Monitoring and Learning by Institutional Investors: Theory and Evidence

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Abstract

This paper revisits information acquisition theory from a corporate governance perspective, provides a novel theoretical motivation for external governance, and enriches the set of feasible empirical tests regarding information acquisition. Institutional investors can enhance firm fundamental values through costly monitoring, while their portfolio decisions are determined by endogenous information acquisition. I provide a simplified model, joining theoretical frameworks of external governance and information acquisition, to understand the intrinsic link between monitoring and learning activities of institutional investors. Intuitively, investors would inevitably acquire some firm-specific information during the process of monitoring a firm. One implication of this “non-separability” assumption, compared to the baseline case, is that investors optimally re-allocate monitoring effort from firms with low value of information acquisition to those with high value of information acquisition. This novel motivation for investors to exert costly monitoring effort, labelled as the “monitoring-for-learning” mechanism, is the major contribution of this paper that can lend theoretical support to recent empirical findings of monitoring and learning activities. Regarding information acquisition, the model predicts that institutional investors tend to acquire more precise information about the firms they can more effectively engage with and about those they initially hold larger stakes in. Consistent with recent research about distracted investor attention, the model suggests that monitoring attention to certain firms be squeezed out when attention for information acquisition is substantially attracted to other firms. Suggestive empirical evidence is provided to support these predictions.

JEL classification: G23, G30.

Keywords: Institutional Investors, Corporate Governance, Information Acquisition.

Jingyu Zhang (Email: j.zhang14@imperial.ac.uk) is a PhD student in Finance at Imperial College London. I am grateful to my supervisors Franklin Allen, Marcin Kacperczyk (Chair) and Alexander Michaelides for their academic guidance and support. I highly acknowledge Brian Bushee for generously sharing his work on classifications of institutional investors’ legal types and investment styles. Besides, I am sincerely thankful for the helpful and educational comments by Andrea Buraschi, Gilles Chemla, Francesca Cornelli, Claudia Custodio, Pasquale Della Corte, Rustam Ibragimov, Haresh Sapra, Laura Starks, Savitar Sundaresan, Katrin Tinn, Stijn Van Nieuwerburgh, Laura Veldkamp, and (seminar) participants at the Doctoral Student Consortium of FMA Annual Meeting 2017, Erasmus School of Economics, Imperial College Business School, and Royal Economic Society PhD Meeting 2017. Supplementary Appendix is available upon request.
1. Introduction

As institutional ownership in US public equity markets has steadily increased over the past few decades, how institutional investors engage with corporate management and how they independently acquire non-public information about portfolio firms have attracted substantial interests from academics and practitioners. To fulfill fiduciary duty to their beneficiary owners, institutional investors exert external governance on portfolio firms and leave less room for corporate executives to pursue private benefits, which eventually enhances firm fundamental values. Besides, they have been documented to collect non-public information to make better portfolio choices or trading decisions. Since both activities occupy valuable resources of time and personnel, monitoring and information acquisition are considered in various contexts as interchangeable terms to investor attention. However, the direct effect of monitoring a firm is to raise its expected payoff while acquiring more precise information results in a lower posterior uncertainty about that firm. That is, in principal, monitoring and information acquisition are conceptually two different things and influence different aspects of a standard portfolio choice problem.

When dealing with monitoring and information acquisition together, one complication is around their intrinsic link: Investors would inevitably acquire some firm-specific information during the process of monitoring a firm. This piece of firm-specific information, in nature, can be very different from the private information collected by investors through independent research but can be informatively useful for their trading decisions. The more monitoring effort exerted on a firm, the more precise this piece of information acquired during the process of monitoring that firm. Thus, in this paper, I provide a theoretical framework to formally examine how investors optimally allocate valuable resources in monitoring and information acquisition activities, respectively. Model predictions regarding information acquisition are

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1“Monitoring” in this paper generally refers to improving corporate governance and performance through engaging with corporate executives and the board of directors and responsibly voting at annual general meetings. Such engagement and responsible ownership demand transparency and feasibility in remuneration policies (and other important corporate policies), independence and diversity of the board, and accountability of board members and executives (Hermes (2012, 2013, 2017)). Theoretically, two forms of external governance have been studied: voice (Shleifer and Vishny (1986), Huddart(1993), Admati, Pfleiderer and Zechner (1994)) and exit (Admati and Pfeiderer (2009), Edmans (2009), and Edmans and Manso (2011)).

