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Institutional presence

Johan SULAEMAN
Southern Methodist University

Chi Shen WEI
Singapore Management University, cswei@smu.edu.sg

Institutional Presence*

Johan Sulaeman
Southern Methodist University
sulaeman@smu.edu

Chishen Wei
Nanyang Technological University
cswei@ntu.edu.sg

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Abstract

We propose an Institutional Presence (IP) measure to capture the latent role of non-owner institutional investors who nevertheless may be observing a firm. We employ this measure to examine whether the 'presence' of institutional investors reduces information asymmetry in the market. Firms in areas with high institutional presence experience higher liquidity, faster information incorporation, lower costs of equity capital, and less financing frictions relative to firms in low IP areas. The results hold after controlling for firm and geographical characteristics including institutional ownership and urban locality. Our findings indicate that being in the presence of institutional investors brings tangible benefits.

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

* Johan Sulaeman is at the Cox School of Business, Southern Methodist University, Dallas, TX 75275; *email*: sulaeman@smu.edu; *phone*: (214) 768-8284. Chishen Wei is at the Nanyang Business School, Nanyang Technological University, *email:* cswei@ntu.edu.sg; *phone:* (+65) 6592 1859. We thank Aydoğan Altı, Brad Barber, Xin Chang, Doug Diamond, Steve Dimmock, John Griffin, Nick Hirschey, Jun-Koo Kang, Paul Malatesta, Chris Parsons, David Reeb, Tao Shu, Sheridan Titman, Kumar Venkataraman, K.C. John Wei, Scott Weisbenner, and seminar participants at Hong Kong Baptist University, National University of Singapore, Singapore Management University, and the SFM conference in Kaohsiung for their helpful comments and suggestions. We thank Zhihong Chen and K.C. John Wei for providing the cost of equity capital data, Andrew Koch for sharing the commonality in liquidity data, and Kelsey Wei for sharing the mutual fund fire-sales data. All remaining errors are our own.

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We propose an Institutional Presence (IP) measure to capture the latent role of non-owner institutional investors who nevertheless may be observing a firm. We employ this measure to examine whether the 'presence' of institutional investors reduces information asymmetry in the market. Firms in areas with high institutional presence experience higher liquidity, faster information incorporation, lower costs of equity capital, and less financing frictions relative to firms in low IP areas. The results hold after controlling for firm and geographical characteristics including institutional ownership and urban locality. Our findings indicate that being in the presence of institutional investors brings tangible benefits.

I. Introduction

Institutional investors play a major role in the allocation of resources in the US economy. They are important providers of capital and spend significant resources monitoring securities they invest in as well as actively observing those they *may* invest in. In the extant literature, the involvement of institutional investors is conventionally measured with a snap-shot of institutional *ownership*, i.e., the aggregate fraction of the firm's shares held by institutional investors. However, this measure ignores a potentially important group of institutional investors: *non-shareholder* institutions who nevertheless may be actively observing the firm.

As an illustrative example, let us compare the cities of Boston, Massachusetts and Atlanta, Georgia. Both are large, thriving urban state capitals, but Boston has a much greater concentration of institutional investors. This clustering of financial intermediaries is likely to result in a larger number of local agents that participate in the information production process. These local agents are likely to have informational advantages as geographical proximity facilitates information collection of nearby companies.[1] While this may result in some local agents becoming shareholders, it may also result in others deciding not to hold the shares. However, their informational advantage puts them in better position to step in when stocks are inefficiently priced.

To study the implication of non-shareholder institutions in information production, we employ an "institutional presence" (IP) measure, which is defined as the aggregate portfolio value –i.e. total assets under management (AUM)– managed by institutional investors that are located in a particular region. We then assume that firms headquartered in that region experience the "presence" of the region's institutional investors, and assign the region's IP

[1] Extant studies demonstrate that financial intermediaries benefit from their proximity-based informational advantages. Institutional equity investors seem to profit from their geographical proximity to nearby U.S. stocks (Coval and Moskowitz, 2001; Baik, Kang, and Kim, 2010). In the banking literature, geographical proximity seems to facilitate the collection of soft information which directly affects loan terms and credit conditions (Petersen and Rajan, 2002; Degryse and Ongena, 2005).

measure to those firms.[2] For example, all firms headquartered in Boston are assigned an IP value of US$ 674M in 2003:Q1, which corresponds to the aggregate AUM of institutional investors located in Massachusetts at the end of 2002:Q4. This includes their holdings of Massachusetts based and non-Massachusetts based firms. This value is more than three times the IP measure assigned to all firms located in Atlanta in 2003:Q1: US$ 185M, corresponding to the aggregate AUM of institutional investors located in Georgia at the end of 2002:Q4.[3]

An attractive feature of the institutional presence (IP) measure is that it avoids the challenging issue of drawing inference from examining the direct shareholder channel as traditionally measured with institutional ownership. For example, a negative correlation between financing frictions and the level of institutional ownership does not necessarily imply that institutional investors *reduce* frictions. Rather, a firm with good investment prospects may simultaneously experience lower financing frictions and attract institutional shareholders. The IP measure is constructed as an ex-ante environmental measure that allows us to side-step potential omitted variable concerns because it exploits the co-location of firms and institutional investors, rather than actual institutional portfolio holdings.[4] While existing studies highlight the direct shareholder channel, to the best of our knowledge, no paper attempts to capture the

[2] Our implicit assumption is that the equity market is not fully integrated across geographical regions. 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.
[3] For the sake of simplicity, we use the total AUM in our analysis rather than the ratio of total AUM to other state-level variables, e.g., the total assets of firms headquartered in the state, or the state's GDP. Our empirical results remain when these ratios are employed; these results are available upon request.
[4] We 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, De Motta, Titman and Uysal, 2010). Please refer to the next section for a more thorough discussion on the motivation and construction of the IP measure.

aggregate effects of local institutional investors including those who decide *not* to hold the firm's shares.[5]

Using the IP measure, we ask our main question: Do companies benefit from being in the presence of institutional investors? Our main hypothesis is that firms located in regions of greater institutional presence should experience less informational asymmetry. This should be reflected in greater informational efficiency in the stock price (Holden and Subrahmanyam, 1992). Our first focus is to examine the hypothesis that firms headquartered in high institutional presence areas –like Boston– will experience greater informational efficiency than firms headquartered in areas with relatively lower institutional presence –like Atlanta. In particular, we hypothesize that institutional presence contributes to the building blocks of efficiency and this effect is reflected in improved liquidity and faster speeds of information diffusion.[6]

Our second focus is to examine the effect of institutional presence on allocational efficiency. While there are no established measures of allocational efficiency, we expect that a reduction in information asymmetry, all else equal, will be reflected in a lower cost of equity capital (Diamond and Verrecchia, 1991) and a loosening of financing frictions. Consequently, we hypothesize that firms located in high institutional presence areas should receive lower costs of equity and have lower investment sensitivity to cash flows compared to their counterparts located in low institutional presence areas.

