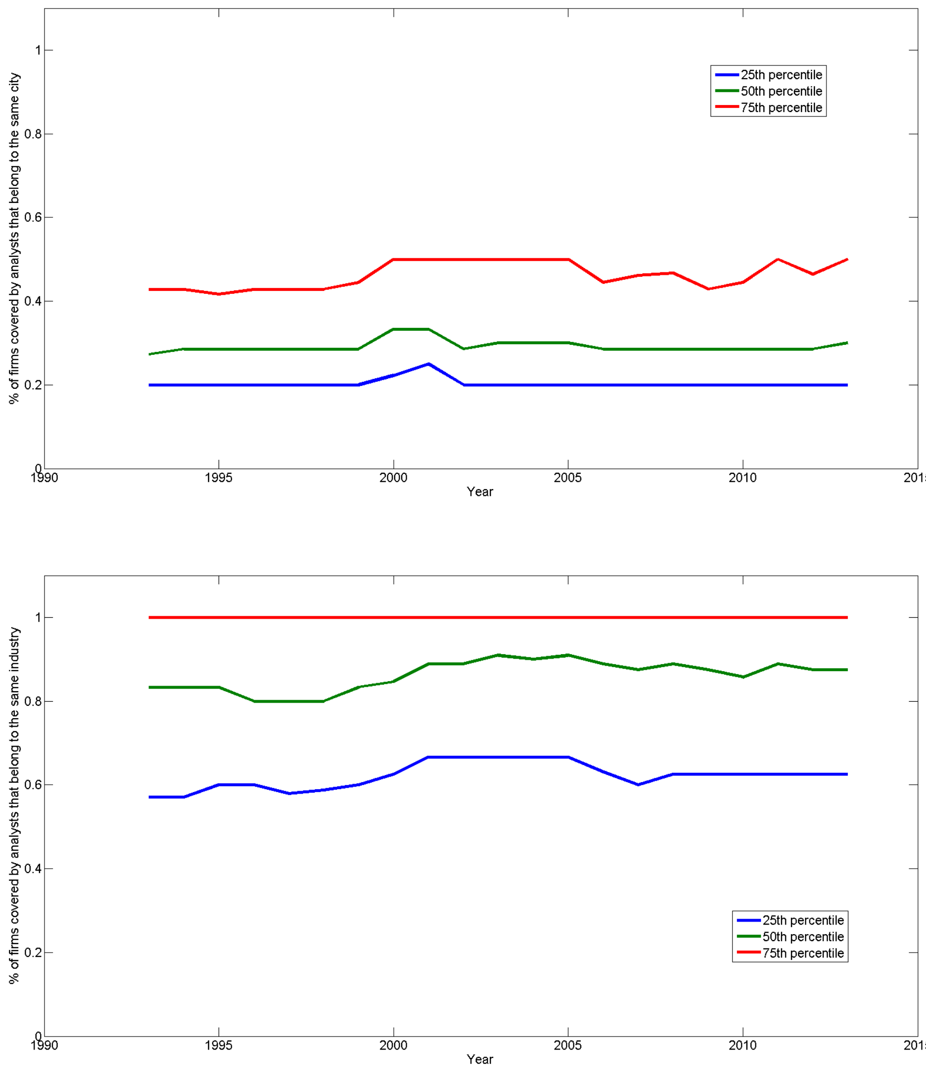

Figure 2: Distribution of analyst coverage by cities and industries. These graphs show the time series distribution of city (top panel) and industry (bottom panel) concentration of analyst coverage. For each analyst in every year, we identify the modal (i.e., most commonly represented) industry and city. Then, for each analyst, we identify the fraction of covered firms in these modal industries and cities and sort the analysts according to these fractions. For example, in the top panel, less than 28% of the firms covered by the median analyst in 1995 are headquartered in the same city. As another example, in the bottom panel, at least a quarter of the analysts, every year, cover only firms that belong to the same industry. Sample: 1993-2013.

