Institutional Presence*

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Abstract

Does being located near institutional investors benefit corporations? We examine whether the 'presence' of local institutional investors, as measured by the equity assets under management of local institutions, reduces information asymmetry in the stock market. Firms in high institutional presence areas experience higher liquidity, faster information incorporation, lower costs of equity capital, and less financing frictions relative to firms in low institutional presence areas. Being located near institutional investors does not increase exposure to price or liquidity shocks. These patterns remain after controlling for firm characteristics (e.g., institutional ownership, firm fixed effects) and geographical features (e.g., urban locality, area fixed effects).

Keywords: institutional investors, non-shareholders, liquidity, cost of capital
JEL *Classification*: G12, G14, G23

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I Introduction

A large body of literature studies how geographic location affects the performance and portfolio choice of professional investment managers. Coval and Moskowitz (2001) and Baik, Kang, and Kim (2010) find that institutional investors benefit from geographical proximity to local stocks, potentially due to proximity facilitating information collection of companies. Yet, it is unclear whether this proximity is mutually beneficial for companies located close to institutional investors. This study seeks to fill this gap by examining potential advantages to being located near institutional investors.

Consider two large, thriving urban cities for which one has a substantially greater concentration of institutional investors. This clustering of financial intermediaries is likely to result in a relatively larger number of local agents participating in the information production process. As mentioned above, these local agents are likely to have advantages in gathering information. As more informed agents trade in a given firm's stock and compete to profit from their informational advantage, information asymmetry between the firm and its investors will be reduced, which should be reflected in greater informational efficiency in the stock price and higher liquidity (Holden and Subrahmanyam, 1992). Moreover, even when their informational advantage does not result in these local agents becoming shareholders, local non-shareholders are in a better position to provide liquidity when stocks become inefficiently priced (e.g., Cheng, Hameed, Subrahmanyam, and Titman, 2014). In these scenarios, the presence of local institutional investors –shareholders or otherwise– is likely to result in higher stock price efficiency and stock liquidity.

We employ an "institutional presence" (IP) measure to capture the latent role of institutional investors in information production. This measure is defined as the aggregate portfolio value –i.e. total value of equity holdings– managed by 13-F institutional investors that are located in a particular U.S. state. We then assume that firms headquartered in that state experience the "presence" of the state's institutional investors, and assign the state's IP measure to those firms. For example, the IP measure assigned to firms located in Atlanta in 2003:Q1 is US$ 185 billion, corresponding to the aggregate equity holdings of institutional investors located in the state of Georgia at the end of 2002:Q4.[1] As each state's IP measure varies over time with the size of the state's money management sector, our approach allows us to examine not only the cross–sectional pattern of institutional presence across states (e.g., Colorado vs. Georgia), but also the effect of *time–series* variation of institutional presence *within* each state.

The institutional presence (IP) measure complements the direct shareholder channel, traditionally measured with institutional ownership in a particular firm (e.g., Boehmer and Kelley, 2009; Ayers, Ramalingegowda, and Yeung, 2011; Chhaochharia, Kumar, and Niessen-Ruenzi, 2012). Relative to the firm—level institutional ownership measure, the state—level IP measure has an attractive feature: it avoids endogeneity issues arising from the propensity of institutions to hold stocks with specific characteristics that are difficult for researchers to observe. Combined with institutional ownership, the IP measure provides a more complete picture of the increasing importance of institutional investors. While existing studies examine the direct shareholder channel, to the best of our knowledge, no paper attempts to quantify the aggregate effects of local institutional investors including those who decide *not* to hold the firm's shares.[2]

Using the IP measure, we address our main research question – whether companies benefit from being located near more institutional investors. We argue that greater institutional presence should lower the information asymmetry between the firm and (potential) market participants due to the lower cost of acquiring information. This reduction in information asymmetry should be reflected in greater informational efficiency in the stock price and higher liquidity (Holden and

[1] We use the total equity holdings in our analysis rather than the ratio of total equity holdings to other state-level variables, e.g., the total assets of firms headquartered in the state, or the state's GDP. However, we control for these state-level variables in our analyses.
[2] Our IP measure is similar in spirit to other measures that focus on potential investors rather than actual shareholders, such as those employed by Becker, Cronqvist, and Fahlenbrach (2011), Becker, Ivković, and Weisbenner (2011), and Bernile, Kogan, and Sulaeman (2013).

Subrahmanyam, 1992). However, there is mounting evidence that institutional trading can drive prices away from fundamentals due to these investors' herding behavior, short trading horizons, flow driven demand, and liquidity demand.[3] Since institutional investors tend to hold and trade disproportionately more local stocks –i.e., local holding bias (Coval and Moskowitz, 1999) and trading bias (Bernile, Kumar, Sulaeman, and Wang, 2013), being located near institutional investors may increase a firm's exposure to these stock price shocks and liquidity dis-locations.[4]

Our first set of findings is consistent with our hypothesis that institutional presence is associated with greater price efficiency. Stocks in high institutional presence regions experience higher liquidity than their low institutional presence counterparts. Our baseline test shows that a one standard deviation increase in the IP measure is related to a 5% standard deviation increase in liquidity. The effect of institutional presence is incremental to the effect of institutional ownership. Comparing the point estimates suggests that the non–shareholder channel –as proxied by the IP measure– is smaller but of a comparable order of economic magnitude relative to the direct shareholder channel –as measured by institutional ownership.

While this evidence points to the importance of institutional presence, an obvious concern is that of latent omitted variables related to the characteristics of a region. We take a number of steps to alleviate these concerns. First, we rule out persistent state–level characteristics by including *state* fixed effects in our baseline analysis. These fixed effects handle time-invariant factors such as the "specialness" of New York and other areas with more developed financial sectors

[3] Recent evidence links institutional investors to herding behavior (Lakonishok, Shleifer, and Vishny, 1992; Choi and Sias, 2009; Dasgupta, Prat, and Verardo, 2011; Brown, Wei, and Wermers, 2014), short trading horizons (Cella, Ellul, and Giannetti, 2013), flow driven demand (Coval and Stafford, 2007; Greenwood and Thesmar, 2011; Lou, 2012; Antón and Polk, 2014), and liquidity demand (Kamara, Lou, and Sadka, 2008; Aragon and Strahan, 2012; Koch, Starks, and Ruenzi, 2012).

[4] We also verify that being located in high IP areas predicts more trading in the firm's stock by local investors, ceteris paribus, which is consistent with our implicit assumption in constructing the IP measure that the U.S. equity market is geographically segmented. Pirinsky and Wang (2006) find higher return co-movement amongst firms headquartered in close proximity. Van Nieuwerburgh and Veldkamp (2009) provide a theoretical argument that proximity-based market segmentation in the equity market can arise endogenously due to information immobility.

(e.g., Boston, Chicago, San Francisco) or state characteristics such as laws on corporate disclosure requirements. Our results are robust to the inclusion of state and even *firm* fixed effects. This suggests that the relation between institutional presence and liquidity is not only a cross–sectional phenomenon but at least partly due to the time–series variation of the IP measure within each state and for each firm.

Second, it is plausible that economic growth and health of a region (e.g., Glaeser, et al., 1992; Glaeser, Scheinkman, and Shleifer, 1995; Korniotis and Kumar, 2013; Dougal, Parsons, and Titman, 2014) may simultaneously improve the liquidity of local stocks and increase institutional presence. Ruling out all potential factors contributing to the regional economic condition is extremely difficult. Instead, we attempt to distinguish the institutional presence effect from some of the more obvious alternative channels. We first control for state income, aggregate GDP, aggregate book value of corporate assets in the state, and regional economic growth rate. While not perfect measures, state income and GDP provide reasonable proxies of the potential role of other market participants –in particular, retail investors– in the price formation process. Next, we also include the aggregate stock returns of firms in the state to capture forward–looking economic effects. Lastly, we rule out slow–moving regional characteristics by controlling for the presence of other local information producers (i.e., local brokerage houses employing equity analysts and local media coverage) and local demographic conditions (e.g., population density or urbanized cities). Our results are robust to the inclusion of these time–varying characteristics, consistent with our conjecture that institutional investors are important contributors to higher stock liquidity.[5]

A related issue is potential reverse causality. Institutional investors may choose to locate near firms with more liquid stocks, or the local holdings component of the IP measure may

[5] Institutional presence affects liquidity even within the subsample of firms located in urban areas, suggesting that our results are not driven by the distinction between firms located in urban versus rural areas as documented in Loughran and Schultz (2005). We provide a more detailed discussion later in the introduction.

mechanically drive our liquidity finding. For example, the price appreciation of locally held shares may simultaneously increase the IP measure and the stock liquidity. To address this issue, we repeat our liquidity test after excluding each institution's local holdings (i.e., stocks located in the institution's state) from the construction of the IP measure. We obtain similar results when this adjusted IP measure is used.

In addition to ruling out potential alternative explanations for our results, we also design several tests that highlight the causal relation between institutional presence and stock liquidity.[6] First, using a sample of firm headquarter relocations, we find that firms moving from low institutional presence regions to high institutional presence regions experience an increase in liquidity. Second, we perform a case study that exploits plausibly exogenous shocks to institutional presence in Colorado around the period of the tech bust (2000–2002) and mutual fund trading scandal of 2003. During this period, Janus Capital –the predominant fund management company in Colorado– experienced large losses and outflows due to its disproportionately large exposure to the tech sector and its involvement in the trading scandal. Using a difference–in–difference analysis, we find that Colorado firms experience a disproportionate reduction in stock liquidity during this period.

Our results are robust to the choice of commonly used liquidity measures. Moreover, the relation between the IP measure and liquidity is more pronounced for firms with more opaque information environments such as small firms and firms with lower analyst coverage, consistent with firms with greater informational asymmetry enjoying the greatest benefits from their geographical proximity to institutional investors.

[6] It is difficult to find a well-defined instrument to "rule in" causality in our context. Mergers of financial institutions offer a potentially promising instrument but even when institutions are located across different states, the target institutions often continue to operate from their original location.

The hypothesis that the presence of local institutional investors results in higher liquidity relies on the information effect of institutional investors, i.e., that local institutional investors improve the informational efficiency of stock prices. The presence of these potentially more informed agents may result in lower liquidity if they generate adverse selection in the market. While our liquidity tests suggest that the information effect dominates the adverse selection effect, we also provide a direct test of how the presence of local institutional investors affects price informativeness. We adopt a measure of the speed of information diffusion, i.e., the 'delay' measure developed in Hou and Moskowitz (2005), to examine the degree to which prices incorporate market wide information. Consistent with the liquidity results, prices of stocks in high institutional presence areas incorporate information faster than stocks in low institutional presence areas. A one standard deviation increase in the IP measure is associated with around 4% standard deviation decrease in delay. This suggests that our liquidity evidence is driven by the information effect of institutional investors.

Our second research focus is related to the effect of institutional presence on allocational efficiency. While there are no established measures of allocational efficiency, a reduction in information asymmetry, all else equal, should be reflected in a lower cost of equity capital (Diamond and Verrecchia, 1991) and a loosening of financing frictions (Myers and Majluf, 1984). Our evidence is consistent with this hypothesis. Institutional presence is significantly and negatively related to the cost of equity capital. There is a −0.14% (t-stat=−5.67) difference in the industry−adjusted cost of equity capital between stocks located in the top and bottom terciles of institutional presence regions. From investment−cash flow sensitivity analysis, we find that firms located in high institutional presence regions have investment−cash flow sensitivities that are 28% lower than their low institutional presence counterparts.

Lastly, we examine potential drawbacks associated with the greater presence of institutional investors. As mentioned above, being located near institutional investors may expose a firm's stock to price shocks and liquidity dis—locations due to institutional investors' herding behavior, short trading horizons, flow driven demand, and liquidity demand. We find no systematic evidence that firms located in high institutional presence areas experience increased herding, fire—sale, or liquidity risk. While our analyses do not consider all potential drawbacks, our evidence suggests that it is unlikely to be manifested in significant liquidity costs or institutional-driven pricing dislocations.

Our study fits into a large literature that explores the growing role of institutional investors. While the direct shareholder channel has been widely examined, the non-shareholder channel is less well understood. Our evidence fills this important gap. Our study also contributes to the literature on the effect of firm location on market outcomes. The most directly related study to ours is Loughran and Schultz (2005, henceforth LS) that finds firms in urban areas having a higher liquidity than their rural counterparts and proposes that this may be explained by "high concentrations of institutional investors, brokers, and investment bankers."

Our findings extend LS in three ways. First, we show that including non-owner institutions in the analysis is crucial as it allows for a more complete empirical description of the role of institutional investors. In particular, while LS provides indirect evidence that the urban liquidity effect is related to institutional ownership, their main analysis indicates that the urban effect is not subsumed by institutional holdings, suggesting that other mechanisms may be afoot in urban areas. In contrast, we find that the urban liquidity effect is not distinct from the effect of institutional investors once local institutional non-owners are taken into account: the urban indicator is no longer significant in regressions predicting liquidity that include institutional presence and ownership measures. Second, our results continue to hold in the subsample of stocks with low local institutional ownership, consistent with the idea that our institutional presence measure captures the prospect of institutional investors stepping in to provide liquidity. Third, our results hold when city (i.e., MSA) fixed effects are included in an analysis of the subsample of urban firms, suggesting that the variation of institutional presence *within* each urban area is related to the liquidity of area firms. Finally, we show that institutional investors provide a host of benefits beyond liquidity improvement, such as faster information incorporation and lower costs of equity capital.

II Measuring Institutional Presence

Our measure of institutional presence is motivated by the findings in Coval and Moskowitz (2001) and Baik, Kang, and Kim (2010) that U.S. institutional investors profit from their geographical proximity to local U.S. stocks. In contrast, Ivković and Weisbenner (2005) and Seasholes and Zhu (2010) find conflicting evidence regarding whether U.S. retail investors obtain similar local profits. Combining these studies suggests that institutional investors are likely to possess significant advantages in collecting information about local firms.

Geographic proximity can lower the barriers to collecting soft information that is not available in standard corporate disclosures. In the banking literature, geographical proximity seems to facilitate the collection of soft information by banks, which directly affects loan terms and credit conditions (Petersen and Rajan, 2002; Degryse and Ongena, 2005). For institutional investors, their information collection costs may be lower due to their proximity to local information sources, e.g., local media coverage, word of mouth conversations, and social ties with local management (Cohen, Frazzini, and Malloy, 2010). This proximity–based information advantage is a commonly proposed rationale for the observation that investors tend to exhibit 'home bias' in their asset holdings (French and Poterba, 1991; Kang and Stulz, 1997; Coval and Moskowitz, 1999).[7] As local institutional investors make portfolio decisions using this type of

[7] While the information rationale for local bias suggests that institutional investors possess significant local advantage, studies also highlight the role of non-information based familiarity bias in investment decisions of both retail and professional investors; see e.g., Grinblatt and Keloharju (2001), Huberman (2001), Massa and Simonov (2006), Bodnaruk (2009), Teo (2009), and Pool, Stoffman, and Yonker (2012).

information, their information is impounded into prices. We therefore argue that the greater presence of local institutional investors is likely to facilitate timelier price formation and improve the information environment of nearby firms.[8]

A. Institutional Presence Measure

To develop a parsimonious measure of the presence of institutional investors, we aggregate the total institutional equity portfolio (i.e. equity assets under management) held by institutional investors located in each state. Our institutional presence measure is simply defined as:

$$\text{Institutional Presence } (\text{IP}_{\text{s,t}}) = \sum_{i \in s} \$AUM_{i,t-1} \qquad (1)$$

where $\$AUM_{i,t-1}$ is the total value of institution i's equity portfolio (comprised of shares in both local and non-local companies) in quarter $t-1$, and I_s is the set of all institutional investors located in state s.