Our first set of findings indicates that institutional presence is associated with greater price efficiency. Stocks in high institutional presence regions experience higher liquidity than

[5] The shareholder channel is highlighted in studies of local institutional shareholders, such as Ayers, Ramalingegowda, and Yeung (2011) and Chhaochharia, Kumar, and Niessen-Ruenzi (2012). In contrast, the IP measure is similar in spirit to other measures that focus on potential investors rather than actual shareholders, which are employed by Becker, Cronqvist, and Fahlenbrach (2011), Becker, Ivković, and Weisbenner (2011), and Bernile, Kogan, and Sulaeman (2013). The latter study is the closest related to this study as it also examines institutional investors, and finds that stock returns increase with the firm's average distance to its potential institutional investors.

[6] Griffin, Kelly and Nardari (2010) examine the building blocks of efficiency across international markets. Their findings emphasize the importance of measuring the informational aspects of efficiency.

their low institutional presence counterparts. Our baseline test shows that a one standard deviation change in the IP measure is related to a 5% standard deviation change in liquidity. This finding is robust after controlling for institutional ownership; the point estimates suggest that the non-shareholder channel –as proxied by the IP measure– is smaller but of a comparable order of economic magnitude as the direct shareholder channel –as measured by institutional ownership. We find similar results across a variety of commonly used liquidity measures. The negative 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. These findings suggest that firms with greater informational asymmetry enjoy the greatest benefits from their geographical proximity to institutional investors.

We adopt the speed of information diffusion measure, 'delay', 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 IP_{ST} is associated with an approximately 4% standard deviation decrease in delay.

We explore several alternative explanations for our findings. A potential concern is that of omitted state-level variables. For example, it is plausible that the IP measure is related to state laws on corporate disclosure requirements that may concurrently affect the liquidity of local stocks. Or regional economic growth may simultaneously improve the liquidity of local stocks and increase local institutional presence. To alleviate these concerns, our main empirical analysis consists of panel regressions that include state fixed effects to capture unobserved state characteristics. We also control for time-varying state characteristics, such as state income (or

GDP), aggregate book value of corporate assets in the state, and regional economic growth.[7] Our results are robust to the inclusion of state fixed effects and characteristics.

A related concern is potential reverse causality: institutional investors choose to locate near firms with more liquid stocks. There is an additional concern that the liquidity findings are mechanically driven by the local holdings component of the IP measure. For example, the price appreciation of locally held shares may simultaneously increase the IP measure and liquidity. To alleviate these concerns, 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 using the adjusted IP measure.

Our inferences also remain unchanged with the inclusion of *firm* fixed effects, suggesting that the relation between institutional presence and liquidity is not only a cross-sectional phenomenon, and is at least partly due to time-series variation of the IP measure within each state and for each firm. Moreover, using a sample of headquarter re-locations, we find that firms that switch from low institutional presence regions to high institutional presence regions experience an increase in liquidity, again suggesting that our results are not due solely to cross-sectional variations in unobserved firm characteristics.

The results are also robust to the inclusion of county-level population density or an indicator variable for highly urbanized cities (Loughran and Schultz, 2005) as control variables. Moreover, the effect of institutional presence on market liquidity is stronger when we focus on the subsample of firms located in urban areas, consistent with the concentrated presence of institutional investors in urban areas. Our results remain after omitting major media markets such as New York, suggesting that we are not simply capturing business media and news attention (Bushee, Core, Guay, and Hamm, 2010). This analysis also suggests that our results

[7] The inclusion of local income and the supply of corporate assets may proxy for local supply and demand of stocks as described in Hong, Kubik, and Stein (2008).

are unlikely driven by the proximity to stock exchanges or the high concentration of sell-side analysts and brokerage houses in New York.

We next turn to examining how institutional presence is linked to allocational efficiency. Our evidence indicates that 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. The results are robust to a variety of estimates of the cost of equity capital commonly used in the literature. We find similar evidence when we control for firm characteristics (e.g., size, volatility), analyst coverage, institutional ownership, and population density.[8]

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. While we do not directly test the governance channel in this paper, it is important to note that this channel is unlikely to explain the informational efficiency results we document earlier.[9]

As institutional presence reduces the cost of equity capital, it should also be reflected in lower financing frictions. To test this conjecture, we estimate investment-cash flow sensitivity regressions across institutional presence regions. Consistent with our hypothesis, firms located in high institutional presence regions have investment-cash flow sensitivities that are 28% lower

[8] In contrast, the effect of institutional ownership on cost of equity capital appears to be sensitive to the inclusion or exclusion of firm characteristics in the regressions, suggesting that any observed relation between institutional ownership and cost of equity capital may be due to the links between institutional investors' portfolio decisions and these firm characteristics.
[9] Recent studies examine the effect of liquidity on governance (Edmans, 2009; Edmans Fang and Zur, 2013, Bharath, Jayaraman and Nagar, 2013), rather than vice versa.

than their low institutional presence counterparts. This effect remains robust when we control for firm fixed effects and various firm characteristics.

After documenting the benefits of being located near the presence of institutional investors, we consider the potential costs associated with the greater presence of institutional investors. Being located in high institutional presence regions may expose a firm's stock to price shocks and liquidity dis-locations due to the industrial organization of institutional money management. Potential sources of these shocks or dis-locations include stock herding (Lakonishok, Shleifer, and Vishny, 1992) or mutual fund fire-sales (Coval and Stafford, 2007). Recent studies also document a link between institutional money management and liquidity risk as well as commonality in liquidity (Kamara, Lou, and Sadka, 2008; Koch, Starks, and Ruenzi, 2012). We find no evidence that firms located in high institutional presence areas experience increased herding, fire-sale or liquidity risk. We find only weak evidence of elevated levels of commonality in liquidity. While our analyses have not considered all possible costs associated with being located in high institutional presence areas, our evidence suggests it is unlikely to be manifested in significant liquidity costs or institutional-driven pricing dislocations.