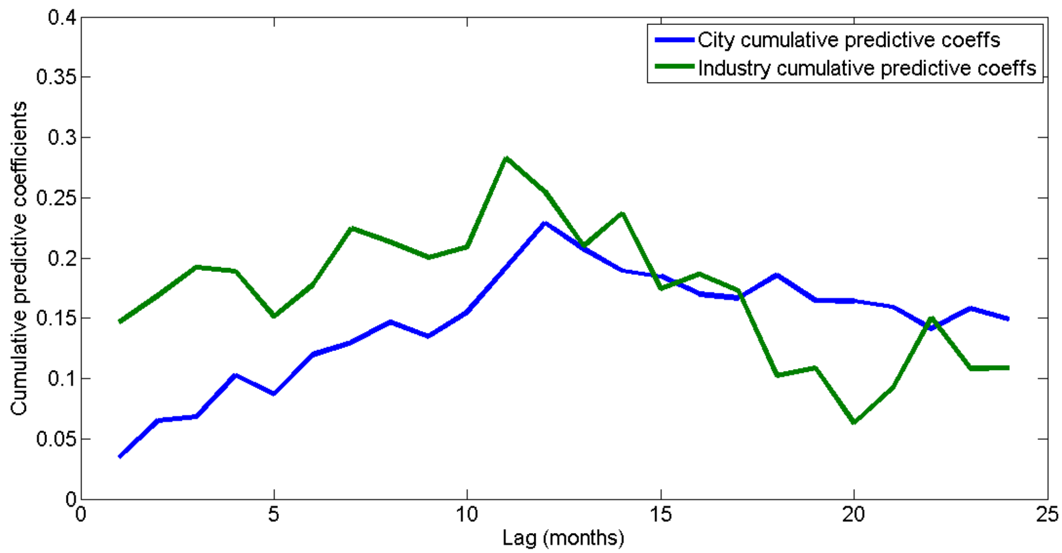

Figure 3: Speed of information diffusion. This graph plots the cumulative coefficients from a one-month predictive regression of firm-level returns on 24 separate monthly return lags, for both an industry and geographic factor. For example, the value of the blue line (the geographic factor) at one lag is the coefficient on month $t-1$ returns when predicting month t returns, whereas the plotted value at two lags represents the sum of the $t-1$ and $t-2$ coefficients. Monthly data, 1970-2013.

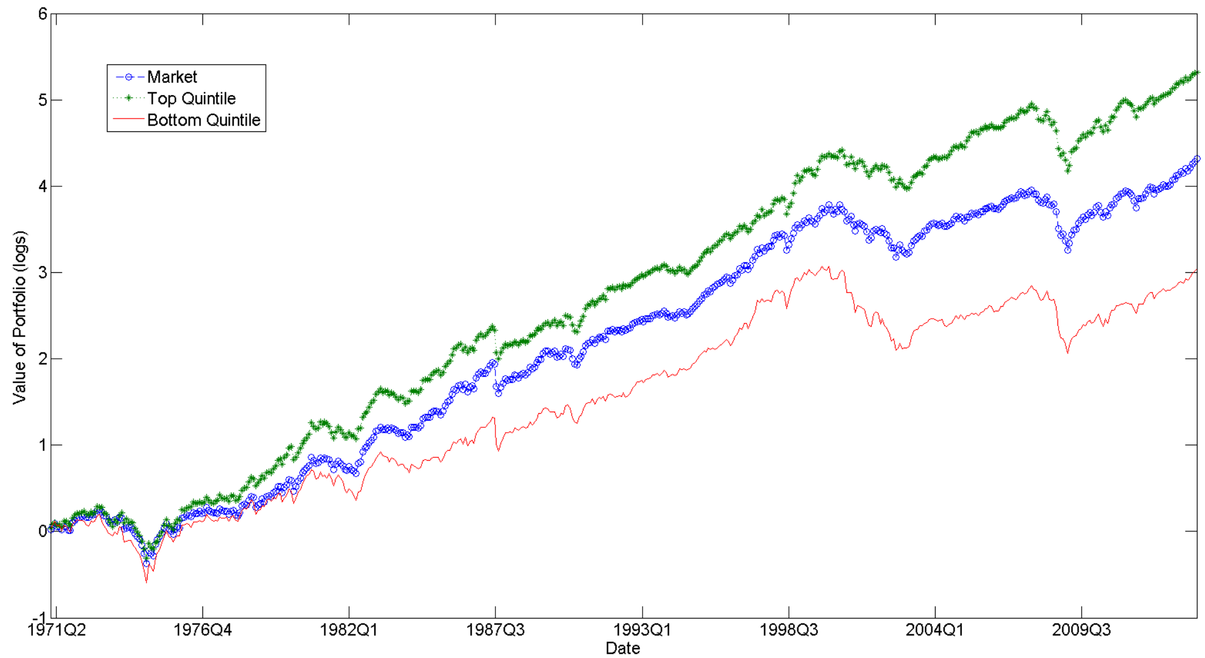

Figure 4: Cumulative performance of the trading strategy. This graph shows the time series evolution of a $1 investment in each of three trading strategies. The blue line is a market (S&P500) strategy, where dividends are reinvested in the market. The green (red) line represents a long-only strategy that value-weights the top (bottom) 20% of firms, when ranked by area-level stock returns the prior month. Monthly rebalancing. Numbers are in logs. Sample period: February 1971 - December 2013.