The IP measure is intended to capture effects such as greater informational efficiency beyond what is captured by traditional institutional ownership measures. Like institutional ownership, institutional *non-ownership* is a result of investors' investment decisions. It does not necessarily reflect lower attention from institutional investors or lower informational efficiency. A disproportionately low level of local institutional ownership in a particular stock may be due to local institutions' poor perception of the stock's expected risk–adjusted return. This is arguably as informative about the information environment as a disproportionately high level of local institutional ownership in another stock. While the variation in local ownership may be useful in predicting future stock performance (Coval and Moskowitz, 2001; Baik, Kang, and Kim, 2010), it is not necessarily helpful in capturing the effect of local institutional investors on price efficiency.

[8] A large literature examines how corporate outcomes are affected by geographical proximity to investors; see e.g., Gaspar and Massa (2007), Kang and Kim (2008), Becker, Cronqvist, and Fahlenbrach (2011), Becker, Ivković, and Weisbenner (2011), and John, Knyazeva, and Knyazeva (2011).

In contrast, our IP measure is an ex-ante measure of local trading and investment.[9] It does not depend on the actual levels of institutional ownership or trading in local stocks. Therefore, it allows us to capture the effect of local investors on price efficiency regardless of their actual investment decisions: long position, no position, or even short position. Consequently, our measure is not directly related to *excess* holdings of local stocks –i.e., local/home bias– and the hypotheses that we examine in this paper neither require nor assume that institutional investors exhibit such behavior.

B. Robustness and Validity of the IP Measure

The IP_{ST} measure intuitively represents the supply of institutional capital available in a state. It is natural to also consider its demand counterpart: investment opportunities (i.e. local public firms) that are available in a state. We measure the availability of local public firms using the total market capitalization (ME_{ST}) or total book value of corporate assets ($Assets_{ST}$) located in the state. The relation between IP_{ST} and these measures of investment opportunities can roughly represent the supply and demand of institutional capital relative to investment opportunities. In the analysis reported in this paper, we include the IP_{ST} measure and $Assets_{ST}$ or ME_{ST} separately in the regression analysis to avoid imposing an ad-hoc functional form to our main variable. We also assume that firms with good prospects do not choose to locate near institutional investors. Our assumption is that corporate headquarter locations are predominantly determined by other established factors such as industry clusters, tax laws, and labor supply (Almazan, et al., 2010).

As mentioned above, we also wish to take into account the relation between institutional investors relative to non-institutional investors (i.e. individual investors). We are interested in capturing when institutions are likely to be the marginal investor relative to individual investors. To capture this relation, we include either the total income of local residents ($Income_{ST}$) or the

[9] We verify this assertion in the next section.

total GDP produced in each state (GDP_{ST}) in our regression analysis to proxy for local individual investors.

C. Trading Analysis

We validate our conjecture that the IP measure captures the probability of local institutional investors being the marginal investor/non-investor in an untabulated analysis. Since data on the actual trading activity of institutional investors is not publicly available, we resort to examining the absolute value of quarterly changes in local institutional ownership for locally based stocks. We define the state–level local institutional trading as the sum of these absolute values for all firms in a particular state. We regress this aggregate measure on the state–level IP measure and other state characteristics such as $Assets_{ST}$ and $Income_{ST}$ to control for variations in state sizes, e.g., New York vs. North Dakota.

The results indicate that the IP measure predicts more trading by local investors, ceteris paribus, consistent with our conjecture that the IP measure captures the probability of local institutional investors being the marginal investor/non-investor in a particular stock. This evidence along with prior evidence that local institutional investors gain from their local trades (Coval and Moskowitz, 2001; Baik, Kang, and Kim, 2010; Bernile, Kumar, Sulaeman, and Wang, 2013) supports our conjecture that local institutions are likely to step in when stocks become inefficiently priced. This potential involvement may additionally attract market making activity as modelled in Cheng, Hameed, Subrahmanyam, and Titman (2014). This activity may also act as an additional source of liquidity improvement in areas of high institutional presence.

It is important to note that our IP measure can potentially capture more than the effect of institutional ownership or even institutional trading. As we argue above, we employ the IP measure to capture the latent role of non-owner institutional investors. This includes those investors that have never traded the stock, and yet nevertheless may be observing it. This motivation essentially rules out using the IP measure as an instrument for institutional ownership and/or institutional trading since it does not satisfy the exclusion restriction.

III Data

Institutional investment manager state—level location data are collected from Nelson's Directories of Investment Managers from 1992 to 2010. Institutional investor quarterly holdings data are obtained from the Thomson Reuters 13(f) institutional holdings database. The 13F form (SEC) requires all institutional investment managers with over $100 million in equity assets under management to report their holdings each quarter. Firm headquarter location data are collected from both COMPUSTAT and Compact Disclosure.

We complement these location data with state–level variables. $Asset_{ST}$ is the total book value of corporate assets of firms headquartered in each state. $Income_{ST}$ is the total income of residents in each state. These variables are used in Hong, Kubik, and Stein (2008), and reflect local demand for equity securities. *Urban* is a variable equal to 1 if the company headquarters is located in one of the ten largest metropolitan areas in the United States, 0 if the company headquarters is located within 100 miles of the center of a Metropolitan State Area (MSA) that has at least 1 million residents, and −1 otherwise.[10] IDX_{ST} is the state economic condition measure developed in Korniotis and Kumar (2013). To proxy for economic growth prospects, we create a state return variable, *State Return*, calculated as the average return of stocks with headquarters in a given state. We additionally include the following county—level demographic variables from the U.S. Census Bureau in some of our tests. *Income Per Capita* is the per capita personal income

[10] This closely follows the urban–rural definitions outlined in Loughran and Schultz (2005) using the 2000 Census data. The ten largest metropolitan areas of the United States as of 2000 are New York City, Los Angeles, Chicago, Washington, San Francisco, Philadelphia, Boston, Detroit, Dallas, and Houston.

measured at the county level. *Pop. Density* is the total county population divided by its area size.[11]

Local analyst data is gathered from Nelson's Directory of Investment Research following Malloy (2005) and Bae, Stulz, and Tan (2008), and is generously provided by Hongping Tan. We measure local analyst presence in a particular state as the number of sell–side analysts located in that state. Newspaper circulation data is gathered from the Alliance for Audited Media (AAM) for 1996, and 2000 through 2008. AAM provides audited circulation totals for US print newspapers. Using the top 25 US newspapers in 1996, we track print circulation totals for that set of newspapers throughout our sample period. For the years without available data, we linearly interpolate between reported years. Next, we aggregate circulation totals for all newspapers located in the state to create our state level newspaper circulation variable. We omit two newspapers, USA Today and Wall Street Journal, because of the national nature of their news coverage.

Stock price data are obtained from CRSP for NYSE, AMEX and NASDAQ common stocks. We perform the standard treatment procedures established in the prior literature. We include only common stocks that have CRSP share code 10 or 11. CRSP delisting returns are used when available. We combine the stock data with accounting data from the CRSP/COMPUSTAT merged database. Analyst forecast estimates are collected from I/B/E/S. Our sample starts in 1991 and ends in 2008. We require that a firm has analyst coverage in order to calculate an estimate for the cost of equity capital.

A. Estimating Liquidity

We estimate liquidity using measures commonly used in the literature. ILLIQ is the price impact measure of illiquidity developed in Amihud (2002) using daily return and volume data. It

[11] Data for *Income* and *Population Density* at the county level are available for 1990 and 2000. We linearly extrapolate this variable for interim years, and apply the value in 2000 to the 2001-2010 period.

is calculated as the average of the absolute daily return divided by the dollar volume during the quarter. Goyenko, Holden, and Trzcinka (2009) find that the ILLIQ measure arguably performs the best in capturing price impact among the many measures they consider. We also calculate an alternative version, ILLIQ_{TO}, which adjusts the ILLIQ measure to account for share turnover (Brennan, Huh, and Subrahmanyam, 2013). By adjusting for turnover, this alternative measure effectively removes the mechanical relation of market capitalization with the original ILLIQ measure. Following the standard treatment in the literature, we winsorize both measure at the 1% level.

Our second measure, Effective Spread, is calculated using high frequency TAQ data. The effective spread sample starts in 1993. As effective spread is non-linearly correlated with firm size, we size-adjust the measure. We first calculate the quarterly average of effective spreads for a particular stock, and then subtract the mean of firms in the same market capitalization decile in that quarter.

B. Estimating the Speed of Information Diffusion

We examine the speed with which stock prices incorporate information using the "delay" measure developed in Hou and Moskowitz (2005). The delay measure (*D1*) is the incremental R^2 of adding four lags of weekly market returns to a market model regression of weekly stock returns. Conceptually, the delay measure is captures the (lack of) speed with which the price of a particular stock responds to market-wide news.

We estimate the delay measure at an annual frequency. As described in Hou and Moskowitz (2005), the delay measure is highly correlated with size: the Pearson rank correlation of their delay variable and size is -0.94. To remove the effect of size on our delay variable, the delay measure is orthogonalized with respect to size by subtracting the mean delay measure of each stock's size decile.

C. Estimating Implied Cost of Equity Capital

Our primary measure of implied cost of equity capital is calculated following the methodology in Gebhardt, Lee, and Swaminathan (2001) and Pástor, Sinha, and Swaminathan (2008) as implemented in Chen, Chen, and Wei (2011). The model is based on the residual income valuation model developed in Ohlson (1995) using current stock prices and analysts' earnings forecasts for various intervals. The benefit of using models of implied cost of equity capital is that it can separate growth and cash flow effects from discount rate effects. Moreover, Pástor, Sinha, and Swaminathan (2008) analytically show that under plausible conditions, the implied cost of equity is perfectly correlated with the conditional expected stock return. The drawback of these measures is that the calculation requires analyst forecasts, which are not available for all firms, as well as assumptions about future evolution of growth rates, dividend payouts and terminal values.

To address the latter concern, we estimate three additional implied cost of equity capital measures based on models developed in Claus and Thomas (2001; COC_{CT}), Easton (2004; COC_{PEG}), and Ohlson and Juettner-Nauroth (2005; COC_{OJ}). The latter two estimates are based on abnormal earnings growth valuation models that provides an alternative to the residual income model valuation techniques used in Gebhardt, Lee, and Swaminathan (2001; COC_{GLS}) and Claus and Thomas (2001; COC_{CT}), respectively. Thus, our analysis includes the most commonly used styles of valuation models and two implementations of each style. Following Hail and Leuz (2009), we are agnostic on the best implied cost of equity capital model and instead calculate the firm-level median (COC_{MED}) and average values (COC_{AVG}) of these four measures in our robustness tests.

A number of studies raise the question regarding the validity of implied cost of equity capital measures (Easton and Monahan, 2005; Lee, So, and Wang, 2010). For example, analyst forecast are known to be optimistic which may cause bias. Chen, Huang, and Wei (2013) provide validation tests to demonstrate that the measures of implied cost of equity capital used in this study are positive and significantly related to future returns suggesting that the measures are reasonably valid over our sample period. To alleviate concerns regarding analyst forecast biases, our regression specifications control for analyst forecast errors following the suggestion in Mohanram and Gode (2013).

D. Descriptive Statistics

Table I reports the descriptive statistics of our sample. Panel A reports the distribution summary of our main variable, Institutional Presence (IP_{ST}), as well as the firm characteristics used as control variables in the regressions. The construction of the control variables is described in the table description. Panel B reports the average state–level Institutional Presence, total book value of corporate assets of firms headquartered in each state, and state-level GDP for states in the following categories: the lowest five IP_{ST}, the highest five IP_{ST}, and four states with the highest GDP_{ST} that are not included in the previous two categories. The pattern of state–level IP_{ST} in Panel B is generally consistent with anecdotal evidence: New York has a high level of institutional investors and therefore a high IP measure. Massachusetts has a similarly high value of the IP measure. In contrast, Texas and Florida contain many urban centers (Miami, Dallas, and Houston), but have relatively lower levels of the IP measure. Idaho and the Dakotas have the lowest presence of institutional investors.

IV Institutional Presence and Efficiency Measures

We begin our analysis by examining how price efficiency relates to institutional presence. If institutional presence improves information production, then this facilitates more timely price formation and should improve price efficiency. We hypothesize that this will be reflected in higher liquidity and quicker speed of information diffusion.

A. Institutional Presence and Liquidity

Before we present empirical evidence on the link between institutional presence and liquidity, we briefly discuss countervailing effects that arise from theoretical models of liquidity. As local institutional investors may possess informational advantages, their presence may be associated with two conflicting effects: (1) improved efficiency as the uncertainty regarding firm value is reduced; and (2) greater information asymmetry between more–informed and less–informed market participants, resulting in more severe adverse selection problems in the market (Holden and Subrahmanyam, 1992). Our empirical analysis on the link between the IP measure and liquidity should shed light on whether the efficiency–improving effect of institutional presence dominates the adverse selection effect, or vice versa.

We start by visually examining the difference in liquidity between firms in various groupings of institutional presence. Panel A of Figure 1 displays the time–series plot of the difference in liquidity between firms in the top and bottom terciles of IP_{ST} during our sample period 1991–2008. Liquidity is measured using the ILLIQ measure developed in Amihud (2002). The difference in illiquidity is consistently negative in both the early and latter halves of the sample. This indicates that firms in the top tercile of institutional presence tend to have higher liquidity (i.e., lower illiquidity) than their counterparts in the bottom tercile.

In our main analysis, we perform panel regressions of quarterly measures of ILLIQ on institutional presence. The variables are standardized to have a mean of zero and standard deviation of one for ease of economic interpretation. The control variables include the following firm characteristics: turnover, market capitalization, return volatility, an indicator variable for young firm ($<$ 5 years from IPO), and analyst coverage. We also control for the direct shareholder channel by including local and non-local institutional ownership, and include the *Urban* variable to control for the urban liquidity effect documented in Loughran and Schultz (2005).[12]

The regressions include trading exchange fixed effects, and size decile dummy variables based on NYSE market capitalization decile breakpoints to control for potential variation in liquidity due to exchange-specific or size-specific characteristics. To capture the effects of industry composition and time trends, we include a combined industry–year fixed effect or separately include industry fixed effects (Fama—French 48 industries) and year fixed effects.

Our regressions also include state characteristics that are known to be related to stock market participation and valuation such as the book value of corporate assets located in the state (Asset_{ST}) and local income of residents ($\text{Income}_{\text{ST}}$), following Hong, Kubik, and Stein (2008). However, it is a daunting challenge to control for all potential state-level variables. For example, it is plausible that there are state laws that affect corporate disclosure that may in turn affect the level liquidity of local firms and the level of institutional presence.

We partially address this issue by including state—level fixed effects in all of our regression specifications. The state–level fixed effects absorb unobserved, state heterogeneity to the extent that these characteristics remain stable throughout our sample.[13] It helps to isolate the variation in liquidity that is due to the variation in institutional presence that is unrelated to unobserved state characteristics. To account for the remaining time—varying state dependence, we adjust the standard errors by employing two—way clustering by firm and state—year. The state—year clustering adjusts for the within state correlation structure each year while firm—level clustering captures within firm correlation.

[12] Please refer to Section III for the full definition of these variables.
[13] To directly account for these potential time–varying changes, the robustness tests in Table III include additional time-varying geography-related characteristics.