The results in this study contribute to our understanding of the growing role of institutional investors (Bennett, Sias and Starks, 2003) in three ways. First, we find evidence consistent with a non-shareholder channel which complements the work on the direct shareholder channel explored in Karpoff, Malatesta, and Walkling (1996), Del Guercio and Hawkins (1999), and Boehmer and Kelly (2009).[10] Second, while several studies document the de-stabilizing effects of institutional investors, our evidence provide an alternative perspective on the benefits of institutional investors. Additionally, we find evidence that the non-shareholder channel is not associated with de-stabilizing episodes. Finally, our study adds to the growing

[10] Recent studies in this area focus on local institutional owners; these studies include Ayers, Ramalingegowda, and Yeung (2011) and Chhaochharia, Kumar, and Niessen-Ruenzi (2012).

literature on how potential investors can effect market outcomes (Becker, Cronqvist, and Fahlenbrach, 2011; Becker, Ivković, and Weisbenner, 2011; and Bernile, Kogan, and Sulaeman, 2013).

The rest of the paper is organized as follows. In the next section, we provide the motivation for our Institutional Presence measure and discuss its construction. In Section III, we briefly discuss and summarize our data. In Section IV, we report the effects of the IP measure on liquidity and informational delay. In Section V, we examine the effects of the IP measure on the cost of equity capital and investment frictions. Section VI explores potential costs that may be associated with institutional presence. Section VII examines alternative explanations. We conclude in Section VIII.

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 which directly effects 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).[11] As local institutional investors make portfolio decisions using this type of 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.[12]

A. Institutional Presence Measure

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

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

where $\$AUM_{i,t-1}$ is the total value of institution i's 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; therefore, it does not necessarily reflect lower attention from institutional investors or lower informational

[11] 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., Huberman (2001), Grinblatt and Keloharju (2001), Massa and Simonov (2006), Bodnaruk (2009), Teo (2009), and Pool, Stoffman, and Yonker (2012).
[12] 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).

efficiency. Also, traditional institutional ownership measures tend to be captured as snapshots at relatively low frequencies (i.e. quarterly or semi-annual). Due to the length of the required reporting intervals, these measures of ownership may not capture shorter term trading movements that reveal how information is impounded into prices.

In addition, our empirical approach also contributes to the more general literature on the effect of local institutional investors on market efficiency and asset pricing. While most studies in this literature focus on the direct link between local institutional ownership and asset prices, we employ an ex-ante framework that captures the environment before the portfolio decision is made. A disproportionately low level of local institutional ownership in a particular stock may be due to local institutions' poor perception about 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 informative in predicting future stock performance, it is not necessarily informative in capturing the effect of local institutional investors on price efficiency.

In contrast, our IP measure is an ex-ante measure of local trading and investment; it does not depend on the actual levels of local ownership or trading. 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 quantity of local public firms using the total market capitalization ($\mathrm{ME_{ST}}$) or total book value of corporate assets ($\mathrm{Assets_{ST}}$) located in the state. The relation between $\mathrm{IP_{ST}}$ 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 $\mathrm{IP_{ST}}$ measure and $\mathrm{Assets_{ST}}$ or $\mathrm{ME_{ST}}$ separately in the regression analysis to avoid imposing an ad-hoc functional form to our main variable. Additionally, we replicate all of our tests and find similar results using the ratio of $\mathrm{IP_{ST}}$ to $\mathrm{Assets_{ST}}$ (or $\mathrm{ME_{ST}}$).[13]

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 ($\mathrm{Income_{ST}}$) or the total GDP produced in each state ($\mathrm{GDP_{ST}}$) in our regression analysis to proxy for local individual investors. We also replicate all of our tests using the ratio of $\mathrm{IP_{ST}}$ to either total state income or total state GDP; we find similar results.

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. Using this aggregate measure, we regress it on the state-level IP measure and other state characteristics such as $\mathrm{Assets_{ST}}$ and $\mathrm{Income_{ST}}$ 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

[13] The results of the untabulated analyses in this subsection are available upon request.

conjecture that the IP measure captures the probability of local institutional investors being the marginal investor/non-investor in a particular stock.

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 and potentially affecting the price. 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. 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 measured at the county level. *Pop. Density* is the total county population divided by its area size.[14] IDX_{ST} is the state economic condition measure proposed in Korniotis and Kumar (2013).

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 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 on 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

[14] 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.

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 Institutional Presence 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 contributes to the building blocks of market 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 the 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 be more informed, perhaps due to lower costs of information collection, 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, indicating 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. The difference is consistently negative in both the earlier and latter halves of the sample.

We next perform panel regressions of quarterly measures of ILLIQ on institutional presence. The variables are standardized 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. To control for the urban liquidity effect in Loughran and Schultz (2005), we include an Urban indicator variable for firms located in urban areas. 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 attempt to address this issue by including state-level fixed effects. This helps to isolate the variation in liquidity due to variation in institutional presence that is unrelated to other potentially unobserved state characteristics. The state-level fixed effects can absorb unobserved, state heterogeneity to the extent that these unobserved characteristics remain relatively stable throughout our sample.[15] 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.

Table II presents standardized parameter estimates and t-statistics 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 presented in column 1 shows that a one standard deviation change in IP_{ST} is related to a –4.5% (t=–3.62) standard deviation change in ILLIQ. The second column includes Asset_{ST}, $\text{Income}_{\text{ST}}$, and the Urban indicator variable. Consistent with the findings in Loughran and Schultz (2005), urban locality is associated with a –3.8%

[15] In our robustness tests in Table III, we include additional geography-related characteristics to directly account for these potential time-varying changes.

decrease in ILLIQ. Column 3 includes stock characteristics. The parameter estimate on IP_{ST} remains negative and statistically significant in this specification. Next, we include institutional ownership (IO%), and a separate decomposition into local institutional ownership (Local IO%) and non-local institutional ownership (Non-local IO%). Institutional ownership is negatively related to ILLIQ. As shown in column 5, this effect is primarily due to non-local institutional ownership, whereas local institutional ownership has a small, but statistically significant positive relation to ILLIQ.

The regression result in column 4 is informative because it allows a direct comparison between the non-shareholder channel (IP_{ST}) versus 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 indeed an economically important channel.

Column 5 presents an alternative econometric specification that includes separate industry and year fixed effects. The parameter estimate on IP_{ST} between column 4 (-0.054; t=-4.67) and column 5 (-0.054; t=-4.63) are identical suggesting that the economic inference is similar across the different econometric specifications.

Column 6 of panel A in Table II includes a firm level fixed effect to capture unobservable firm-level heterogeneity that may drive the link between IP_{ST} and ILLIQ in the previous columns. This is a critical concern if institutional investors choose to cluster in regions with firms that have a certain difficult to quantify characteristic that is associated with higher levels of liquidity (e.g., possibly 'well-known' stocks as described in Merton, 1987). To a large degree, state fixed effects may absorb these geographically driven effects, but the possibility lingers that unobserved firm heterogeneity remains unaccounted for.