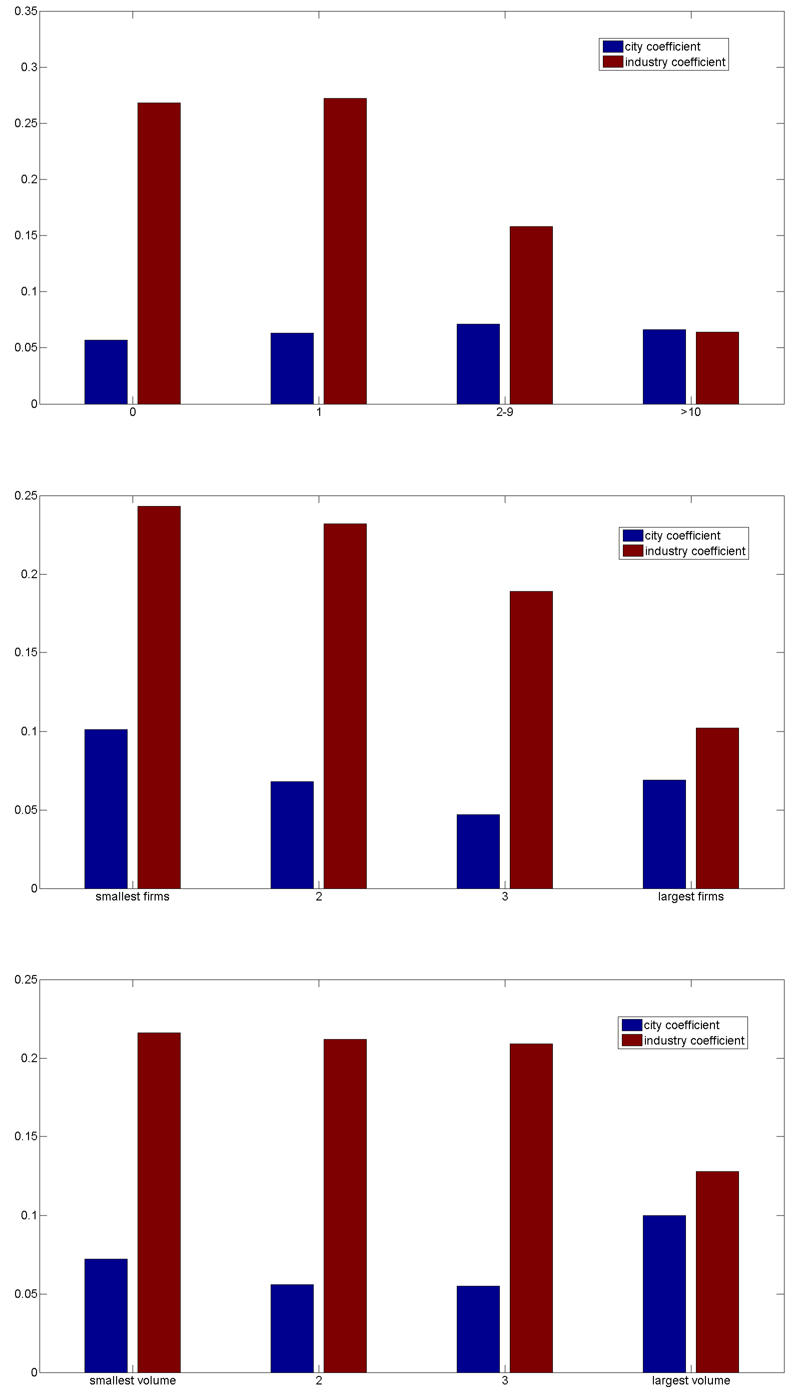

Figure 5: Plot of cross-sectional lead-lag coefficients. This graph corresponds to Table 5, and plots the lead-lag coefficients for industry (red) and area (blue) portfolios, which are estimated from one-month Fama-MacBeth predictive regressions. Cross-sectional cuts are obtained by splitting the sample into four groups based on number of analysts following a firm (top figure) and quartiles based on firm size (middle figure) and trading volume (bottom figure).