Table II presents results from panel regressions with state fixed effects. Panel A presents the main regression analysis. The parameter estimate on IP_{ST} is significant and negatively related to ILLIQ across all regression specifications. The baseline regression in column 1 shows that a one standard deviation change in IP_{ST} is related to a −4.5% (t=−3.63) standard deviation change in ILLIQ.

The second column includes $Asset_{ST}$, $Income_{ST}$, and the *Urban* variable. The parameter estimate on IP_{ST} remains negative and statistically significant. The direction of the control variables are as predicted. $Asset_{ST}$ has a positive and statistically significant parameter estimate, consistent with our conjecture that $Asset_{ST}$ representing the demand analog (i.e. local investment opportunities) of IP_{ST}. Therefore, it is associated with lower liquidity, all else equal. $Income_{ST}$ represents local individual investor participation and the likelihood that institutional investors are not the marginal investors. It is also positive and statistically significant implying that stock liquidity is lower when individual investors are more likely to be the marginal shareholder. Consistent with the findings in Loughran and Schultz (2005), urban locality is associated with lower ILLIQ. These findings are not affected by the inclusion of stock characteristics in Column 3.

Next, we include firm−level institutional ownership (IO%) in column 4. Institutional ownership is negatively related to ILLIQ. This regression is particularly informative because it allows for a direct comparison between the non-shareholder channel (IP_{ST}) and the direct shareholder channel (IO%). A one standard deviation increase in IO% is associated with a 9.1% decrease in ILLIQ compared to a 5.4% decrease in ILLIQ due to a one standard deviation increase in IP_{ST}. As expected, the direct shareholder channel has a greater economic impact. However, even after controlling for the direct shareholder channel, the non−shareholder channel is of the same order of magnitude, suggesting that it is an economically important channel.

In column 5, we decompose institutional ownership into local institutional ownership (Local IO%) and non–local institutional ownership (Non-local IO%). The liquidity enhancing effect from the direct shareholder channel is primarily caused by non–local institutional ownership, whereas local institutional ownership has a small but statistically significant, positive relation with ILLIQ. The latter may be related to the adverse selection effect we describe above. This model also presents an alternative econometric specification that includes separate industry and year fixed effects. The economic inference is similar across different econometric specifications as the parameter estimates on IP_{ST} in column 4 (–0.054; t=–4.65) and column 5 (–0.054; t=–4.67) are practically identical.

Column 6 includes *firm*–level fixed effects to capture unobservable heterogeneity at the firm level. This is a critical concern if institutional investors choose to cluster in regions with firms that possess difficult to measure characteristics that are associated with higher levels of liquidity (e.g., possibly 'well–known' stocks as described in Merton, 1987). To a large degree, state fixed effects absorb geographical effects, but the possibility lingers that unobserved firm heterogeneity remains unaccounted for. The parameter estimate on IP_{ST} remains negative and statistically significant (–0.056; t=–4.67) with the inclusion of firm fixed effects. This suggests that unobservable firm heterogeneity is unlikely to cause the observed relation between IP_{ST} and ILLIQ to the extent that firm heterogeneity is relatively constant throughout our sample. The stringency of this econometric specification suggests that time–series changes in institutional presence affect liquidity beyond industry effects and unobservable state/firm effects.

We more narrowly focus on the non–shareholder channel by examining the subsample of firms with local institutional ownership below the state median.[14] By focusing on stocks with low

[14] The evidence is quantitatively similar using a subsample of firms with zero local institutional ownership. These results are available upon request. We choose to report the results obtained using state medians as cutoffs to avoid capturing differences in local institutional ownership across states.

local institutional ownership, we effectively shut down the direct institutional shareholder channel. The results are reported in the last column of Panel A in Table II. The parameter estimate on IP_{ST} remains negative and statistically significant (−0.046; t=−4.61). We interpret this finding as further evidence that the non−shareholder channel has an important effect on liquidity.

In Panel B of Table II, we shift our focus to the types of firms that are likely to receive the greatest benefit from locating near the presence of institutional investors. This analysis may bring to light the channel through which institutional presence benefits firms. We hypothesize that firms whose information is more difficult to process will have the most to gain from the attention and information processing abilities of nearby institutional investors. In contrast, firms with a more transparent information environment are already well known and their corporate information is already widely disseminated.

To test this assertion, we interact the IP_{ST} measure with firm characteristics that are unconditionally related to higher information asymmetry between the firm and market participants. We use three variables to measure firm−level information asymmetry following Zhang (2006): firm size, analyst coverage, and firm age. For ease of interpretation, we create categorical dummy variables of each measure and interact these dummy variables with IP_{ST}. *Small* dummy is set to 1 if the stock's market capitalization at the end of June t−1 is below the 50th NYSE size percentile. *COV* dummy variable is set to 1 if analyst coverage is in the bottom quartile of all firms at the beginning of each quarter. *Young* dummy is set to 1 if the firm is less than 5 years away from its IPO. We also create a composite variable of information asymmetry, *High IA*, which is an indicator variable set to 1 if all three dummy variables (Small, COV and Young dummies) are equal to 1, and zero otherwise.

The first column of panel B in Table II presents the regression using the High IA indicator variable. The results show that firms with opaque information environments experience large benefits from being located in high IP regions. The parameter estimate on the interaction term of

IP_{ST} * High IA dummy is negative and statistically significant, –0.026 (t=–3.21). For firms with high informational asymmetry, a one standard deviation change in IP_{ST} leads to an additional 2.6% standard deviation decrease in ILLIQ on top of a 5.1% standard deviation decrease associated with the average IP_{ST} effect.

The next three columns individually examine each component of the composite information asymmetry variable. We find that the parameter estimates on the interaction between IP_{ST} and the dummy variable are negative and statistically significant for size (–0.045; t=–7.89) and analyst coverage (–0.053; t=–9.42).[15] The parameter estimates on the dummy for young firms is negative but not significant. Perhaps age is a weak proxy for information asymmetry in our setting due to its high correlation with other firm characteristics such as institutional ownership or size.

Robustness checks

To ensure that our results are robust, we present various alternative regression specifications in Table III. Panel A presents alternative measures of institutional presence. Panel B presents additional results using alternative measures of liquidity and different regression specifications. Panel C reports results across various sub–samples of our data. We suppress the parameter estimates on firm characteristics to conserve space; the full set of parameter estimates is available upon request.

First, we employ an alternative definition for our institutional presence measure that aggregates only the *non–local* portion of equity assets under management of institutional investors located in a state ($IP_{ST,\ Non\text{-}Local}$). This is an important test because removing the portion of locally–held institutional shares avoids three serious issues. The first concern is that institutional investors actively choose to locate near stocks with higher liquidity with the intention of investing in those companies' stocks. We avoid this reverse causality concern by using only the non–local

[15] The size dummy variable is not reported because it is already captured by the size decile fixed effects.

portion of institutional holdings. The second concern is that a positive shock to stocks in a state will mechanically increase the IP_{ST} measure and improve future liquidity. By excluding local ownership holdings from the calculation of the institutional presence measure, we alleviate concerns of a spurious relation between institutional presence and liquidity. Lastly, this test should alleviate any potential concern that our results are somehow related to the 'home bias' phenomenon.

Column 1 in Panel A reports the parameter estimates from the panel regression model using $IP_{ST,\ Non\text{-}Local}$ as the main independent variable. The regression specifications are identical to panel models used in Table II, which include state fixed effects. The parameter estimate on $IP_{ST,\ Non\text{-}Local}$ is almost identical (−0.046; t=−4.54) to the corresponding estimate for IP_{ST} in the last column of Panel A. This result should alleviate concerns that our main results are due to a reverse causality or a mechanical relation.

Second, we attempt to control for time−varying state characteristics that may drive both institutional investors' decision to locate in a particular state and the liquidity of firms located in the state. Our baseline model already includes state fixed effects that capture time-invariant state characteristics. Model 2 includes state returns (lagged, contemporaneous, and lead) to capture (potential) economic growth at the state level that may be correlated with both the dependent variable and the independent variable of interest. In Model 3, we add county−level demographic variables, e.g., population density, education, and per capita income, as well as the state economic indicator measure, IDX_{ST}, as proposed in Korniotis and Kumar (2013). The effect of institutional presence remains significant with similar magnitude in both Model 2 and 3, after controlling for these time-varying local variables.

Third, we broaden our geographical units by employing U.S. Census geographical divisions as our geographical boundaries.[16] We generate division–level versions of our key state-level measures: institutional presence, total book value of corporate assets, and total income of residents. Then, we calculate the difference between the division level and state level variables (e.g., $IP_{Division, Non\text{-}State}$). This allows us to estimate the incremental effect of expanding the geographical area and makes for easier interpretation of our key measures. Model 4 shows that the parameter estimate on $IP_{Div, Non\text{-}State}$ is also negative and statistically significant, consistent with liquidity being positively affected by the presence of nearby institutional investors even when these investors are located outside of the firm's domicile state. As we intuitively expect, the magnitude of the parameter estimate (–0.047; t=–4.95) is economically smaller compared to the parameter estimate on IP_{ST} (–0.133; t=–6.97). As we expand the geographical area, the effect of institutional presence on liquidity drops.[17]

Fourth, we narrow our geographic boundaries to the consolidated metropolitan area unit (CMSA) to address concerns that our state boundaries are crude. For example, a firm located in Newark, New Jersey would likely experience the institutional presence of institutions located in Manhattan, New York. In this setting, we focus our attention to "Urban" firms as defined as top 10 largest cities following Loughran and Schultz (2005), and swap out state fixed effects for CMSA fixed effects. Using a CMSA–level version of our IP measure, Model 5 shows that the parameter estimate on IP_{CMSA} is negative and statistically significant.

[16] The full list of divisions is available at: http://www.census.gov/geo/maps-data/maps/docs/reg_div.txt. The nine divisions are New England (Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont), Mid-Atlantic (New Jersey, New York, Pennsylvania), East North Central (Illinois, Indiana, Michigan, Ohio, Wisconsin), West North Central (Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota), South Atlantic (Delaware, D.C., Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia), East South Central (Alabama, Kentucky, Mississippi, Tennessee), West South Central (Arkansas, Louisiana, Oklahoma, Texas), Mountain (Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming) and Pacific (Alaska, California, Hawaii, Oregon, Washington).

[17] Our findings are similar when directly replacing IP_{ST} with its IP_{DIV} analog, but are more difficult to compare with previous regressions. These results are available upon request.

Fifth, we examine the possibility that institutional presence may be correlated with other potential producers of local information: local stock analysts and local newspapers. Previous studies show that analysts tend to cover stocks that institutional investors tend to own. In addition, analyst coverage is associated with increased transparency and lower informational asymmetry. Furthermore, Malloy (2005) reports that local equity analysts are more accurate than other analysts. These analysts and the business media may act as external monitors and impact the information asymmetry between the market and company. We construct measures of local analyst presence and local newspaper presence using a similar methodology to our construction of institutional presence, and include them in Models 6 and 7, respectively. The effect of institutional presence continues to be significant after controlling for these local agents. This suggests that our main findings are not simply capturing the effects of local analysts or business media and news attention (Bushee, Core, Guay, and Hamm, 2010).

This also highlights an important difference between the role of analysts and institutional money managers in the market. While both groups are sophisticated participants, institutional investors directly invest capital and as such are constantly monitoring a set of investment possibilities beyond their current holdings. On the other hand, analysts tend to solely monitor the stocks they currently cover. Thus it is less obvious that the presence of local analysts would necessarily affect the information environment of nearby companies.

In Panel B of Table III, we consider alternative regression specifications and liquidity measures. The first column reports the parameter estimates from a cross-sectional standardized Fama-MacBeth (1973) quarterly regression of ILLIQ on lagged values of IP_{ST} and control variables. The Fama-MacBeth regression is an average cross-sectional specification that provides a useful comparison to the panel regression. Due to the cross-sectional nature of this test, we include Fama-French 48 industry fixed effects but exclude year fixed effects. The result indicate that the parameter estimate on IP_{ST} remains negative and statistically significant (-0.019; t-stat=–6.85). This parameter estimate implies that a one standard deviation change in IP_{ST} in the cross–section is associated with a 1.9% standard deviation decrease in ILLIQ.

Next, we examine alternative measures of liquidity: effective spread in Model 2, and $ILLIQ_{TO}$ in Model 3. Our inferences are robust to the use of alternative liquidity measures. The parameter estimates are statistically significant and of comparable economic magnitude to our findings in Table II. A one standard deviation increase in IP_{ST} is associated with a 3.5% decrease in effective spread and a 7.8% decrease in $ILLIQ_{TO}$, respectively.

Lastly in Panel B, we consider variants of our state–level control measures. In the last column of Panel B, we replace $Assets_{ST}$ with total U.S. market capitalization of firms headquartered in the state (ME_{ST}). $Income_{ST}$ is replaced with total state gross domestic product (GDP_{ST}). Our inferences are robust to these alternative measures.

Panel C of Table III focuses on various sub–samples of our data. First, we isolate a sub-sample of firms with headquarters in urban locations, i.e., one of the top 10 MSAs. The purpose is to address the concern that our earlier findings are caused by cross–sectional differences across urban and rural areas as documented in Loughran and Schultz (2005). The parameter estimate on IP_{ST} remains negative and statistically significant in column 1, suggesting that the effect of institutional presence on liquidity exists amongst urban firms.

An additional benefit of focusing on urban localities is that it narrows our examination to major metropolitan areas (MSAs) from the broader state level definition used in our primary tests. Arguably, the MSA geographical level represents a more pertinent parameterization of the geographical boundary that we wish to capture. The larger parameter estimate in the urban sub–sample analysis implies a stronger effect of institutional presence on ILLIQ for urban firms. This is consistent with both the higher concentration of institutional investors in urban areas, and with the intuition that the impact of institutional presence increases with closer proximity.

Model 2 focuses on a larger subsample that excludes rural locations. It includes both firms located in one of the top 10 MSAs (i.e,. those in Model 1) as well as firms within 100 miles of an MSA with a population of at least 1 million residents. The parameter estimate for IP in this subsample is statistically significant and smaller than the urban only sample.

Model 3 shows that our results remain after excluding firms located in the state of New York from our sample. This is important for two reasons. First, this suggests that our findings are unlikely to be driven by the proximity to large stock exchanges (i.e., NYSE, NASDAQ, or AMEX). Second, since much of the business media and brokerage houses operate out of New York City, this result corroborates our earlier finding that the effects of business media and news attention or the high concentration of sell-side analysts and brokerage houses in New York do not drive our results.

Finally, we estimate the analysis for the early (1991—1999) and late (2000—2008) period of our sample in columns 4 and 5. The parameter estimate for IP_{ST} is negative and statistically significant in both sample periods.

Colorado Analysis: Evidence from the 2000 Tech Bust and 2003 Mutual Fund Trading Scandal

In this subsection, we focus on the experience of Colorado stocks during the time of the technology crash in 2000—2002 and the mutual fund trading scandal of 2003 to illustrate the causal nature of institutional presence on stock liquidity. This provides an interesting case study for three reasons. First, Colorado is the headquarters of the Janus Group, a large mutual fund company. It is the predominant investment manager in the state, and has been located in Colorado since its founding in 1969.

Second, the Janus mutual fund family was well—known for heavily investing in technology stocks during the NASDAQ run—up in the late 1990s and early 2000. At its peak, the share of technology stocks in Janus' largest funds exceeds 40 percent of AUM.[18] As technology stocks achieved high valuations, Janus' AUM also grew. Subsequently, Janus funds performed poorly during the ensuing technology bust in 2000–2002. We use this event to study the disproportionate effect of a significant decline of local institutional presence on (mostly non-tech) stocks that are headquartered in Colorado.