The results indicate that the parameter estimate on IP_{ST} remains negative and statistically significant (−0.056; t=−4.64) with the inclusion of firm fixed effects. This evidence suggests that it is unlikely that the relation between IP_{ST} and ILLIQ is caused by unobservable firm heterogeneity 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 effects.

We more formally test the impact of the non-shareholder channel by examining the subsample of firms with local institutional ownership that is below the state median.[16] By only examining stocks with low 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=−4.58). 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 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

[16] The evidence is quantitatively similar using a subsample of firms with 0% local institutional ownership. These results are available upon request. We choose to report the results using below state median to avoid capturing differences in local institutional ownership across states.

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 top 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, *HighIA*, 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 HighIA 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} * HighIA dummy is negative and statistically significant, −0.026 (t=−3.25). For firms with high informational asymmetry, a one standard deviation change in IP_{ST} leads to an additional 2.6% standard deviation decrease in cost of equity capital 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=−7.90) and analyst coverage (−0.053; t=−9.45).[17] The parameter estimates on the dummy for young firms is negative but not significant. Perhaps age is a weak proxy for information asymmetry due to its high correlation with other firm characteristics such as institutional ownership or size.

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

Robustness checks

To ensure that our results are robust, we present eleven alternative regression specifications in Table III. In panel A, we present additional results using alternative measures of liquidity and alternative measures of institutional presence. In addition to these tests, we also examined alternative transformations of our variable in untabulated analyses as discussed in Section II.B. In panel B, we examine various sub-samples of our data to confirm that our results are robust. We suppress the parameter estimates on the firm characteristics control variables to conserve space. The full set of results is available upon request.

First, we employ an alternative definition for our institutional presence measure that aggregates the *non-local* portion of assets under management of institutional investors located in a state ($IP_{ST,\text{ Non-Local}}$). 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 locate near stocks with higher liquidity with the intention of holding shares in those companies. We side-step this reverse causality concern by using only the non-local portion of institutional presence. 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 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.

In column 1, panel A, Table III, we present the results from estimating the panel regression model with state fixed effects used in Table II using $IP_{ST,\text{ Non-Local}}$. The parameter estimate on $IP_{ST,\text{ Non-Local}}$ is negative and statistically significant (−0.046; t=−4.52). This result is important because it lessens concerns that our main results are due to a reverse causality explanation or a mechanical relation.

Second, we broaden our geographical level and re-estimate our panel regression tests by employing U.S. Census geographical divisions as our geographical boundary.[18] 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 for our key measures.

The results in column 2 show 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 would intuitively expect, the economic magnitude of the parameter estimate (−0.047; t=−4.95) is smaller compared to the negative parameter estimate on IP_{ST} (−0.133; t=−6.94). As we expand the geographical area, the effect of institutional presence on liquidity drops.[19]

Third, we consider alternative measures of liquidity: effective spread in column 3, and $ILLIQ_{TO}$ in column 4. Our inferences from the previous set of results that use the ILLIQ measure 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

[18] 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).

[19] 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.

standard deviation increase in IP_{ST} is associated with a 3.5% decrease in effective spread, and a 7.8% decrease in $ILLIQ_{TO}$.

Fourth, we consider alternative variants of our state-level control measures. Our main specifications employ the total book value of corporate assets ($Assets_{ST}$) and the total state income ($Income_{ST}$) in the company's headquarter state. In column 5, 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.

In the last column of panel A, we examine the possibility of complementing the urban dummy with other 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). Our main inference is not affected by the inclusion of these variables.

Panel B of Table III focuses on various sub-samples of our data. In the first column of panel B, we estimate a cross–sectional standardized Fama–MacBeth 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 must exclude state fixed effects. The result indicate that the parameter estimate on IP_{ST} remains negative and statistically significant (–0.020; t-stat=–6.83). This parameter estimate implies that a one standard deviation change in IP_{ST} in the cross-section is associated with a 2% standard deviation decrease in ILLIQ.

Next, we isolate a sub-sample of firms with headquarters in urban locations. The purpose is to address the concern that our earlier findings are caused by differences across urban and rural areas as documented in Loughran and Schultz (2005). The results in column 2 indicate that the parameter estimate on IP_{ST} remains negative and statistically significant, 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.

In column 3, we show that our results remain after excluding the state of New York from our sample. This is important for two reasons. First, the business media may act as an external monitor and impact the information asymmetry between the market and company. Since much of the business media operates out of New York City, this result suggests that we are not simply capturing the effects of business media and news attention (Bushee, Core, Guay, and Hamm, 2010). Second, this result suggests that our findings are unlikely to be driven by the proximity to stock exchanges or the high concentration of sell-side analysts and brokerage houses in New York.

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.

B. Institutional Presence and Speed of Information Diffusion

The analysis in the previous section suggests that institutional presence acts to improve 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 R2 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 perform a rigorous analysis of 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 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 for ease of economic interpretation.

Table IV presents the regression results. The first column of Table IV 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 4.3% (t=−2.35) decrease in information delay. This result implies a similar economic effect of institutional presence on the speed of information diffusion compared to our earlier ILLIQ tests.

In columns 2 and 3, we add institutional ownership (IO%) and the decomposition of institutional ownership into two components, local and non-local institutional ownership (Local IO%/Non-local IO%). The parameter estimates on IP_{ST} continue to be significant in columns 2 and 3. IO% is also associated with lower delay. This effect is mainly due to Non-local% 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 a subsample of urban firms. The effect of IP_{ST} on information diffusion remains within the subsample of urban stocks. This is consistent with our previous urban-only subsample findings in Table 3 on the link between IP_{ST} and ILLIQ.

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=−2.57 vs. −0.041; t=−2.21). Column 6 reports a particularly stringent regression specification with the inclusion of a firm fixed effect. The parameter estimate is statistically significant at the 10% level, but more importantly the point estimate (−0.042) 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 econometric models, a one standard deviation increase in IP_{ST} is associated with a decrease in delay between 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=-8.99). 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 Table IV provide supportive evidence for the positive effect of institutional presence on the speed of information diffusion.

V. Institutional Presence, Cost of Capital, and Investment Friction

In this section, we turn our focus to 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 V 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.

As reported in Panel A, 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 -0.135% (COC_{GLS}, COC_{PEG}). 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 example, the difference in COC_{GLS} between the high and low IP_{ST} tercile is negative 0.15% (t=–7.55) for small stocks. 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 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 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 regression tests 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 allow 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 VI reports the standardized parameter estimates and t-statistics from panel regressions with state fixed effects. IP_{ST} has a negative effect on cost of equity capital across all regression specifications. In the second column, we add an indicator variable for urban locality (Urban), 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 (−0.037, t=−2.33).