A Supplementary results

Momentum Trading Strategy - Deciles											
	returns						**portfolio characteristics**			
	Mean (%)	*CAPM* α	*t-stat*	*FF-3* α	*t-stat*	*Sharpe Ratio*	*Volatility (%)*	*Mkt share (%)*	*Size*	*B/M*
lowest city return	0.721	-0.253	-2.554	-0.276	-2.809	0.199	5.274	0.087	15.109	0.613
	0.788	-0.206	-1.799	-0.188	-1.709	0.233	5.508	0.094	15.282	0.597
	0.854	-0.097	-0.954	-0.116	-1.029	0.294	5.130	0.102	15.453	0.581
	0.937	-0.024	-0.235	0.046	0.475	0.336	5.348	0.109	15.616	0.568
	0.980	0.050	0.495	0.070	0.639	0.388	5.009	0.110	15.636	0.565
	1.096	0.167	1.548	0.182	1.615	0.468	5.015	0.108	15.586	0.575
	1.008	0.071	0.776	0.042	0.446	0.408	5.003	0.105	15.543	0.573
	0.930	-0.041	-0.394	-0.040	-0.367	0.331	5.356	0.100	15.445	0.579
	1.104	0.138	1.398	0.084	0.759	0.451	5.264	0.094	15.273	0.592
highest city return	1.132	0.190	2.021	0.191	2.136	0.487	5.071	0.086	15.042	0.602
10-1 spread	0.410 [2.88]	0.444	[3.167]	0.467	[3.301]		3.198			

Table A1: Area Momentum Trading Strategy (Deciles). This table reports the performance of a trading strategy that exploits return continuation at the geographic level. Every month, we rank each firm i by the equally-weighted lagged return of firms headquartered in the same city, outside its industry. We then construct decile value-weighted portfolios of the sorted firms, and hold them for one month. Portfolios are rebalanced every month. Displayed are mean returns, CAPM α, FF-3 α of each decile portfolio. *Volatility* is the monthly standard deviation of the portfolio returns, *Mkt share* is the proportional market share of the individual portfolios, *Size* is the natural logarithm of the market value of the portfolios (in thousands), *B/M* is the book-to-market ratio of the portfolios. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West (5 lags) standard errors. Monthly data, 1971-2013.

Momentum Trading Strategy - Only 20% Largest Firms											
	returns						portfolio characteristics				
	Mean (%)	*CAPM* α	*t-stat*	*FF-3* α	*t-stat*	*Sharpe Ratio*	*Volatility (%)*	*Mkt share (%)*	*Size*	*B/M*
lowest city return	0.778	-0.198	-2.214	-0.191	-2.210	0.238	5.225	0.169	15.679	0.591
	0.829	-0.114	-1.313	-0.032	-0.396	0.289	4.926	0.213	16.054	0.564
	0.972	0.055	0.667	0.102	1.219	0.408	4.701	0.221	16.131	0.554
	0.902	-0.047	-0.525	-0.001	-0.012	0.336	4.982	0.210	16.043	0.565
highest city return	1.208	0.271	3.187	0.302	3.193	0.557	4.909	0.187	15.770	0.583
5-1 spread	0.429 [3.07]	0.468	[3.366]	0.493	[3.438]		2.963			

Table A2: Area Momentum Trading Strategy with the 20% largest firms. This table reports the performance of a trading strategy that exploits return continuation at the geographic level only using the top 20% firms by market capitalization. Every month, we rank each firm i by its market capitalization and keep the top 20%. We then re-rank those firms by the equally-weighted lagged return of firms headquartered in the same city, outside its industry. We then construct quintile value-weighted portfolios of the sorted firms, and hold them for one month. Portfolios are rebalanced every month. Displayed are mean returns, CAPM α, FF-3 α of each quintile portfolio. *Volatility* is the monthly standard deviation of the portfolio returns, *Mkt share* is the proportional market share of the individual portfolios, *Size* is the natural logarithm of the market value of the portfolios (in thousands), B/M is the book-to-market ratio of the portfolios. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Newey-West (5 lags) standard errors. Monthly data, 1971-2013.