Third, Janus was infamously embroiled in the 2003 late–trading scandal. They eventually settled for $225 million in fines, but experienced large outflows during the period.[19] A number of large investors, including pension plans withdrew funds and severed ties with Janus.

The technology bust and the 2003 mutual fund scandal created losses and caused outflows from Janus funds that were unlikely related to the fundamentals of firms located in Colorado or to other unobservable, Colorado–level effects. This provides an arguably exogenous shock to the size of institutional capital located in Colorado. We use a differences-in-differences approach to examine these two events by estimating the following regression:

$$\mathrm{ILLIQ}_{it} = a_{ind,t} + a_j + \beta \times \mathit{treatment}_{it} + \gamma' \mathbf{X}_{it} + \varepsilon_{it} \tag{2}$$

where i indexes firms, j indexes states, *ind* indexes industry, and t indexes quarters. $a_{ind,t}$ is the industry*quarter fixed effect, a_j is the state fixed effect, $\mathit{treatment}_{it}$ is a treatment dummy, $\mathbf{X}_{it}$ is a vector of firm characteristics, and ε_{it} is the error term. The variables are standardized to have a mean of 0 and standard deviation of 1.

β measures the treatment effect of the 2000 tech bust and 2003 late–trading scandal on stocks located in Colorado. We use three specifications to measure the treatment effect: 1.) *Tech*

[18] "Janus: Tiptoeing Out of Tech" (Businessweek, April 2, 2002)

[19] "Between September 2003 and February 2004, investors pulled out $14 billion from Janus funds. At the same time, competitors such as the American Funds managed by Capital Research & Management Co. and the Vanguard Group fund family have raked in tens of billions of dollars as the stock market has come back to life" (from "Janus's CEO is Latest Casualty in Mutual-Fund Trading Scandal", *Wall Street Journal*, April 21, 2004).

*Bust * Colorado* is a dummy variable = 1 if the firm is located in Colorado during the tech bust (2000:Q4–2002:Q4). We choose these dates because the NASDAQ composite index begins its sustained descent in 2000:Q3 and bottoms out in 2002:Q3, and mutual fund flows tend to operate with a quarterly lag. 2.) *MF Scandal * Colorado* is a dummy variable=1 if the firm is located in Colorado during the period of the mutual fund trading scandal (2003:Q1–2003:Q4). Although a probe of Janus was not officially announced until September 2003, it was widely suspected that Janus was involved in late trading practices. As Janus executives were named in the original Canary Capital Partners settlement, investors anticipated charges and withdrew from Janus funds before complaint filings. 3.) We create a combined treatment effect = 1, *Combined * Colorado*, if the firm is located in Colorado during the two time periods (i.e., 2000:Q4–2003:Q4).

As standard errors tend to be understated in difference-in-difference regressions due to serial correlation of the error terms, we cluster standard errors at the state level following the suggestion in Bertrand, Duflo, and Mullainathan (2004). This clustering accounts for the presence of serial correlation within the same firm and potential correlation of the error terms across firms in the same state over time. We additionally cluster standard errors at the state*year level to account for potential correlation in the error term for firms that share the same state in particular year. The results are similar if standard errors are double clustered at the state and firm level, or singled clustered at the state or firm level.

Table IV presents the results of the diff-in-diff analysis. Column 1 shows the effect of the technology bust on stocks located in Colorado. The parameter estimate on the *Tech Bust*Colorado* dummy is 0.035 and statistically significant. It implies that during the tech bust period, stocks located in Colorado are disproportionately less liquid. From the beginning of 2000:Q4 to the end of 2002:Q4, the total institutional presence in Colorado drops by 48% ($73 billion in AUM). Our finding is unlikely to be explained by unobserved factors particular to

Colorado or time-varying industry heterogeneity as we include state fixed effects and industry*quarter fixed effects in the regression.

Column 2 includes the *MF Scandal*Colorado* treatment effect. During the 2003 mutual fund scandal period, the parameter estimate implies stocks located in Colorado experience 2.4% (t=1.92) of a standard deviation lower liquidity. The final column shows that during tech bust and mutual fund scandal periods, stocks located in Colorado were 3.3% (t=3.31) of a standard deviation less liquid.

While this Colorado—based analysis is a case study out of our overall sample, it provides a compelling causal evidence of the effect of institutional presence on stock liquidity. The large shock to the level of institutional presence in Colorado during this period is arguably exogenous to the fundamentals of firms located in the state. We find consistent evidence that this shock harms the stock liquidity of local companies. We acknowledge that these tests cannot rule out possible alternative stories related to other local shocks in Colorado during the same period. However, we check and verify that measures of economic activities in Colorado such as unemployment and state GDP largely mirror U.S. averages during our treatment periods.

B. Institutional Presence and Speed of Information Diffusion

The analysis in the previous section suggests that institutional presence improves liquidity. This is consistent with our main hypothesis that institutional presence reduces the information asymmetry between the firm and (potential) market participants. If this is true, we should also expect that prices incorporate information more quickly in regions with greater institutional presence. To examine this prediction, we employ the measure of information 'delay' developed in Hou and Moskowitz (2005). This measure is designed to capture how quickly market prices respond to information. The delay measure (*D1*) is the incremental R^2 of adding four lags of weekly market returns to a market model regression of weekly stock returns. Conceptually, 'delay' measures how slowly a stock responds to market–wide news.

We analyze the link between institutional presence and delay by estimating annual panel regressions of the delay measure on IP_{ST} measured at the end of the preceding year, and a host of control variables including firm characteristics. The control variables are similar to the variables used in the liquidity analysis and include: turnover, market capitalization, return volatility, an indicator variable for young firm (< 5 years from IPO), and analyst coverage. Like the previous panel regressions, the regressions include state fixed effects, exchange fixed effects, and either industry–year fixed effects or industry and year fixed effects to absorb unobservable heterogeneity. Standard errors are clustered two–way by state–year and firm. All variables are standardized to have a mean of 0 and standard deviation of 1 for ease of economic interpretation.

Table V presents the delay regression results. The first column reports the baseline regression with firm–level control variables. The result shows that IP_{ST} has a negative effect on delay, i.e., a positive effect on the speed of information diffusion. A one standard deviation increase in IP_{ST} is associated with a 4.4% (t=2.36) of a standard deviation decrease in information delay. This result implies a similar economic effect of institutional presence on the speed of information diffusion relative to our earlier liquidity tests.

Columns 2 and 3 include institutional ownership (IO%) and the decomposition of institutional ownership into two components, local and non-local institutional ownership (Local IO%/Non-local IO%), respectively. The parameter estimates on IP_{ST} continue to be significant in both columns. Similar to IP, IO% is also associated with lower delay. The IO effect is mainly due to Non–local IO% as seen in column 3, as Local IO% does not have a significant marginal effect on information diffusion. Overall, the effect of institutional presence on the speed of information diffusion is not materially affected by institutional ownership.

Column 4 reports the regressions results on the subsample of urban firms. The effect of IP_{ST} on information diffusion remains within this subsample. This is consistent with our previous urban–only subsample findings on the link between IP and liquidity in Table III. Alternative regression specifications are presented in columns 5 and 6. Column 5 replaces industry–year fixed effects with separate industry and year fixed effects. Compared to column 3, the parameter estimate on IP_{ST} is similar in economic magnitude and remains statistically significant (–0.051; t=–2.59 vs. –0.041; t=–2.22). Column 6 reports a stringent regression specification with the inclusion of firm fixed effects. The parameter estimate is statistically significant at the 10% level, but more importantly the point estimate (–0.043) is similar in magnitude to the previous specifications.

Overall, this set of findings indicates a negative relation between institutional presence and information delay across all regression specifications. The link appears economically significant in comparison to the direct shareholder channel. Across our full sample models, a one standard deviation increase in IP_{ST} is associated with a decrease in delay of 4.1% to 5.1% of a standard deviation. This is of a similar order of magnitude as the parameter estimate on IO% (–0.069, t=–8.98). This suggests that stocks located in high institutional presence areas incorporate market-wide information at least 4% faster than the average firm. The results are robust to the inclusion of measures of local and non-local institutional ownership.

It is important to note that the negative relation between institutional ownership and the delay measure may reflect a preference for stocks with low spread or low information delay. In contrast, the IP_{ST} variable is unlikely to be driven by stock characteristics (including the delay measure). As such, it is relatively easier to make a causal inference that the IP_{ST} variable affects the delay measure instead of vice versa. In sum, the results in this section provide supportive evidence for the positive effect of institutional presence on market liquidity and the speed of information diffusion.

V Institutional Presence, Cost of Capital, and Investment Friction

In this section, we turn our focus to the link between institutional presence and allocational efficiency. Unlike price efficiency, there are no established measures of allocational efficiency. However, we hypothesize that if high institutional presence reduces information asymmetry, all else equal, this should subsequently lead to a lower cost of equity capital (Diamond and Verrecchia, 1991) and a reduction in financing frictions.

A. Institutional Presence and the Cost of Equity Capital

Our analysis on the link between cost of equity capital and institutional presence proceeds in two parts. First, we present results based on portfolio sorts. This provides an easy interpretation of any observed differences in the cost of equity capital among regions with different levels of institutional presence. Second, we estimate panel regressions with state fixed effects to ensure that our results are not caused by differences in firm characteristics known to be related to the cost of equity capital.

Sorting analysis

We separate stocks into tercile portfolios based on rankings of Institutional Presence (IP). Table VI displays the average monthly cost of equity capital for IP_{ST} sorted portfolios. We report results using all firms (Panel A) for the four measures of cost of equity capital plus the average and median of the four measures. This insures that our findings are not measure specific and provides a range of estimates to quantify the magnitude of the economic effect. For the sort analysis, the cost of equity capital measures are industry-adjusted by subtracting the corresponding Fama-French 10 industry group average from each firm's cost of equity capital. This industry adjustment accounts for the clustering of industries in a particular location.

Statistical significance is assessed by calculating t−statistics of the time series of each portfolio's average monthly cost of equity capital and differences across portfolios.

Panel A shows that the average difference in the monthly industry-adjusted cost of equity capital between the high and low IP_{ST} portfolio is −0.136% (t=−5.67) for our main cost of equity capital measure COC_{GLS}. The magnitude of this difference varies from as low as −0.104% (COC_{CT}) to as high as −0.136% (COC_{GLS}). The last two columns report similar results using firm-level mean (COC_{AVG}; −0.135%, t=−5.73) or median (COC_{MED}; −0.128%, t=−5.53) of the four cost of equity capital measures.

We expect that the relation between institutional presence and cost of equity capital will be predominantly focused in smaller firms. Large firms should already have low information asymmetry as they tend to produce more information (Diamond and Verrecchia, 1991) and are widely followed and reported on. Panel B reports separate results for small and large market capitalization groups using the COC_{GLS} and COC_{AVG} measures. We define small stocks as those with market capitalizations below the 50^{th} NYSE size percentile at the end of the previous June following size breakpoints provided on Ken French's website.

The results indicate that the difference in the cost of equity capital between high and low IP_{ST} regions is driven by small stocks for both the COC_{GLS} (left panel) and COC_{AVG} (right panel) measures. For small stocks, the difference in COC_{GLS} between the high and low IP_{ST} tercile is negative 0.15% (t=−7.55). The patterns are similar using the COC_{AVG} measure with a difference of −0.09% (t=−4.39) between the high and low IP_{ST} terciles for small stocks.

Panel B of Figure 1 presents the time series plot of this difference during our sample period of 1991-2008. There is a strong downward trend in this difference from the start of the sample in 1991 which peaks around 2000, the height of the technology run up. This also coincides with the strong growth of institutional investors over this time period as documented in Bennett, Sias, and Starks (2003). The difference remains on average negative in the latter half of the sample. The results hold in various sub-periods including the exclusion of the period around the run-up of technology stocks. It is interesting to note that the time-series pattern of the difference in cost of capital (Panel B) lines up with that of the difference in liquidity (Panel A), suggesting that the time-series variation in the cost of equity capital gap across IP_{ST} terciles is related to the corresponding variation in price efficiency.

Panel regression analysis

We next estimate panel regressions to confirm the findings in the previous sort analysis. The dependent variable is our primary measure of cost of equity capital, COC_{GLS}, but we find similar evidence using alternative cost of equity capital measures. The parameter estimates are standardized to have mean of zero and standard deviation of 1 for easier economic interpretation. The regressions include state fixed effects and industry—year fixed effects using Fama-French 48 industry classifications. Standard errors are two—way clustered by firm and state—year, similar to the regression models in our liquidity tests.

Table VII presents the results. IP_{ST} has a negative effect on cost of equity capital across all regression specifications. The second column includes the *Urban* variable, total book value of corporate assets located in the state ($Asset_{ST}$), and total income of residents residing in the state ($Income_{ST}$). Local and non-local institutional ownership is included in the third column. Column 4 shows that the effect of institutional presence on the cost of equity capital is robust to controlling for various firm characteristics. The firm characteristics include beta, idiosyncratic volatility (iVol), the logarithmic transformation of market capitalization measured at the end of the prior month (ME), the log of the book-to-market ratio (BM), the cumulative return from prior months t–12 to t–1 ($Ret_{12,1}$), the turnover-adjusted illiquidity measure developed in Brennan, Huh, and Subrahmanyam (2013), $ILLIQ_{TO}$, book leverage (Leverage), analyst forecast error (Forecast Error), analyst long term earnings growth (LT Growth), an indicator variable for firms with less than 5 years from IPO (Young), R&D expenditure, and the logarithmic transformation of the number of analyst covering the firm (# Analyst).

The parameter estimates for IP_{ST} remain statistically significant throughout columns 2, 3, and 4, indicating that the negative effect of institutional presence on the cost of equity capital is unlikely due to the links between institutional presence and stock characteristics. In column 5, we include firm fixed effects to capture unobserved firm heterogeneity. The parameter estimate on IP_{ST} continues to be significant in this column.

In sum, we confirm our previous findings from the sort analysis on the relation between institutional presence and the cost of equity capital. The parameter estimates on IP_{ST} are consistently negative across all models of Table VII. As indicated in our motivation for the IP_{ST} variable, these consistent results indicate that the observed negative relation between institutional presence and the cost of equity capital is unlikely to be driven by stock characteristics.

The negative link between institutional presence and cost of equity capital can be generated through two potential channels: the informational efficiency link we document above or improved corporate governance. The latter channel can be described as follows. Firms in high institutional presence areas may be less prone to agency issues as there are more potential 'monitors' in the form of local institutional investors, who are not necessarily shareholders. In turn, the lower prevalence of agency issues may result in lower costs of capital.

B. Institutional Presence and Investment–Cash Flow Sensitivity

In this subsection, we examine how a firm's financing constraints relate to the presence of institutional investors. The motivation behind this analysis is to provide additional evidence to support our earlier findings that greater institutional presence is associated with a lower cost of equity capital. This implies that firms located in high institutional presence areas should be less financially constrained. We argue that there are at least two reasons for this. First, since firms located in high institutional presence areas have lower information asymmetry, these firms should find it easier to obtain financing all else equal. Second, the geographical proximity to the supply of capital may reduce the information–gathering costs of prospective capital suppliers. This supply effect has the potential to loosen financial constraints for firms in high institutional presence regions.