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 VI. 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.

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. An implication of this result is 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):

$$\mathrm{I}_{i,t} = a_t + \beta_1\,\mathrm{CF}_{i,t} + \beta_2\,\mathrm{IP}_{i,t-1}{*}\mathrm{CF}_{i,t} + \beta_3\,\mathrm{IP}_{i,t-1} + \gamma\,\mathrm{Controls} + \varepsilon_{i,t} \qquad (2)$$

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

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, $\text{CAPXRND}_{i,t}$, 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 headquarter state. We include 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 (Items 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 VII. 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.[22] 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

[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.

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 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 would 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 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 VIII 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 VIII show that $\mathrm{IP_{ST}}$ is not related to an increase in the commonality in liquidity. Rather, the parameter estimate on $\mathrm{IP_{ST}}$ 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) cites 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.[23,24] 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:

$$\text{Pressure}_{jt} = \frac{\sum_j (\max(0, \Delta \text{Hldgs}_{jit} | \text{Flow}_{jt} > 90^{\text{th}} \, pctl.) - \sum_j (\max(0, -\Delta \text{Hldgs}_{jit}) | \text{Flow}_{jt} < 10^{th} \, pctl.)}{\text{Shares Outstanding}_{jt-1}} \quad (3)$$

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.[25]

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 IX. 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-

[23] 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.

[24] 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.

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

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 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).

First, we address the possibility that analyst attention could be the source of our findings. 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. In the previous analysis, we control for this effect by directly including analyst coverage in the regression specifications and find that our results are robust to this inclusion. However, it is possible that the effect of "analyst presence" drives our main findings. To explore this possibility, we construct a measure of analyst presence using a similar methodology to our construction of institutional presence. We re-estimate our regressions including analyst presence as an explanatory variable. The effect of institutional presence is robust to the inclusion of this variable.

This evidence 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.

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. While this analysis also allows us to control for the possibility that our results is driven by variations in unobserved firm characteristics, 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 57 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 size and exchange adjusted effective spread reduction of 0.95% (t=−1.74) between year t−2 to year t+2 (where year t is the estimated relocation year).[26] This beneficial effect of relocation is primarily isolated to smaller firms. For firms outside the top market capitalization quintile, firms that relocate into the top tercile of the IP_{ST} measure

[26] We omit the years immediately surrounding headquarters relocation due to potential noise associated with the abundant amount of media coverage associated with the relocation itself.

experience a decrease in their industry-adjusted cost of equity capital from year $t-2$ to year $t+2$ of 129 basis points (t=−2.54) versus 56 basis points (t=−1.75) for all other relocations of similarly sized firms. Although the difference of 73 basis points is not statistically significant, its magnitude is larger than the cross-sectional differences we observe between the top and bottom IP_{ST} terciles (between −10 to −14 basis points) in earlier sort analyses using the full sample. We speculate that the lack of statistical significance may simply reflect the small sample and noise issues of analyzing relocating firms as discussed.[27]

VIII. Concluding Remarks

In this paper, we propose an Institutional Presence (IP) measure to capture the potential latent role of non-owner institutional investors who nevertheless may be observing a firm. We argue 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, consistent with financial intermediation improving price efficiency. Moreover, this measure is associated with lower cost of equity capital as well as less financing friction in corporate investments. Our analysis also suggests that institutional presence does not seem to entail significant costs. In particular, our evidence suggests institutional presence is unlikely to result in significant liquidity-related costs or institutional-driven dislocations.

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 these documented benefits? Why do we not observe more firms moving into higher institutional

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

presence area? Are there barriers to entry or prohibitively expensive re-location costs into high institutional presence areas? Are there any other benefits of higher institutional presence? We leave these questions for future research.

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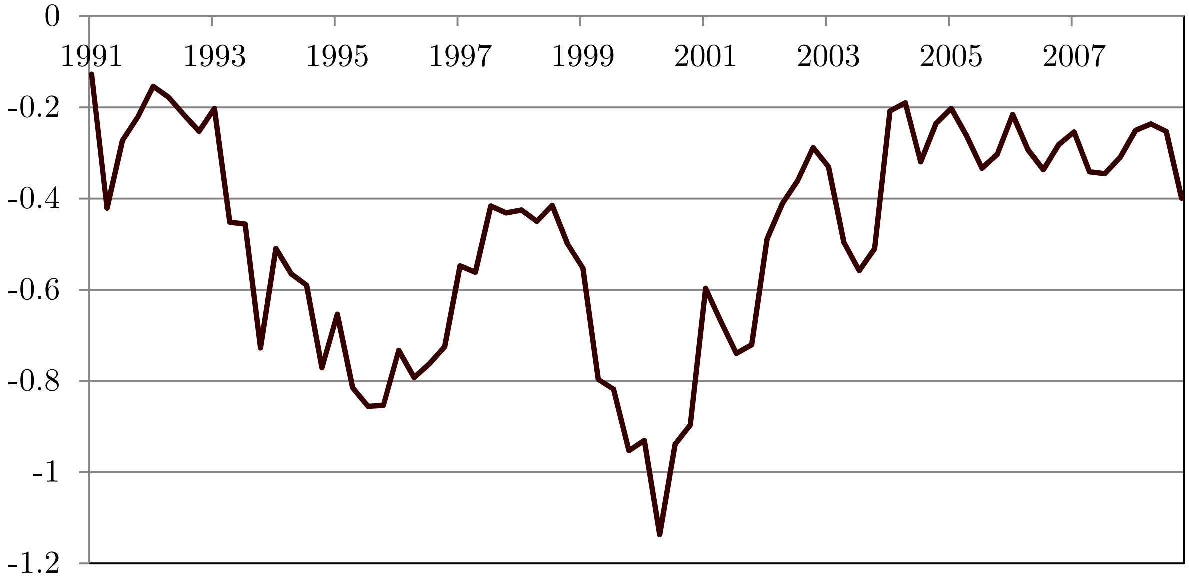
Figure 1. Difference in Liquidity and Cost of Equity Capital between the Top Institutional Presence Tercile and the Bottom Tercile

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)