To test our hypothesis, we estimate investment regressions across institutional presence areas to observe the cross–sectional differences in investment sensitivity to cash flow. We expect firms located in high institutional presence areas to be less dependent upon internally generated cash flows to fund investment opportunities. These firms should exhibit lower investment sensitivity to cash flow to the extent that investment-cash flow sensitivities reflect financing constraints.[20]

Our baseline regression closely follows the specification in Chen, Goldstein, and Jiang (2007):

$$I_{i,t} = a_t + \beta_1\, CF_{i,t} + \beta_2\, IP_{i,t-1}{*}CF_{i,t} + \beta_3\, IP_{i,t-1} + \gamma\, \text{Controls} + \varepsilon_{i,t} \qquad (3)$$

where $I_{i,t}$ is the investment of firm i in year t. The regressions include year, industry and firm-fixed effects following Chen, Goldstein, and Jiang (2007). We also include state fixed effects in all regression specifications. Investment is defined as capital expenditure (Compustat Annual Item CAPX) scaled by beginning-of-the-year total assets (AT). We also use an alternative investment measure, $CAPXRND_{i,t}$, defined as capital expenditure plus research and development scaled by beginning-of-the-year total assets.

The set of independent variables includes the following state-level variables. IP_{ST} is our measure of Institutional Presence. We also include the total book value of corporate assets, $Assets_{ST}$, and total income of residents, $Income_{ST}$, in the company's headquarters state. We include

[20] A large literature discusses whether investment-cash flow sensitivities represent financing constraints.

additional independent firm-level variables following the convention in the literature. Cash flow, $CF_{i,t}$, is measured as net income before extraordinary items, depreciation and amortization expenses (Compustat Annual Items IB, DP, XRD) scaled by beginning-of-the-year total assets. Tobin's Q is calculated as the market value of equity (from CRSP) plus book value of assets minus the book value of equity (Item AT-Item CEQ) scaled by total assets all at year-end t−1. 1/Asset is the inverse of total assets. RET3 is the three-year cumulative stock return from t+1 to t+3. The sample excludes firms in financial industries (SIC code 6000-6999). Standard errors are clustered by firm.

The results are reported in Table VIII. Our main variable of interest is the interaction term of the IP_{ST} measure with cash flow, CF. In the baselines specification in column 1, the parameter estimate on the interaction term is negative and statistically significant. Consistent with our hypothesis, this evidence suggests that firms in high IP_{ST} areas have lower investment-cash flow sensitivities.

Column 2 report a similar regression using IP_{ST} terciles to estimate the economic differences in investment—cash flow sensitivity across broad IP_{ST} regions. The parameter estimate on $CF*IP_{ST}$ (−2.551, t=−2.69) suggests that moving from the bottom to the top IP_{ST} terciles (2 x −2.551) results in a 28% decrease in the sensitivity of investment to cash flow relative to the unconditional parameter estimate on cash flow (18.07, t=7.62).

We additionally interact the IP_{ST} measure with Q in column 3. The $CF*IP_{ST}$ interaction term remains negative and statistically significant. Investment—Q sensitivities are difficult to interpret since these sensitivities may measure investment sensitivity to either the mispricing component of stock prices (Baker, Stein, and Wurgler, 2003) or the embedded information value as in Chen, Goldstein, and Jiang (2007). For our purposes, we verify that our findings are not due to differences in investment-Q sensitivities across IP_{ST} regions.[21]

To ensure that our results are robust to our choice of econometric specification, we replace industry and year fixed effects with industry—year fixed effects in column 4. The parameter estimates on the interaction of CF*IP_{ST} remains negative and statistically significant. Since the industry—year fixed effect captures time-varying industry shocks that may affect overall industry investment patterns, this specification provides a more rigorous econometric specification. In column 5, we use the alternative measure of investment, CAPXRND, and find similar effects. The parameter estimate on the interaction of CF*IP_{ST} remains negative and statistically significant.

A potential concern of this analysis is that our investment-cash flow results reflect differences in firm types across institutional presence areas. One possibility that is consistent with our evidence thus far is if equity dependent firms happen to locate in low institutional presence areas. Baker, Stein, and Wurgler (2003) find that equity dependent firms exhibit higher investment-cash flow sensitivities. Thus, an alternative interpretation of the previous findings is that the differences in investment—cash flow sensitivities across institutional presence areas is due to differences in firm composition rather than variation in IP_{ST}. To address this alternative explanation, we follow the prediction offered in Baker, Stein, and Wurgler (2003) that equity-dependent firms display a more negative sensitivity of investment to future stock returns. We include an interaction of IP_{ST}*RET3 to control for this potential explanation. Column 6 presents the results of this regression. IP_{ST}*CF interaction remains negative and statistically significant after controlling for this possibility. The parameter estimate on IP_{ST}*RET3 is positive and

[21] The negative Q*IP_{ST} parameter estimate suggests that firms located in high IP_{ST} areas are less-prone to making investment due to fluctuations in their stock price. There could be several reasons for this. First, a firm located in a high institutional presence area could have lower 'irrational gyrations' in its stock price. Second, these firms could be less financially constrained and therefore less reliant on stock price movements to gain access to capital. Alternatively, higher investment-Q sensitivities could reflect differences in equity dependence as proposed in Baker, Stein and Wurgler (2003). We consider this sample-selection possibility shortly.

statistically significant, consistent with the possibility that companies located in low institutional presence regions are more equity dependent. However, this explanation does not explain our overall finding because the parameter estimate on our key interaction term, IP_{ST}*CF, is comparable to earlier specifications. In summary, these results suggest that stocks located in high institutional presence areas have lower financing frictions. We interpret this evidence to support the notion that institutional presence impacts real corporate decisions and consequently the allocational efficiency of the real economy.

VI Potential Adverse Effects: Liquidity Risk and Destabilization

In this section, we explore potential adverse effects of institutional presence. Institutional presence may expose local stocks to excessive shocks created by the trading behavior of institutional investors. To examine these concerns, we focus on whether the presence of institutional investors heightens liquidity risk and/or increases the risk that a local stock experiences destabilizing institution–driven flows.

A. Liquidity Risk

We are interested in the possibility that institutional presence may heighten the liquidity risk of nearby stocks. This presents the cost of being located near institutional investors. Recent studies also find that commonality in liquidity is related to institutional money management (i.e. Kamara, Lou, and Sadka, 2008; Koch, Starks, and Ruenzi, 2012). This also suggests that institutional investors may be a source of liquidity dis–locations perhaps due to exposure to funding risk.

We examine two types of liquidity risk measures for our tests. The first measure is the liquidity beta measure introduced in Pástor and Stambaugh (2003). The Pástor and Stambaugh (PS) liquidity beta measures how a stock's return co–moves with the market liquidity factor. In particular, we use the Pástor and Stambaugh liquidity innovation factor. We also use the Sadka

(2010) liquidity beta measure in our second test. Liquidity beta loadings are estimated based on the next 36 months (minimum 24 months) time-series of individual stock returns based on the Carhart (1997) four-factor model augmented with either the PS liquidity innovation factor or the Sadka factor.

Columns 1 and 2 in Table IX present standardized parameter estimates from panel regressions of each liquidity beta measure on IP_{ST} and firm characteristics. The regressions include trading exchange dummies, size decile fixed effects based on NYSE break points, state fixed effects, and industry-year fixed effects. Standard errors are two–way clustered by firm level and state–year level. The insignificant parameter estimate on IP_{ST} indicates that institutional ownership does not heighten liquidity risk.

Next, we examine how institutional presence is related to the commonality in liquidity measure developed in Chordia, Roll, and Subrahmanyam (2000) as implemented by Koch, Ruenzi, and Starks (2012). This measure captures the co-variation between stock liquidity and market liquidity. Commonality betas are measured over the subsequent quarter or year on NYSE stocks. Following the convention in the literature, we winsorize the estimates at the 1% and 99% levels. Similar to the previous columns in the table, we estimate standardized quarterly panel regressions on these two measures.

The results in columns 3 and 4 of Table IX show that IP_{ST} is not related to an increase in the commonality in liquidity. Rather, the parameter estimate on IP_{ST} is significantly negative for the annual commonality measure (in column 4). This suggests that being located in areas of high institutional presence is associated with *lower* commonality in liquidity. Taken together, the set of results in Table VIII indicates that institutional presence does not heighten the liquidity risk or commonality in liquidity of nearby stocks.

B. Destabilizing Effects

There are reasons to suspect that stocks in high institutional presence regions are likely to experience problematic episodes of price instability since institutional investors may trade for non-information reasons. Scharfstein and Stein (1990) cite a passage from Keynes (1936) that highlights the perception of how "it is better for reputation to fail conventionally than to succeed unconventionally." They argue that this reputation effect gives rise to non-informational herding behavior among institutional managers. Another potential channel of price dislocations due to the presence of institutional investors is the volatility in their fund flows. Coval and Stafford (2007) documents that correlated trading by mutual funds that experience extreme fund flows is likely to result in mispricing events that are not corrected immediately by other market participants.

Given these potential de-stabilizing effects caused by institutional investors, we perform several examinations of the link between institutional presence and these de-stabilizing behaviors and events. First, we examine the link between institutional presence and herding behavior. We use the herding measure developed in Sias (2004) to capture inter-temporal dependence in institutional trading.[22,23] Second, we examine the link between institutional presence and trades driven by extreme fund flows. We use the measures developed in Coval and Stafford (2007) to capture these trades. In particular, we calculate the amount of flow-induced trading as:

$$\text{Pressure}_{jt} = \frac{\sum_j (\max(0, \Delta\text{Hldgs}_{jit} | \text{Flow}_{jt} > 90^{\text{th}}\, \textit{pctl.}) - \sum_j (\max(0, -\Delta\text{Hldgs}_{jit}) | \text{Flow}_{jt} < 10^{th}\, \textit{pctl.})}{\text{Shares Outstanding}_{jt-1}} \quad (4)$$

[22] Sias (2004) herding measure is an inter-quarter measure of trading, and therefore directly measures the inter-temporal (i.e., inter-quarter) dependence in institutional trading. This measure is an alternative to the LSV herding measure developed in Lakonishok, Shleifer, and Vishny (1992). The latter only indirectly captures temporal dependence by recognizing that if later institutional traders follow earlier institutional investors' trades within a period, total institution trades are tilted to one side within that period. However, the LSV herding measure may also inadvertently capture information-based herding, i.e., when all institutions receive similar information within the quarter and therefore trade in one direction.

[23] More precisely, we use the *Average Herding Contribution* measure (equation 10 in Sias, 2004) to avoid potential issues related to the cross-sectional variation in the number of traders in each stock. For conciseness, we refer to this measure as the Sias (2004) measure throughout the paper.

where $\Delta Hldgs_{jit}$ is the change in fund j's holding of stock i in quarter t and $Flow_{jt}$ is the capital flow for fund j in quarter t. We employ the absolute value of this raw *Pressure* measure to capture both positive and negative extreme of price pressure. Additionally, we employ two indicator variables that capture the incidence of stock-quarters for which this raw measure is at the extreme, i.e., below the 10th percentile or above the 90th percentile among all stocks during the quarter. Those below 10^{th} percentile (above 90^{th} percentile) receive extreme negative (positive) pressure and are identified as fire-sale (fire-purchase) stocks.[24]

We regress each of these measures on the IP measure and a host of control variables, including non-local IO%. The results are reported in Table X. The first column presents the Sias (2004) herding measure, while the last three columns present related measures of the likelihood of flow-driven price pressure: the absolute value of the raw Pressure measure (to capture both positive and negative extreme-flow-driven price pressure), an indicator variable for fire-sale (i.e., negative pressure), and an indicator variable for fire-purchase (i.e., positive pressure). We do not find any evidence that institutional presence increases the incidence of de-stabilizing events associated with herding or correlated trading. In contrast, the non—local IO% measure seems to be correlated with a reduction in herding, but an increase in the likelihood of flow-driven price pressure in both directions.

VII Alternative Explanations

In this section, we consider possible alternative explanations for our results that were not addressed in earlier analyses. Before discussing these alternative explanations, we note that we already explored several alternative explanations in earlier sections. Our findings are robust to alternative measures of liquidity, cost of equity capital and institutional presence. We show that

[24] This measure is similar to those used in Coval and Stafford (2007) and Khan, Kogan, and Serafeim (2012).

our results are unlikely due to the business media, the geographical proximity to trading exchanges, or a New York phenomenon. We examined the possibility that our IP measure simply captures urban locality as described in Loughran and Schultz (2005). In our main regression specifications, we include urban locality and find that our results survive the inclusion of this measure. Furthermore, the beneficial effects of institutional presence on various market outcomes remain even within the subsample of urban firms (as defined in Loughran and Schultz, 2005).

A. Firm Re–location

Our analyses so far document multiple benefits of locating in areas of high institutional presence. This may imply that companies that *move* into high institutional presence areas would also experience improvements in liquidity and cost of equity capital. We examine this hypothesis by exploring relocations of firm headquarters. A benefit of this analysis is that it controls for unobserved firm characteristics beyond which is captured by firm fixed effects used in our panel regression models. However, the drawback is that it is limited by the infrequency of headquarter relocations and the noise surrounding the exact timing and impact of the re–location (Pirinsky and Wang, 2006; John, Knyazeva, and Knyazeva, 2012). For example, in our 18 year sample, we only have 49 firms that relocate from lower IP_{ST} terciles into the top IP_{ST} tercile.

Despite the small sample, we find suggestive evidence that benefits accrue to firms that re-locate into high institutional presence areas. Firms that move to a new area with a higher institutional presence experience a reduction in ILLIQ/$ILLIQ_{TO}$ of 0.90 (t=–4.28)/0.50 (t=–3.70) between year t–1 to year t+1 (where year t is the estimated relocation year).[25]

[25] We do not tabulate these results, but the full results are available upon request.

B. Institutional Re–location

A common concern that we have yet to address is the endogenous choice of institutional location. Are our results caused by the strategic choice of institutional location? This alternative story implies that improvements in the information environment attract institutional capital, reversing the causal claims we make thus far.

We find this alternative explanation unlikely for three reasons. First, it is not obvious how institutions would benefit from chasing these types of stocks. Institutional investors are in the business of generating higher returns for their clients. However, our evidence suggests that stocks located in high institutional presence areas are likely to exhibit lower returns because they have lower cost of equity capital.

Second, we have ruled out of the possibility that our results are caused by shocks to the information environment driving changes in institutional capital. In Table III, we create an alternative measure, $IP_{ST,Non\text{-}Local}$, that excludes the holdings of firms headquartered in the same state as the institutional investor. Our results are similar using this measure. Finally, institutional investors in our sample rarely re–locate their headquarters. This suggests that it is unlikely that improvements in the information environment of stocks attract local institutional capital. Of the top 50 institutional investors as measured at the end of 2008, only one institution moved headquarters across state borders.[26]

VIII Concluding Remarks

We propose an Institutional Presence (IP) measure to capture the latent role of non–owner institutional investors who nevertheless may be observing a firm's potential, performance, and

[26] This institutional investor, Lord, Abbett & Co, moved from New York to New Jersey in 2000.

stock price. Our evidence suggests that this presence captures the key role that institutional investors play in reducing information asymmetry between the firm and market participants.

We document that the IP measure is related to higher liquidity and lower information delay in stocks headquartered in the same region. This is consistent with the notion that financial intermediation improves price efficiency. Institutional presence is also associated with lower cost of equity capital as well as lower financing frictions in corporate investments. Our analysis suggests that institutional presence does not seem to entail significant costs. In particular, institutional presence is unlikely to result in significant liquidity—related costs or institutional-driven dislocations.

While our evidence is obtained from U.S. data, it also sheds some light on the role of financial development –in this case, the size of the money management industry– in the economic development of the corresponding regions or countries through channels such as the reduction of cost of capital and the relaxation of financing constraints. As such, the evidence in this paper provides several important policy—related questions. How can a firm (or a regional/national government) promote higher institutional presence to capture the benefits documented in this study? Why do we not observe more firms moving into higher institutional presence regions/countries? Are there barriers to entry or prohibitively expensive re—location costs into high institutional presence areas? Are there unobserved costs of higher institutional presence? We leave these questions for future research.