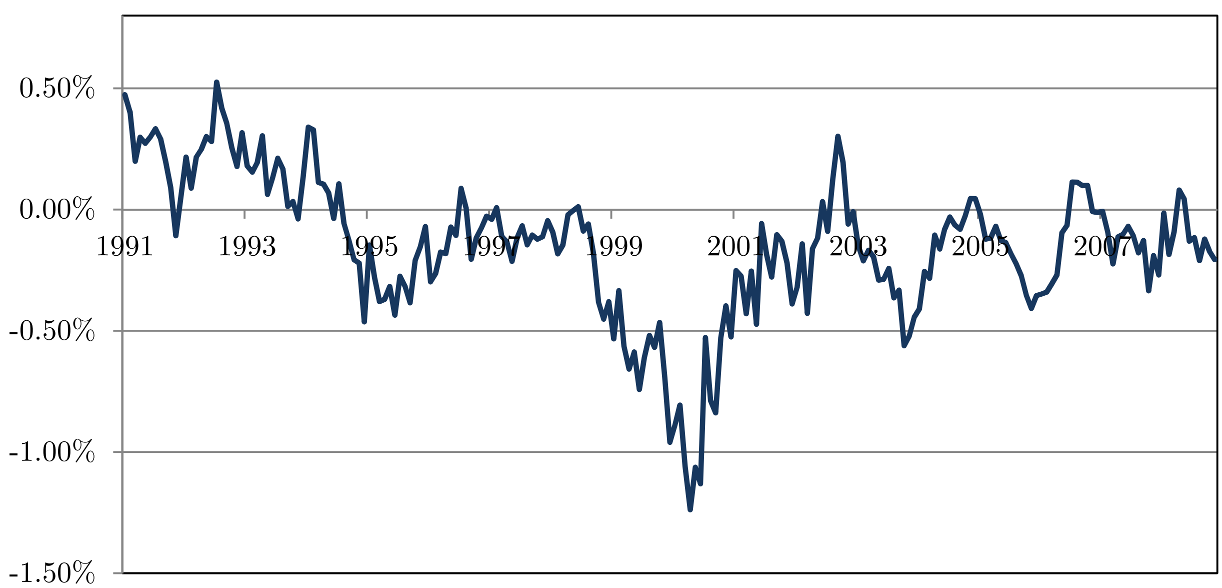


Table I. Summary Statistics

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 dummy variable=1 if the firm is headquartered in an urban area. 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 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	0.494	0.5	0	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. $\text{Presence}_{\text{ST}}$	Inst. $\text{Presence}_{\text{ST}}$ (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 standardized parameter estimates from panel regression of quarterly ILLIQ on Institutional Presence and stock characteristics. The dependent variable is, ILLIQ, is the Amihud (2002) measure of illiquidity. 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. 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***	−0.052***	−0.056***	−0.054***	−0.054***	−0.056***	−0.046***
	(−3.62)	(−4.33)	(−4.74)	(−4.67)	(−4.63)	(−4.64)	(−4.58)
$Assets_{ST}$		0.025**	0.025***	0.027***	0.026***	0.038***	0.031***
		(2.49)	(2.94)	(3.31)	(3.20)	(4.15)	(3.56)
$Income_{ST}$		0.172*	0.198***	0.228***	0.238***	0.105	0.156**
		(1.95)	(2.84)	(3.33)	(3.47)	(1.27)	(1.98)
Urban		−0.038***	0.001	0.010	0.010	−0.004	0.014
		(−3.21)	(0.15)	(1.30)	(1.31)	(−0.13)	(1.55)
IO%				−0.091***			
				(−23.98)			
Local IO%					0.009***	0.005*	−0.027***
					(3.17)	(1.73)	(−2.59)
Non-local IO%					−0.092***	−0.078***	−0.094***
					(−24.37)	(−18.10)	(−20.18)
Ln(Turnover)			−0.215***	−0.194***	−0.194***	−0.154***	−0.206***
			(−35.07)	(−32.04)	(−32.12)	(−31.42)	(−30.07)
Ln(ME)			−0.499***	−0.486***	−0.485***	−0.361***	−0.462***
			(−37.61)	(−40.28)	(−40.06)	(−31.16)	(−35.57)
Return Volatility			−0.003	−0.018***	−0.0172***	0.014**	−0.023***
			(−0.71)	(−3.86)	(−3.72)	(2.33)	(−4.83)
Young			0.066***	0.057***	0.057***	−0.002	0.065***
			(11.49)	(10.13)	(10.18)	(−0.30)	(9.94)
Ln(# of Analysts)			−0.126***	−0.105***	−0.104***	−0.083***	−0.105***
			(−27.19)	(−22.60)	(−22.62)	(−16.40)	(−18.62)
Intercept	−1.380***	−1.230***	−0.037	−0.064	−0.059	−0.165	−0.180***
	(−39.01)	(−16.47)	(−0.57)	(−1.02)	(−0.94)	(−1.33)	(−2.60)
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	167,026	167,026	167,026	167,026	167,026	167,026	93,490
Adjusted R^2	0.822	0.822	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**	−0.031***	−0.053***
	(−4.49)	(−2.03)	(−3.10)	(−4.57)
IP_{ST}*High IA Dummy	−0.026***			
	(−3.25)			
IP_{ST}*Small Dummy		−0.045***		
		(−7.90)		
IP_{ST}*COV Dummy			−0.053***	
			(−9.45)	
IP_{ST}*Young				−0.009
				(−1.53)
High IA Dummy	0.025**			
	(2.56)			
COV Dummy			−0.013**	
			(−2.14)	
$Assets_{ST}$	0.026***	0.027***	0.025***	0.026***
	(3.20)	(3.39)	(3.09)	(3.18)
$Income_{ST}$	0.243***	0.246***	0.234***	0.241***
	(3.55)	(3.62)	(3.44)	(3.52)
Urban	0.010	0.007	0.006	0.010
	(1.29)	(0.92)	(0.82)	(1.31)
Local IO%	0.009***	0.010***	0.009***	0.009***
	(3.20)	(3.73)	(3.45)	(3.19)
Non-local IO%	−0.092***	−0.092***	−0.092***	−0.092***
	(−24.36)	(−24.45)	(−24.61)	(−24.43)
ln(Turnover)	−0.194***	−0.196***	−0.196***	−0.194***
	(−32.31)	(−32.99)	(−33.35)	(−32.16)
ln(ME)	−0.484***	−0.482***	−0.482***	−0.485***
	(−40.16)	(−40.87)	(−41.27)	(−40.09)
Volatility	−0.017***	−0.016***	−0.016***	−0.017***
	(−3.59)	(−3.45)	(−3.51)	(−3.67)
Young	0.041***	0.056***	0.056***	0.057***
	(5.86)	(9.98)	(10.01)	(10.18)
# Analyst	−0.102***	−0.102***	−0.109***	−0.104***
	(−22.24)	(−22.19)	(−21.71)	(−22.55)
Intercept	−0.059	−0.068	−0.073	−0.057
	(−0.94)	(−1.11)	(−1.18)	(−0.91)
Exchange Dummy	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓
Industry−Year F.E.	✓	✓	✓	✓
Sample	Full	Full	Full	Full
Observations	167,026	167,026	167,026	167,026
Adjusted R^2	0.890	0.890	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). 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. 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. Alternative Measures						
	1	2	3	4	5	6
Dependent Variable:	ILLIQ	ILLIQ	Effective Spread	$ILLIQ_{TO}$	ILLIQ	ILLIQ
IP_{ST}		−0.133***	−0.035**	−0.078***	−0.094***	−0.053***
		(−6.94)	(−2.55)	(−4.28)	(−4.61)	(−4.55)
$IP_{ST,\ Non-Local}$	−0.046***					
	(−4.52)					
$Assets_{ST}$	0.024***	0.003	0.027	0.042***		0.025***
	(3.03)	(0.35)	(1.50)	(2.65)		(3.01)
$Income_{ST}$	0.236***	0.082	−0.117	0.577***		0.252***
	(3.45)	(1.01)	(−0.69)	(3.81)		(3.59)
$IP_{Division,\ Non-State}$		−0.047***				
		(−4.95)				
$Assets_{Division,\ Non-State}$		0.034*				
		(1.84)				
$Income_{Division,\ Non-State}$		0.034***				
		(4.22)				
ME_{ST}					0.067***	
					(2.86)	
GDP_{ST}					0.145**	
					(2.06)	
Pop. $Density_{County}$						−0.002
						(−0.57)
$Education_{County}$						−0.019***
						(−3.62)
Income Per $Capita_{County}$						0.025***
						(3.94)
IDX						0.002
						(0.41)
Firm Characteristics	✓	✓	✓	✓	✓	✓
Exchange Dummy	✓	✓	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓	✓	✓
Regression Type	Panel	Panel	Panel	Panel	Panel	Panel
State Fixed Effect	✓	✓	✓	✓	✓	✓
Industry−Year F.E.	✓	✓	✓	✓	✓	✓
Sample	Full	Full	Full	Full	Full	Full
Observations	167,026	166,888	150,944	167,026	165,222	166,397
Adjusted R^2	0.890	0.891	0.670	0.706	0.890	0.890