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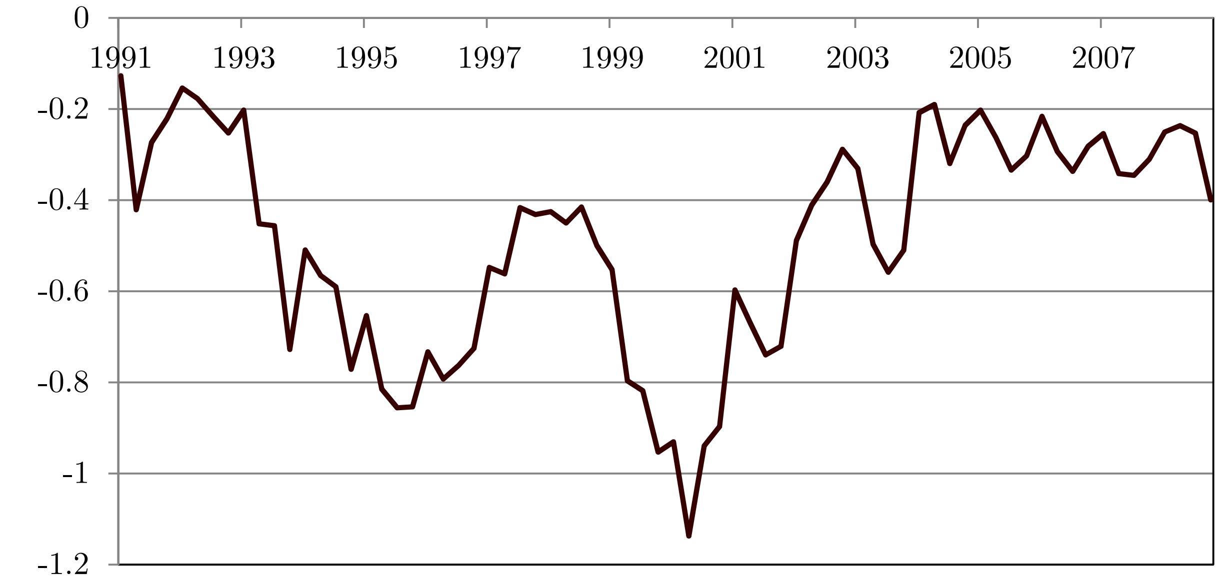
Figure 1. Difference in Liquidity and Cost of Equity Capital between the Top Institutional Presence Tercile and the Bottom Tercile

This figure presents the difference in liquidity (Panel A) and cost of equity capital (Panel B) between portfolios of stocks located in the top Institutional Presence (IP) terciles minus the portfolio of stocks located in the bottom IP tercile over the sample period 1991-2008. IP is calculated as the total AUM of the institutional portfolio in the company's headquarter state. Liquidity is measured as ILLIQ following Amihud (2002). Cost of equity capital is COC_{GLS} measure developed in Gebhardt, Lee and Swaminathan (2001).

Panel A: ILLIQ (Quarterly)



Panel B: Cost of Equity Capital (Monthly)

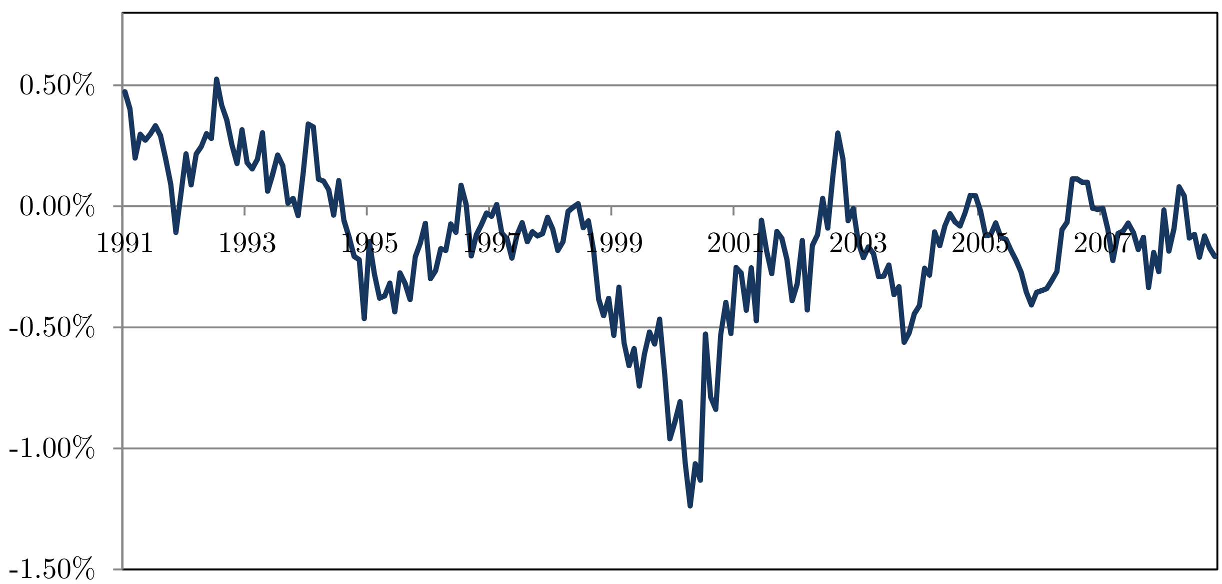


Table I. Summary Statistics

This table presents summary statistics for the key variables used in this study. Panel A presents distribution characteristics. Panel B presents summary statistics of the top and bottom 5 Institutional Presence states. Institutional Presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the state. $Asset_{ST}$ is the total book value of publicly-traded firms headquartered in each state. $Income_{ST}$ is the total income of the residents of each state. COC_{GLS} is the implied costs of capital measure developed in Gebhardt, et al. (2001). COC_{AVG} is the firm-level average of four implied cost of equity capital measures from Gebhardt, et al. (2001), Claus and Thomas (2001), Easton (2004) and Ohlson and Juettner-Nauroth (2005). IO% (Local IO%/Non-Local IO%) is the total number of shares held by (local/non-local) institutions divided by total number of shares outstanding. ME is the market capitalization of the firm at the end of June of the prior year. BM is the log of the book value divided by the market capitalization at the end of Dec (t−1). Urban is a variable=1 if the firm is headquartered in an urban area, =0 if located within 100 miles of an MSA with at least 1 million residents, and =−1 otherwise. Beta is the market beta of the stock estimated on the CRSP value-weighted market return over the prior 60 months. iVol is the idiosyncratic volatility calculated from residuals of annual market-model regressions of monthly stock returns. Return volatility is the stock return volatility calculated over the past year. Turnover is the stock turnover over the past quarter. $Ret_{12,1}$ is the cumulative stock return from month t−12 to t−1. Delay is the measure of information delay developed in Hou and Moskowitz (2005). ILLIQ is the illiquidity measure developed in Amihud (2002). $ILLIQ_{TO}$ is the turnover-adjusted illiquidity measure developed in Brennan, et al. (2013). Leverage is book leverage calculated as book value of long-term debt/total assets. Forecast Error is the analyst forecast error of forthcoming annual earnings calculated as the actual EPS from I/B/E/S minus the forecasted EPS scaled by price in the current month. LT Growth is analysts' forecast long-term growth rate. Young is a dummy variable=1 if the firm had an IPO in the past 5 years. R&D is the ratio of R&D to total assets. # of analysts is the number of analyst covering the firm.

Panel A. Stock Characteristics

			Percentile				
Variable	Mean	Std. Dev.	1st	25st	Median	75th	99^{th}
IP_{ST}	5.16	1.64	1.15	4.14	5.32	6.29	8.21
$Asset_{ST}$	6.29	1.48	2.50	5.35	6.45	7.37	9.30
$Income_{ST}$	2.39	0.75	0.55	1.84	2.39	3.00	3.56
COC_{GLS}	10.3%	3.2%	3.8%	8.4%	10.0%	11.9%	20.1%
COC_{AVG}	11.3%	3.7%	5.2%	9.1%	10.6%	12.7%	23.9%
IO%	57.3%	26.5%	5.1%	37.4%	58.4%	76.5%	115.5%
Local IO%	2.6%	6.7%	0.0%	0.0%	0.3%	2.1%	30.1%
Non-Local IO%	54.7%	26.3%	3.0%	35.2%	55.9%	73.9%	111.7%
ME	4,063	16,889	21	207	630	2,127	66,237
BM	0.60	0.53	0.06	0.31	0.50	0.76	2.41
Urban	0.407	0.64	−1	0	0	1	1
Beta	1.12	0.79	−0.19	0.59	1.00	1.49	3.76
iVol	0.015	0.025	0.001	0.005	0.009	0.018	0.088
Return Volatility	0.128	0.068	0.04	0.081	0.111	0.157	0.363
Turnover	0.146	0.164	0.007	0.046	0.091	0.183	0.806
$Ret_{12,1}$	20.1%	70.1%	−72.9%	−13.2%	10.5%	37.3%	261.8%
Delay	0.40	0.29	0.02	0.16	0.33	0.62	1.00
ILLIQ	−4.86	2.55	−9.87	−6.72	−5.05	−3.18	1.55
$ILLIQ_{TO}$	1.73	1.23	−0.42	0.86	1.58	2.37	5.43
Leverage	0.17	0.16	0.00	0.02	0.13	0.28	0.63
Forecast Error	−0.011	0.043	−0.301	−0.008	0	0.002	0.05
LT Growth	0.19	1.11	0.03	0.10	0.15	0.20	0.60
Young	0.183	0.39	0	0	0	0	1
R&D	0.036	0.092	0	0	0	0.033	0.356
# of Analysts	8.9	7.2	1	4	7	12	32

Table I. Summary Statistics (Continued)

Panel B. State Level Averages						
State	Inst. $Presence_{ST}$	Inst. $Presence_{ST}$ (as fraction of U.S. aggregate)	$Asset_{ST}$	$Asset_{ST}$ (as fraction of U.S. aggregate)	Total GDP_{ST}	Total GDP_{ST} (as fraction of U.S. aggregate)
			Top 5 Institutional Presence			
New York	7.05	29.73%	8.53	26.14%	13.96	7.92%
California	6.27	12.09%	7.33	7.74%	14.44	12.99%
Massachusetts	6.18	14.78%	6.67	4.76%	12.91	2.67%
Illinois	5.90	5.57%	7.19	6.74%	13.45	4.79%
Pennsylvania	5.64	5.21%	6.54	3.79%	13.38	4.09%
			Large GDP			
Texas	5.27	3.10%	6.95	5.33%	13.79	7.37%
Florida	4.58	0.86%	5.28	1.04%	13.56	4.98%
Ohio	5.40	2.33%	6.52	3.62%	13.25	3.82%
New Jersey	5.06	1.90%	6.46	3.65%	13.22	3.56%
			Bottom 5 Institutional Presence			
South Dakota	−1.95	0.00%	−0.70	0.02%	10.53	0.25%
North Dakota	−1.07	0.00%	0.81	0.03%	10.30	0.20%
Idaho	−0.75	0.01%	1.99	0.12%	10.88	0.36%
Alaska	−0.07	0.02%	0.18	0.02%	10.48	0.31%
South Carolina	1.67	0.07%	3.48	0.18%	12.03	1.17%

Table II. Panel Regressions of Liquidity on Institutional Presence

This table reports parameter estimates from panel regression of quarterly ILLIQ on Institutional Presence and stock characteristics. The dependent variable is the ILLIQ measure developed in Amihud (2002). Independent variables are measured at the end of the previous quarter (t–1). Institutional presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the firm's headquarter state. All variables are standardized to have a mean of zero and standard deviation of one. Panel A reports the main regression analysis. Panel B reports interaction terms of IP_{ST} and firm characteristics dummies. Please refer to Table I for exact definitions of the control variables. Exchange dummy are trading exchange fixed effects. Size deciles are size decile fixed effects based on NYSE breakpoints. Industry fixed effects are based on Fama-French 48 industries. The < Median local IO% sample are firms that were below the median local IO% in each state at the end of the previous quarter (t–1). The sample period is from 1991-2008. T-statistics, reported in parenthesis, are based on two-way clustered standard errors by firm and state-year.

Panel A. Main Regression Analysis

Dependent Variable: ILLIQ	1	2	3	4	5	6	7
IP_{ST}	–0.045***	–0.053***	–0.056***	–0.054***	–0.054***	–0.056***	–0.046***
	(–3.63)	(–4.35)	(–4.76)	(–4.69)	(–4.65)	(–4.67)	(–4.61)
$Assets_{ST}$		0.025**	0.024***	0.027***	0.026***	0.038***	0.030***
		(2.52)	(2.94)	(3.30)	(3.18)	(4.17)	(3.54)
$Income_{ST}$		0.169*	0.196***	0.227***	0.237***	0.101	0.154*
		(1.92)	(2.82)	(3.32)	(3.46)	(1.23)	(1.96)
Urban		–0.038***	–0.003	0.005	0.005	0.011	0.008
		(–4.20)	(–0.57)	(0.96)	(0.93)	(0.65)	(1.26)
IO%				–0.091***			
				(–23.99)			
Local IO%					0.009***	0.005*	–0.027***
					(3.16)	(1.75)	(–2.60)
Non-local IO%					–0.092***	–0.078***	–0.094***
					(–24.36)	(–18.06)	(–20.21)
Ln(Turnover)			–0.215***	–0.194***	–0.194***	–0.154***	–0.206***
			(–35.08)	(–32.05)	(–32.13)	(–31.44)	(–29.95)
Ln(ME)			–0.498***	–0.486***	–0.484***	–0.360***	–0.461***
			(–37.51)	(–40.15)	(–39.93)	(–31.07)	(–35.50)
Return Volatility			–0.004	–0.018***	–0.017***	0.013**	–0.023***
			(–0.75)	(–3.91)	(–3.76)	(2.31)	(–4.90)
Young			0.066***	0.057***	0.058***	–0.002	0.065***
			(11.56)	(10.22)	(10.28)	(–0.28)	(10.02)
Ln(# of Analysts)			–0.125***	–0.104***	–0.104***	–0.083***	–0.105***
			(–27.18)	(–22.63)	(–22.65)	(–16.35)	(–18.59)
Exchange Dummy	✓	✓	✓	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓	✓	✓	✓
Year Fixed Effect					✓	✓	
Industry Fixed Effect					✓	✓	
Industry–Year F.E.	✓	✓	✓	✓			✓
Firm Fixed Effect						✓	
Sample	Full	Full	Full	Full	Full	Full	< Median Local IO%
Observations	166,847	166,847	166,847	166,847	166,847	166,847	93,401
Adjusted R^2	0.822	0.823	0.886	0.890	0.890	0.922	0.902

Table II. Panel Regressions of Liquidity on Institutional Presence (Continued)