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

Panel B. Sub-samples					
	1	2	3	4	5
Dependent Variable:	ILLIQ	ILLIQ	ILLIQ	ILLIQ	ILLIQ
IP_{ST}	−0.020***	−0.329***	−0.050***	−0.037***	−0.221***
	(−6.83)	(−6.37)	(−4.50)	(−4.64)	(−3.40)
$Assets_{ST}$	0.005**	0.181	0.280***	−0.063	−0.356***
	(2.34)	(1.22)	(4.10)	(−0.47)	(−2.84)
$Income_{ST}$	−0.020***	−0.329***	−0.050***	−0.037***	−0.221***
	(−6.83)	(−6.37)	(−4.50)	(−4.64)	(−3.40)
Firm Characteristics	✓	✓	✓	✓	✓
Exchange Dummy	✓	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓	✓
Regression Type	Fama–MacBeth	Panel	Panel	Panel	Panel
State Fixed Effect		✓	✓	✓	✓
Industry–Year F.E.		✓	✓	✓	✓
Industry Fixed Effect	✓				
Sample	Full	Urban Only	No–NY	1991–1999	2000–2008
Observations	167,026	82,440	154,677	83,144	83,882
Adjusted R^2	0.891	0.890	0.889	0.879	0.891

Table IV. The Effect of Institutional Presence on Information Diffusion

This table reports standardized 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). 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}	–0.043**	–0.041**	–0.041**	–0.343***	–0.051**	–0.042*
	(–2.35)	(–2.21)	(–2.21)	(–3.05)	(–2.57)	(–1.65)
$Assets_{ST}$	0.062***	0.064***	0.064***	0.035	0.086***	0.079***
	(3.25)	(3.39)	(3.38)	(1.32)	(4.16)	(2.94)
$Income_{ST}$	0.397**	0.423***	0.426***	0.566	0.509***	0.357
	(2.45)	(2.62)	(2.64)	(1.57)	(2.79)	(1.36)
Urban	–0.000	0.007	0.007		0.013	–0.012
	(–0.00)	(0.39)	(0.39)		(0.72)	(–0.15)
IO%		–0.069***				
		(–8.99)				
Local IO%			0.001	–0.009	0.005	0.015*
			(0.29)	(–1.45)	(0.91)	(1.87)
Non–local IO%			–0.069***	–0.051***	–0.068***	–0.084***
			(–8.91)	(–4.74)	(–8.48)	(–5.94)
Ln(Turnover)	–0.039***	–0.021**	–0.021**	–0.026**	–0.034***	–0.011
	(–5.02)	(–2.45)	(–2.46)	(–2.29)	(–3.84)	(–1.14)
Ln(ME)	–0.108***	–0.106***	–0.105***	–0.081**	–0.098***	0.017
	(–4.58)	(–4.58)	(–4.57)	(–2.49)	(–4.14)	(0.52)
Return Volatility	–0.048***	–0.058***	–0.058***	–0.050***	–0.061***	–0.076***
	(–5.04)	(–5.95)	(–5.92)	(–3.90)	(–5.69)	(–3.96)
Young	0.080***	0.073***	0.073***	0.067***	0.061***	–0.013
	(5.68)	(5.16)	(5.17)	(3.42)	(4.41)	(–0.67)
Ln(# of Analysts)	–0.044***	–0.029***	–0.029***	–0.028**	0.003	0.013
	(–4.52)	(–2.99)	(–2.98)	(–2.20)	(0.29)	(0.79)
Intercept	1.308***	1.365***	1.375***	0.891	1.429***	–0.881**
	(2.62)	(2.77)	(2.78)	(0.94)	(2.67)	(–2.08)
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	38,463	38,463	38,463	18,917	38,463	38,463
Adjusted R^2	0.331	0.333	0.333	0.333	0.293	0.345

Table V. 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 VI. Panel Regressions of Cost of Equity Capital on Institutional Presence

This table reports standardized 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). 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 VI. Panel Regressions of Cost of Equity Capital on Institutional Presence (Continued)