Panel B: Interactions with Firm Characteristic Dummy				
Dependent Variable: ILLIQ	1	2	3	4
IP_{ST}	–0.051***	–0.022**	–0.032***	–0.053***
	(–4.51)	(–2.04)	(–3.12)	(–4.59)
IP_{ST}*High IA Dummy	–0.026***			
	(–3.21)			
High IA Dummy	0.026***			
	(2.61)			
IP_{ST}*Small Dummy		–0.045***		
		(–7.89)		
IP_{ST}*COV Dummy			–0.053***	
			(–9.42)	
COV Dummy			–0.013**	
			(–2.13)	
IP_{ST}*Young				–0.009
				(–1.50)
$Assets_{ST}$	0.026***	0.027***	0.025***	0.026***
	(3.19)	(3.37)	(3.07)	(3.16)
$Income_{ST}$	0.242***	0.245***	0.233***	0.240***
	(3.53)	(3.61)	(3.42)	(3.50)
Urban	0.005	0.003	0.003	0.005
	(0.94)	(0.61)	(0.59)	(0.93)
Local IO%	0.009***	0.010***	0.009***	0.009***
	(3.20)	(3.73)	(3.45)	(3.18)
Non-local IO%	–0.092***	–0.092***	–0.092***	–0.092***
	(–24.35)	(–24.45)	(–24.61)	(–24.43)
ln(Turnover)	–0.194***	–0.195***	–0.196***	–0.194***
	(–32.31)	(–33.01)	(–33.37)	(–32.17)
ln(ME)	–0.484***	–0.482***	–0.481***	–0.484***
	(–40.03)	(–40.75)	(–41.15)	(–39.96)
Volatility	–0.017***	–0.016***	–0.016***	–0.017***
	(–3.64)	(–3.50)	(–3.56)	(–3.72)
Young	0.041***	0.056***	0.056***	0.057***
	(5.86)	(10.07)	(10.10)	(10.27)
# Analyst	–0.102***	–0.102***	–0.109***	–0.104***
	(–22.26)	(–22.21)	(–21.72)	(–22.59)
Exchange Dummy	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓
Industry–Year F.E.	✓	✓	✓	✓
Sample	Full	Full	Full	Full
Observations	166,847	166,847	166,847	166,847
Adjusted R^2	0.890	0.891	0.891	0.890

Table III. Regressions of Liquidity on Institutional Presence - Robustness

This table reports regressions of liquidity measures on Institutional Presence. All regressions contain firm characteristics (suppressed to conserve space) that are used in Table II, column 5 which include Urban, Local IO%, Non-local%, Ln(Turnover), Ln(ME), Return Volatility, Young and Ln(#Analysts). Independent variables are measured at the end of the previous quarter (t–1). All variables are standardized to have a mean of zero and standard deviation of one. Panel A present standardized parameter estimates from panel regression of quarterly measures of liquidity on various measures of Institutional Presence and stock characteristics. Panel B presents regressions from sub-samples of the data. Column 1 of panel B presents the average standardized parameter estimates from quarterly cross-sectional Fama-MacBeth regression of liquidity on Institutional Presence and stock characteristics. Columns 2 through 5 of panel B present standardized parameter estimates from panel regression of quarterly measures of liquidity on Institutional Presence and stock characteristics. Institutional presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the firm's headquarter state. $IP_{ST,\ Non\text{-}local}$ is calculated as the total AUM of the non-local institutional portfolio in the firm's headquarter state. $IP_{Division,\ Non\text{-}State}$ is the difference between the total AUM of the institutional portfolio located in the firm's headquartered US Census division minus the corresponding headquarter state. $Asset_{Division,Non\text{-}ST}$ is the difference between the total book value of publicly-traded firms headquartered in each U.S. Census division minus the corresponding value headquartered in each state. $Income_{Division,\ Non\text{-}State}$ is the total income of the residents located in the firm's headquarter U.S. geographical division minus the corresponding value headquartered in each state. Analyst Presence is the fraction of US analysts located in the state. Newspaper Circulation is the log of the total circulation of newspapers located in the state (see Section III for further details). ILLIQ is the Amihud (2002) measure of illiquidity. Effective spread is the size-adjusted effective spread. $ILLIQ_{TO}$ is the turnover-adjusted ILLIQ measure following Brennan et al. (2013). GDP_{ST} is the total state GDP in the company's headquarter state. $Pop.Density_{County}$ / $Education_{County}$ / $Income\ Per\ Capita_{County}$ is the population density/education level/income per capita in the company's headquarter county. IDX_{ST} is the state economic indicator measure developed in Korniotis and Kumar (2013). Exchange dummy are trading exchange fixed effects. Size deciles are size decile fixed effects based on NYSE breakpoints. Industry fixed effects are based on Fama-French 48 industries. T-statistics are reported in parenthesis. For the panel regression models, t-statistics in parenthesis are based on two-way clustered standard errors by firm and state-year.

Table III. Regressions of Liquidity on Institutional Presence – Robustness (Continued)

Panel A. Controlling for Regional Characteristics							
	1	2	3	4	5	6	7
Dependant Variable	ILLIQ	ILLIQ	ILLIQ	ILLIQ	ILLIQ	ILLIQ	ILLIQ
$IP_{ST, Non-local}$	-0.046***						
	(-4.54)						
IP_{ST}		-0.042***	-0.041***	-0.134***	-0.080***	-0.055***	-0.054***
		(-4.00)	(-3.89)	(-6.97)	(-4.96)	(-4.65)	(-4.64)
$IP_{Division-Non-State}$				-0.047***			
				(-4.95)			
IP_{CMSA}					-0.091***		
					(-3.28)		
Local $Return_{ST(t-1)}$		-0.006	-0.005				
		(-1.48)	(-1.42)				
Local $Return_{ST(t)}$		-0.025***	-0.025***				
		(-6.42)	(-6.40)				
Local $Return_{ST(t+1)}$		-0.026***	-0.026***				
		(-4.90)	(-4.88)				
Pop. $Density_{COUNTY}$			-0.002				
			(-0.51)				
$Education_{COUNTY}$			-0.018***				
			(-3.39)				
Income Per $Capita_{COUNTY}$			0.024***				
			(3.81)				
IDX			0.002				
			(0.41)				
Analyst Presence						0.012***	
						(3.25)	
Newspaper Circulation							-0.013***
							(-2.73)
$Assets_{Division-Non-State}$				0.035*			
				(1.86)			
$Income_{Division-Non-State}$				0.034***			
				(4.23)			
Urban	0.005	0.004	0.001	0.005	-	0.003	0.005
	(0.93)	(0.77)	(0.20)	(0.91)	-	(0.58)	(0.93)
$Assets_{ST}$	0.024***	0.014	0.012	0.003	0.017**	0.027***	0.026***
	(3.01)	(1.50)	(1.30)	(0.33)	(2.49)	(3.25)	(3.15)
$Income_{ST}$	0.235***	0.225***	0.241***	0.081	0.034***	0.245***	0.237***
	(3.43)	(3.28)	(3.46)	(1.00)	(2.91)	(3.63)	(3.47)
Firm Controls?	✓	✓	✓	✓	✓	✓	✓
Region F.E.		State	State	State	CMSA	State	State
Industry*Year F.E.	✓	✓	✓	✓	✓	✓	✓
Sample	Full	Full	Full	Full	Urban Only	Full	Full
Observations	166,847	154,033	153,459	166,709	82,336	166,847	166,847
Adjusted R-square	0.890	0.895	0.896	0.891	0.890	0.890	0.890

Table III. Regressions of Liquidity on Institutional Presence – Robustness (Continued)

Panel B: Alternative Specifications and Measures				
	1	2	3	4
Dependent Variable	ILLIQ	Effective Spread	$ILLIQ_{TO}$	ILLIQ
IP_{ST}	−0.019***	−0.035***	−0.078***	−0.094***
	(−6.85)	(−2.60)	(−4.31)	(−4.62)
Market Cap_{ST}				0.066***
				(2.86)
GDP_{ST}				0.144**
				(2.05)
$Assets_{ST}$	−0.002	0.016	0.006	0.005
	(−1.16)	(1.38)	(0.47)	(0.87)
$Income_{ST}$	0.010***	0.026	0.041***	
	(3.57)	(1.48)	(2.65)	
Firm controls?	✓	✓	✓	✓
Regression Type	Fama-MacBeth	Panel	Panel	Panel
Exchange Dummy	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓
State Fixed Effects	—	✓	✓	✓
Industry-Year F.E.	—	✓	✓	✓
Observations	166,847	150,791	166,847	165,043
Adjusted R-square	—	0.670	0.706	0.890

Panel C: Sub-samples					
	1	2	3	4	5
Dependent Variable	ILLIQ	ILLIQ	ILLIQ	ILLIQ	ILLIQ
IP_{ST}	−0.329***	−0.192***	−0.050***	−0.037***	−0.221***
	(−6.39)	(−7.81)	(−4.52)	(−4.65)	(−3.40)
$Assets_{ST}$	0.003	0.008	0.024***	0.049***	0.002
	(0.23)	(0.93)	(2.99)	(5.70)	(0.12)
$Income_{ST}$	0.173	0.219***	0.279***	−0.067	−0.350***
	(1.17)	(3.23)	(4.09)	(−0.51)	(−2.92)
Firm Controls?	✓	✓	✓	✓	✓
Exchange Dummy	✓	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓	✓
State Fixed Effects	✓	✓	✓	✓	✓
Industry-Year F.E.	✓	✓	✓	✓	✓
Sample	Urban Only	Non-Rural	Non-NY	1991−1999	2000−2008
Observations	82,336	152,829	154,506	83,090	83,757
Adjusted R-square	0.890	0.891	0.889	0.879	0.891

Table IV. The Effect of the Tech Bust and Mutual Fund Scandal on Stocks Located in Colorado

This table reports a difference in difference test of stocks located in Colorado during the internet crash and subsequent mutual fund late trading scandal. The dependent variable is the ILLIQ measure developed in Amihud (2002). The Tech Bust is a dummy=1 if the time period is between 2000Q4–2002Q4. MF Scandal is a dummy=1 if the time period is between 2003Q1–2003Q4. Combined is a combined dummy of the Tech Bubble and Scandal. Please refer to Table I for exact definitions of the control variables. The regressions include the following fixed effects: trading exchange, size decile based on NYSE breakpoints, industry–quarter, and state. We separately report the state fixed effect for Colorado. The sample period is from 1991-2008. T–statistics, reported in parenthesis, are based on two–way clustered standard errors by state and state*year.

Dependent Variable: ILLIQ	1	2	3
Colorado	0.028	0.026	0.026
	(1.13)	(1.05)	(1.05)
Colorado * Tech Bust	0.035***	0.038***	
	(3.90)	(3.78)	
Colorado * MF Scandal		0.024*	
		(1.92)	
Colorado * Combined			0.033***
			(3.31)
$\text{Assets}_{\text{ST}}$	0.004	0.003	0.003
	(0.44)	(0.39)	(0.39)
$\text{Income}_{\text{ST}}$	0.272***	0.272***	0.272***
	(3.62)	(3.62)	(3.62)
Urban	0.012	0.012	0.012
	(1.61)	(1.61)	(1.61)
Local IO%	0.011***	0.011***	0.011***
	(3.46)	(3.46)	(3.46)
Non-local IO%	−0.093***	−0.093***	−0.093***
	(−22.53)	(−22.53)	(−22.53)
Turnover	−0.205***	−0.205***	−0.205***
	(−24.79)	(−24.80)	(−24.80)
ln(ME)	−0.479***	−0.479***	−0.479***
	(−33.51)	(−33.51)	(−33.51)
Volatility	−0.028***	−0.028***	−0.028***
	(−7.58)	(−7.57)	(−7.57)
Young	0.058***	0.058***	0.059***
	(8.86)	(8.86)	(8.86)
# Analyst	−0.099***	−0.099***	−0.099***
	(−33.75)	(−33.74)	(−33.74)
Exchange Dummy	✓	✓	✓
Size Deciles	✓	✓	✓
State Fixed Effects	✓	✓	✓
Industry-Quarter F.E.	✓	✓	✓
Observations	166,897	166,897	166,897
Adjusted R−square	0.917	0.917	0.917

Table V. The Effect of Institutional Presence on Information Diffusion

This table reports parameter estimates from panel regressions of annual information delay on Institutional Presence and stock characteristics. Institutional presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the firm's headquarter state. The dependent variable is Delay calculated following Hou and Moskowitz (2005). Independent variables are measured at the end of the previous year (t–1). All variables are standardized to have a mean of zero and standard deviation of one. Exchange dummy are trading exchange fixed effects. Size deciles are size decile fixed effects based on NYSE breakpoints. Industry fixed effects are based on Fama–French 48 industries. The sample period is from 1991–2008. Please refer to Table I for exact definitions of the control variables. T–statistics, reported in parenthesis, are based on two–way clustered standard errors by firm and state–year.

Dependent Variable: Delay	1	2	3	4	5	6
IP_{ST}	–0.044**	–0.041**	–0.041**	–0.353***	–0.051***	–0.043*
	(–2.36)	(–2.22)	(–2.22)	(–3.11)	(–2.59)	(–1.67)
$Assets_{ST}$	0.062***	0.064***	0.064***	0.035	0.086***	0.080***
	(3.25)	(3.39)	(3.38)	(1.32)	(4.17)	(2.95)
$Income_{ST}$	0.394**	0.420***	0.423***	0.577	0.507***	0.352
	(2.44)	(2.61)	(2.62)	(1.61)	(2.78)	(1.34)
Urban	–0.004	0.003	0.003		0.007	–0.015
	(–0.31)	(0.20)	(0.19)		(0.50)	(–0.31)
IO%		–0.069***				
		(–8.98)				
Local IO%			0.001	–0.009	0.005	0.015*
			(0.28)	(–1.46)	(0.90)	(1.87)
Non–local IO%			–0.069***	–0.051***	–0.068***	–0.084***
			(–8.90)	(–4.74)	(–8.47)	(–5.92)
Ln(Turnover)	–0.039***	–0.021**	–0.021**	–0.026**	–0.034***	–0.011
	(–5.01)	(–2.44)	(–2.45)	(–2.26)	(–3.83)	(–1.14)
Ln(ME)	–0.108***	–0.106***	–0.105***	–0.082**	–0.098***	0.017
	(–4.58)	(–4.58)	(–4.57)	(–2.54)	(–4.14)	(0.52)
Return Volatility	–0.048***	–0.058***	–0.058***	–0.050***	–0.061***	–0.076***
	(–5.03)	(–5.95)	(–5.92)	(–3.95)	(–5.68)	(–3.96)
Young	0.080***	0.073***	0.073***	0.067***	0.061***	–0.013
	(5.70)	(5.17)	(5.18)	(3.45)	(4.43)	(–0.66)
Ln(# of Analysts)	–0.044***	–0.029***	–0.029***	–0.028**	0.003	0.013
	(–4.51)	(–2.99)	(–2.98)	(–2.17)	(0.29)	(0.79)
Intercept	–0.044**	–0.041**	–0.041**	–0.353***	–0.051***	–0.043*
	(–2.36)	(–2.22)	(–2.22)	(–3.11)	(–2.59)	(–1.67)
Exchange Dummy	✓	✓	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓	✓	✓
Year Fixed Effect					✓	✓
Industry Fixed Effect					✓	✓
Industry–Year F.E.	✓	✓	✓	✓		
Firm Fixed Effect						✓
Sample	Full	Full	Full	Urban	Full	Full
Observations	38,457	38,457	38,457	18,824	38,457	38,457
Adjusted R^2	0.331	0.333	0.333	0.333	0.293	0.345

Table VI. Average Monthly Cost of Equity Capital for Institutional Presence Sorted Portfolios

This table presents average monthly industry–adjusted cost of equity capital of (terciles) portfolios sorted on institutional presence. Panel A presents sorts based on different cost of equity capital measures. Panel B presents size subsample sorts based on Fama–French size groupings (micro/small/large). Institutional Presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the firm's headquarter state. Cost of equity capital is measured in 6 different ways: COC_{GLS}, COC_{CT}, COC_{OJ}, COC_{PEG}, COC_{AVG}, COC_{MED}. COC_{GLS} is the cost of equity capital measure based on the residual income model developed in Gebhardt, et al. (2001). COC_{CT} is the cost of equity capital measure based on the residual income model developed in Claus and Thomas (2001). COC_{OJ} is the cost of equity capital measure based on the residual income model developed in Ohlson and Juettner–Nauroth (2005). COC_{PEG} the cost of equity capital measure based on the PEG model developed in Easton (2004). COC_{AVG} / COC_{MED} is the firm–level average/median of the four models previous measures. The sample includes NYSE, Nasdaq, and AMEX firms from January 1991 to December 2008. The t–statistics of the differences are reported in the line below.

Panel A. Industry Adjusted Cost of Equity Capital Measures

Institutional Presence Terciles	COC_{GLS}	COC_{CT}	COC_{OJ}	COC_{PEG}	COC_{AVG}	COC_{MED}
Low IP_{ST}	0.009%	–0.069%	–0.020%	–0.023%	–0.018%	–0.027%
Mid IP_{ST}	–0.009%	–0.012%	0.019%	0.007%	0.022%	0.032%
High IP_{ST}	–0.127%	–0.174%	–0.130%	–0.158%	–0.153%	–0.155%
High – Low	–0.136%	–0.104%	–0.110%	–0.135%	–0.135%	–0.128%
t–stat	–5.67	–5.76	–5.15	–4.56	–5.73	–5.53

Panel B. Industry Adjusted Cost of Equity Capital Measures across Fama–French Size Groups

	COC_{GLS}		COC_{AVG}	
Institutional PresenceTerciles	Small	Large	Small	Large
Low IP_{ST}	0.54%	–0.90%	0.50%	–0.90%
Mid IP_{ST}	0.59%	–0.82%	0.58%	–0.74%
High IP_{ST}	0.39%	–0.85%	0.41%	–0.95%
High – Low	–0.15%	0.04%	–0.09%	–0.05%
t–stat	–7.55	1.70	–4.39	–1.94

Table VII. Panel Regressions of Cost of Equity Capital on Institutional Presence

This table reports parameter estimates from panel regressions of quarterly cost of equity capital on Institutional Presence, various characteristics, and fixed effects. Independent variables are measured at the end of the previous quarter (t–1). Institutional Presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the company's headquarter state. The dependent variable is the cost of equity capital measure calculated following Gebhardt, Lee, and Swaminathan (2001). All variables are standardized to have a mean of zero and standard deviation of one. Please refer to Table I for exact definitions of the control variables. Exchange dummy are trading exchange fixed effects. Size decile are size decile fixed effects based on NYSE breakpoints. Industry fixed effects are based on Fama–French 48 industries. The sample period is from 1991–2008. T–statistics, reported in parenthesis, are based on two–way clustered standard errors by firm and state–year.

Table VII. Panel Regressions of Cost of Equity Capital on Institutional Presence (Continued)

Dependent Variable: COC_{GLS}	1	2	3	4	5
IP_{ST}	−0.058***	−0.073***	−0.074***	−0.030**	−0.037**
	(−2.64)	(−3.49)	(−3.55)	(−2.23)	(−2.35)
$Assets_{ST}$		0.051***	0.051***	0.012	0.023
		(2.73)	(2.74)	(0.79)	(1.35)
$Income_{ST}$		−0.013	−0.046	−0.023	0.337*
		(−0.08)	(−0.26)	(−0.17)	(1.70)
Urban		0.038*	0.032	0.023	0.112*
		(1.81)	(1.57)	(1.51)	(1.94)
Local IO%			−0.016***	−0.010**	0.010**
			(−2.64)	(−2.38)	(2.09)
Non−local IO%			0.051***	0.077***	0.017*
			(4.87)	(9.85)	(1.82)
Beta				0.011	0.017*
				(1.31)	(1.87)
iVol				0.039**	0.025**
				(2.35)	(2.00)
Ln(ME)				−0.095***	0.021
				(−4.93)	(0.69)
Ln(BM)				0.326***	0.226***
				(27.40)	(15.17)
$Ln(1+Ret_{12,1})$				−0.253***	−0.238***
				(−34.68)	(−34.19)
$ILLIQ_{TO}$				0.009	0.077***
				(1.26)	(11.32)
Leverage				0.077***	0.026***
				(10.69)	(2.68)
Forecast Error				−0.162***	−0.138***
				(−28.41)	(−26.27)
LT Growth				0.034***	0.021**
				(3.53)	(2.40)
Young				0.044***	−0.009
				(3.72)	(−0.62)
R&D				0.000	0.026**
				(0.00)	(2.55)
Ln(# Analyst)				−0.067***	−0.071***
				(−7.16)	(−6.58)
Exchange Dummy	✓	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓	✓
Year Fixed Effect					✓
Industry Fixed Efect					✓
Industry−Year F.E.	✓	✓	✓	✓	
Firm Fixed Effect					✓
Observations	166,897	166,897	166,897	166,897	166,897
Adjusted R^2	0.293	0.293	0.295	0.507	0.662

Table VIII. Investment Cash Flow Sensitivity Regressions

This table presents the results from panel regressions of investment on cash flow and Q. Institutional presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the company's headquarter state. CAPX is capital investment scaled by total assets at t–1. CAPXRND is capital investment plus R&D scaled by total assets at t–1. GDP in the company's headquarter state. CF is net income before extraordinary items, depreciation and amortization expense scaled by total asset at t–1. Q is defined as the sum(market equity, total assets–book value of equity) scaled by total assets. 1/Asset is 1/total assets. Ret3 is three–year cumulative stock return from t+1 to t+3. Industry fixed effects are based on Fama–French 48 industries. Robust t–statistics reported in parentheses are based on standard errors clustered by firm.

	1	2	3	4	5	6
Dependent Variable:	CAPX	CAPX	CAPX	CAPX	CAPXRND	CAPX
CF(t)	29.04***	18.07***	24.11***	23.15***	34.16***	25.27***
	(9.83)	(7.62)	(7.32)	(7.36)	(7.94)	(7.52)
CF(t) * IP_{ST} (t–1)	–3.072***		–2.154***	–2.112***	–1.962***	–2.387***
	(–6.28)		(–3.92)	(–4.02)	(–2.66)	(–4.24)
CF(t)* IP_{ST} Tercile(t–1)		–2.551***				
		(–2.69)				
Q (t–1) * IP_{ST} (t–1)			–0.125***	–0.129***	–0.0667	–0.101***
			(–3.33)	(–3.54)	(–1.35)	(–2.58)
IP_{ST} (t–1)	0.474***		0.701***	0.706***	0.443**	0.632***
	(2.77)		(4.17)	(4.03)	(2.18)	(3.80)
IP_{ST} Tercile (t–1)		0.300				
		(1.46)				
$Assets_{ST}$(t–1)	0.042	0.055	0.041	0.010	0.151	0.046
	(0.25)	(0.33)	(0.24)	(0.06)	(0.73)	(0.27)
$Income_{ST}$(t–1)	–0.562	–0.451	–0.539	–0.408	–0.290	–0.577
	(–1.26)	(–0.98)	(–1.23)	(–0.95)	(–0.49)	(–1.32)
Q (t–1)	0.731***	0.710***	1.410***	1.419***	1.302***	1.280***
	(10.42)	(10.13)	(6.07)	(6.33)	(4.42)	(5.32)
1/Asset (t–1)	55.41***	67.60***	50.12***	55.03***	150.6***	52.42***
	(3.08)	(3.76)	(2.74)	(3.21)	(6.05)	(2.87)
Ret3	–0.376***	–0.370***	–0.376***	–0.342***	–0.238***	–0.840***
	(–6.97)	(–6.82)	(–6.97)	(–6.49)	(–3.42)	(–3.96)
Ret3 * IP_{ST} (t–1)						0.093**
						(2.37)
State Fixed Effect	✓	✓	✓	✓	✓	✓
Year Fixed Effect	✓	✓	✓		✓	✓
Industry Fixed Effect	✓	✓	✓		✓	✓
Industry–Year F.E.				✓		
Firm Fixed Effect	✓	✓	✓	✓	✓	✓
Observations	23,850	23,850	23,850	23,850	23,850	23,850
Adjusted R^2	0.687	0.685	0.687	0.703	0.730	0.688

Table IX. Panel Regressions of Liquidity Risk and Commonality in Liquidity on Institutional Presence

This table reports parameter estimates from panel regressions of liquidity risk and commonality in liquidity on Institutional Presence and stock characteristics. Independent variables are measured at the end of the previous quarter (t–1). Institutional presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the firm's headquarter state. PS Beta / Sadka Beta is the firm–level Pástor and Stambaugh (2003) / Sadka (2010) liquidity beta estimated over the next 36 months. Commonality Beta is the commonality in liquidity beta estimated over the next quarter or year of NYSE only stocks, as implement by Koch, Ruenzi and Starks (2012). All variables are standardized to have a mean of zero and standard deviation of one. Please refer to Table I for exact definitions of the control variables. Exchange dummy are trading exchange fixed effects. Size decile are size decile fixed effects based on NYSE breakpoints. Industry–year fixed effects are based on Fama–French 48 industries. The sample period is from 1991–2008. T–statistics, reported in parenthesis, are based on two–way clustered standard errors by firm and state–year.

	1	2	3	4
	Liquidity Risk Measures		Commonality Measures	
Dependent Variable:	PS Beta	Sadka Beta	Commonality Beta (Quarterly)	Commonality Beta (Annual)
IP_{ST}	–0.003	–0.118	–0.037	–0.035**
	(–0.60)	(–1.48)	(–1.42)	(–2.31)
$Asset_{ST}$	0.012	0.209*	0.026	0.023
	(1.50)	(1.86)	(0.96)	(1.04)
$Income_{ST}$	–0.110	1.663	0.027	–0.080
	(–1.33)	(1.53)	(0.12)	(–0.43)
Urban	0.001	0.091	0.061***	0.027
	(0.11)	(0.78)	(2.95)	(1.48)
Local IO%	–0.000	0.041	–0.011	–0.017***
	(–0.18)	(0.93)	(–1.36)	(–2.93)
Non–local IO%	0.005	0.149**	0.037***	0.048***
	(1.38)	(2.42)	(3.25)	(4.89)
Ln(Turnover)	0.004	–0.312***	0.000	–0.012
	(1.13)	(–5.38)	(0.00)	(–1.10)
Return Volatility	–0.002	–0.130*	–0.036**	–0.037**
	(–0.33)	(–1.90)	(–2.32)	(–2.15)
Ln(ME)	–0.000	–0.256*	0.122***	0.144***
	(–0.02)	(–1.94)	(4.23)	(5.71)
Ln(BM)	0.007**	0.011	0.019**	0.016*
	(2.08)	(0.21)	(2.25)	(1.92)
$Ln(1+Ret_{12,1})$	–0.004*	0.008	0.026**	0.026***
	(–1.94)	(0.21)	(2.45)	(3.15)
Young	0.003	0.387***	–0.059**	–0.087***
	(0.42)	(3.20)	(–2.44)	(–3.68)
Ln(#of Analysts)	–0.005	–0.124	0.010	0.033**
	(–1.16)	(–1.62)	(0.70)	(2.50)
Exchange Dummy	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓
Industry–Year F.E.	✓	✓	✓	✓
Observations	125,069	117,099	71,526	76,283
Adjusted R^2	0.073	0.098	0.025	0.084

Table X. The Destabilizing Effects of Institutional Presence

This table reports parameter estimates of quarterly panel regressions of herding and price pressure measures on Institutional Presence and stock characteristics. Independent variables are measured at the end of the previous quarter (t–1). Institutional presence (IP_{ST}) is calculated as the total AUM of the institutional portfolio in the company's headquarter state. The herding measure is calculated following the *Average Herding Contribution* measure (equation 10 in Sias, 2004) to avoid potential issues related to the cross–sectional variations in the number of traders in each stock. The price pressure measure is calculated following Coval and Stafford (2007):

$$\text{Pressure}_{jt} = \frac{\sum_j (\max(0, \Delta \text{Hldgs}_{jit} | \text{Flow}_{jt} > 90^{\text{th}} \, pctl.) - \sum_j (\max(0, -\Delta \text{Hldgs}_{jit}) | \text{Flow}_{jt} < 10^{th} \, pctl.)}{\text{Shares Outstanding}_{jt-1}}$$

where $\Delta Hldgs_{jit}$ is the change in fund j's holding of stock i in quarter t and $Flow_{jt}$ is the capital flow for fund j in quarter t. We use the absolute value of this raw *Pressure* measure, as well as two indicator variables, i.e., whether the *Pressure* measure is below the 10th percentile (fire–sale) or above the 90th percentile (fire–purchase) among all stocks during the quarter. The pressure measures are size–adjusted by subtracting the mean delay measure of each stock's size decile. All variables are standardized to have a mean of zero and standard deviation of one. Please refer to Table I for exact definitions of the control variables. Exchange dummy are trading exchange fixed effects. Size decile are size decile fixed effects based on NYSE breakpoints. Industry–year fixed effects are based on Fama–French 48 industries. T–statistics, reported in parenthesis, are based on two–way clustered standard errors by firm and state–year.

Table X. The Destabilizing Effects of Institutional Presence (Continued)

	1	2	3	4
		Flow–Driven Trading Pressure		
Dependent Variable:	Herding (Sias, 2004)	|Pressure|	Probability of (Fire–Sale)	Probability of (Fire–Purchase)
IP_{ST}	−0.000	0.005	0.000	0.000
	(−0.12)	(1.10)	(0.08)	(1.16)
$Assets_{ST}$	−0.000	−0.009*	−0.002	−0.000
	(−0.49)	(−1.65)	(−0.38)	(−0.69)
$Income_{ST}$	0.005	−0.018	−0.060	−0.001
	(1.07)	(−0.49)	(−1.40)	(−1.27)
Urban	−0.000	0.002	0.002	0.000
	(−1.15)	(0.73)	(0.73)	(0.42)
Local IO%	−0.000	−0.004***	0.000	−0.000
	(−0.35)	(−2.92)	(0.12)	(−0.20)
Non–local IO%	−0.001***	0.025***	0.033***	0.001***
	(−4.56)	(12.12)	(15.45)	(19.01)
Turnover	−0.000	0.017***	0.009***	0.000***
	(−0.88)	(6.89)	(3.38)	(8.66)
$ILLIQ_{TO}$	−0.000	−0.015***	−0.017***	−0.000***
	(−1.14)	(−6.35)	(−6.05)	(−4.99)
Return Volatility	0.000**	0.010***	0.005*	0.000***
	(2.36)	(4.06)	(1.86)	(4.02)
Ln(ME)	0.001***	−0.027***	−0.036***	−0.001***
	(2.60)	(−4.03)	(−5.21)	(−6.61)
Ln(BM)	0.000***	−0.012***	−0.001	−0.000***
	(3.65)	(−5.84)	(−0.63)	(−3.65)
$Ln(1+Ret_{12,1})$	0.000	−0.028***	0.019***	−0.000***
	(0.60)	(−13.78)	(8.48)	(−3.73)
Young	0.000	0.018***	0.016***	0.001***
	(0.73)	(4.05)	(3.31)	(6.04)
Ln(# Analyst)	0.000	0.017***	−0.002	0.000***
	(0.57)	(6.53)	(−0.74)	(4.24)
Exchange Dummy	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓
Industry–Year F.E.	✓	✓	✓	✓
Observations	98,364	75,333	75,333	78,429
Adjusted R^2	0.022	0.047	0.041	0.069