Dependent Variable: COC_{GLS}	1	2	3	4	5
IP_{ST}	−0.057***	−0.073***	−0.074***	−0.030**	−0.037**
	(−2.63)	(−3.46)	(−3.51)	(−2.23)	(−2.33)
$Assets_{ST}$		0.050***	0.051***	0.011	0.023
		(2.71)	(2.72)	(0.78)	(1.34)
$Income_{ST}$		−0.005	−0.037	−0.016	0.339*
		(−0.03)	(−0.21)	(−0.12)	(1.70)
Urban		0.060**	0.055*	0.045**	0.125**
		(2.10)	(1.91)	(2.02)	(2.15)
Local IO%			−0.016***	−0.010**	0.010**
			(−2.62)	(−2.38)	(2.09)
Non−local IO%			0.051***	0.076***	0.017*
			(4.87)	(9.83)	(1.78)
Beta				0.011	0.017*
				(1.34)	(1.92)
iVol				0.039**	0.025**
				(2.35)	(2.00)
Ln(ME)				−0.095***	0.021
				(−4.98)	(0.67)
Ln(BM)				0.325***	0.226***
				(27.20)	(15.15)
$Ln(1+Ret_{12,1})$				−0.252***	−0.238***
				(−34.17)	(−34.11)
$ILLIQ_{TO}$				0.009	0.077***
				(1.28)	(11.34)
Leverage				0.078***	0.026***
				(10.74)	(2.64)
Forecast Error				−0.163***	−0.138***
				(−28.24)	(−26.27)
LT Growth				0.034***	0.021**
				(3.55)	(2.40)
Young				0.043***	−0.010
				(3.68)	(−0.66)
R&D				−0.001	0.026**
				(−0.09)	(2.57)
Ln(# Analyst)				−0.067***	−0.071***
				(−7.17)	(−6.57)
Intercept	−0.780***	−0.743***	−0.776***	−0.116	0.023
	(−12.97)	(−5.13)	(−5.40)	(−1.03)	(0.07)
Exchange Dummy	✓	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓	✓
Year Fixed Effect					✓
Industry Fixed Efect					✓
Industry−Year F.E.	✓	✓	✓	✓	
Firm Fixed Effect					✓
Observations	167,090	167,090	167,090	167,090	167,090
Adjusted R^2	0.293	0.293	0.295	0.506	0.661

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

This table reports standardized 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). 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}	–0.004	–0.121	–0.038	–0.037**
	(–0.61)	(–1.53)	(–1.50)	(–2.51)
$Asset_{ST}$	0.012	0.221**	0.026	0.024
	(1.54)	(1.98)	(0.94)	(1.08)
$Income_{ST}$	–0.108	1.605	0.029	–0.067
	(–1.32)	(1.48)	(0.14)	(–0.36)
Urban	–0.004	0.094	0.071***	0.020
	(–0.35)	(0.58)	(2.72)	(0.80)
Local IO%	–0.001	0.040	–0.010	–0.017***
	(–0.22)	(0.91)	(–1.33)	(–2.94)
Non–local IO%	0.005	0.152**	0.037***	0.049***
	(1.44)	(2.47)	(3.33)	(4.99)
Ln(Turnover)	0.004	–0.308***	0.001	–0.011
	(1.17)	(–5.31)	(0.04)	(–0.97)
Return Volatility	–0.002	–0.127*	–0.039**	–0.041**
	(–0.31)	(–1.85)	(–2.45)	(–2.29)
Ln(ME)	0.000	–0.252*	0.122***	0.144***
	(0.05)	(–1.90)	(4.24)	(5.75)
Ln(BM)	0.007**	0.008	0.019**	0.017**
	(2.10)	(0.16)	(2.28)	(2.00)
$Ln(1+Ret_{12,1})$	–0.005**	–0.004	0.026**	0.026***
	(–2.00)	(–0.10)	(2.46)	(3.18)
Young	0.003	0.376***	–0.061**	–0.086***
	(0.46)	(3.11)	(–2.52)	(–3.66)
Ln(#of Analysts)	–0.006	–0.125	0.010	0.033**
	(–1.18)	(–1.64)	(0.72)	(2.51)
Intercept	–0.011	0.931	–1.061	0.690***
	(–0.17)	(1.03)	(–0.66)	(3.66)
Exchange Dummy	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓
Industry–Year F.E.	✓	✓	✓	✓
Observations	125,140	117,160	71,568	76,339
Adjusted R^2	0.073	0.097	0.025	0.084

Table IX. The Destabilizing Effects of Institutional Presence

This table reports standardized 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. 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 IX. The Destabilizing Effects of Institutional Presence (Continued)

	1	2	3	4
	Herding	Flow−Driven Trading Pressure		
Dependent Variable:	(Sias, 2004)	|Pressure|	Probability of (Fire–Sale)	Probability of (Fire–Purchase)
IP_{ST}	–0.000	0.004	0.001	0.000
	(–0.11)	(1.03)	(0.20)	(1.16)
$Assets_{ST}$	–0.000	–0.009*	–0.002	–0.000
	(–0.51)	(–1.65)	(–0.41)	(–0.70)
$Income_{ST}$	0.005	–0.018	–0.059	–0.001
	(1.07)	(–0.50)	(–1.40)	(–1.31)
Urban	–0.000	0.004	0.002	0.000
	(–0.49)	(1.09)	(0.54)	(1.52)
Local IO%	–0.000	–0.004***	0.000	–0.000
	(–0.36)	(–2.94)	(0.12)	(–0.19)
Non–local IO%	–0.001***	0.025***	0.033***	0.001***
	(–4.61)	(12.15)	(15.51)	(19.12)
Turnover	–0.000	0.016***	0.009***	0.000***
	(–0.91)	(6.86)	(3.37)	(8.62)
$ILLIQ_{TO}$	–0.000	–0.015***	–0.017***	–0.000***
	(–1.18)	(–6.33)	(–6.04)	(–4.99)
Return Volatility	0.000**	0.010***	0.005*	0.000***
	(2.30)	(4.05)	(1.88)	(3.95)
Ln(ME)	0.001***	–0.026***	–0.035***	–0.001***
	(2.60)	(–3.97)	(–5.19)	(–6.58)
Ln(BM)	0.000***	–0.012***	–0.001	–0.000***
	(3.68)	(–5.87)	(–0.64)	(–3.67)
$Ln(1+Ret_{12,1})$	0.000	–0.028***	0.019***	–0.000***
	(0.63)	(–13.76)	(8.44)	(–3.73)
Young	0.000	0.018***	0.016***	0.001***
	(0.75)	(4.03)	(3.29)	(6.01)
Ln(# Analyst)	0.000	0.016***	–0.002	0.000***
	(0.54)	(6.51)	(–0.76)	(4.18)
Intercept	0.011***	0.048	0.039	0.002*
	(3.42)	(1.53)	(1.14)	(1.94)
Exchange Dummy	✓	✓	✓	✓
Size Deciles	✓	✓	✓	✓
State Fixed Effect	✓	✓	✓	✓
Industry–Year F.E.	✓	✓	✓	✓
Observations	98,444	75,401	75,401	78,501
Adjusted R^2	0.022	0.047	0.041	0.069