2For example, in the framework of “limited attention” or “rational inattention”, Kacperczyk, Van Nieuwerburgh and Veldkamp (2014) empirically document investor attention re-allocation among mutual fund managers in terms of information acquisition while Kempf, Manconi and Spalt (2017) provide firm-level evidence to argue for the impact of investor attention re-allocation on corporate actions in terms of monitoring.

3For example, institutional investors may, via board meetings or board members, acquire some “soft information” about CEO ability and internal operating conditions of a firm. Accessing such soft information requires monitoring effort. Stock analysts at mutual funds' research departments normally have little access to such information.
supported by suggestive empirical evidence using US institutional investors’ holdings data.

The major contribution of my paper is to revisit the information acquisition literature from a corporate governance perspective and provide a novel motivation for investors to exert costly monitoring effort. In particular, my paper theoretically distinguishes between monitoring and information acquisition, formally models the intrinsic link between these two activities, and further explores their within-firm and cross-firm interactions. The intrinsic link between monitoring and information acquisition is coined as the “non-separability” assumption, and this non-separability feature has meaningful implications. In particular, when compared to the baseline case, within-firm complementarity suggests that investors optimally re-allocate monitoring effort from firms with low value of information acquisition to those with high value of information acquisition. That is, besides the motivation purely for enhancing fundamental values, investors optimally choose monitoring effort by rationally anticipating the beneficial effects of monitoring on information acquisition and ultimately on portfolio choices. This “monitoring-for-learning” mechanism constitutes a new layer of motivation to exert monitoring effort that can lend theoretical support to recent empirical findings of monitoring and learning activities.

Another contribution of my paper is to enrich the set of feasible empirical tests for information acquisition theory. Veldkamp (2011, pp.146-147) highlights difficulty of both observability and empirical testability as the potential problems with theoretical models of information acquisition, because empirical tests require observables are regressed on observables. My paper explores the cross-sectional patterns of monitoring and information acquisition, and forms predictions regarding information acquisition in terms of determinants of exerting external governance. In particular, my model predicts that institutional investors tend to acquire more precise information about the firms they can more effectively engage with and about those they initially hold larger stakes in. In addition, my model also confirms the attention-reallocation story in Kempf, Manconi and Spalt (2017) via the monitoring-for-learning mechanism.

4The model in this paper reserves the flexibility that investors may optimally choose to devote all valuable resources to information acquisition and not to engage with corporate executives at all. My model still reserves the flexibility that some investors can exert zero monitoring effort while actively acquiring private information for portfolio choice.

5Several established ways to measure information flows are summarized in Chapter Ten of Veldkamp’s book.

6Li and Schwartz-Ziv (2018) empirically analyse how mutual fund managers’ voting and trading activities are related using data of fund-level votes and daily trades.
One empirical obstacle impeding previous literature from jointly considering both monitoring and information acquisition is the difficulty of directly observing or quantitatively measuring these two activities. My paper circumvents this obstacle by introducing determinants of exerting external governance into information acquisition models and delivering predictions regarding the relation between information acquisition and these determinants. My model enables researchers to provide at least suggestive empirical evidence to support the argument that monitoring and information acquisition decisions are linked, in particular, via exploiting the observable heterogeneity in these determinants. Following Kacperczyk and Seru (2015), I construct a measure of reliance on private information (RPI) that serves as a proxy for how much private information an institutional investor has acquired when adjusting holdings in portfolio firms on a quarterly basis. Besides, my paper exploits the heterogeneity of firm-level equity-based awards (i.e. stock/option grants) and argues that it is more effective for institutional investors to engage with firms recently granting such awards.

The empirical results show that institutional investors, when adjusting their holdings in portfolio firms, rely more on private information among firms with managerial equity-based awards (than without) and among firms they initially hold larger stakes in. Specifically, institutional investors’ RPI among firms with managerial equity-based awards is 1.32 percentage points higher than that among firms without managerial equity-based awards, indicating a 62.69% differential in RPI between firms with and without managerial equity-based awards. Along the second dimension, I adopt two ways of measuring “initial stakes”. The first one follows the model and uses the percentage of a firm an institutional investor initially holds. Empirical evidence suggests that institutional investors’ RPI among firms they hold larger initial stakes in is 0.17 percentage points higher than that among firms they hold smaller initial stakes, indicating a 7.07% differential in RPI between large-initial-stake firms and small-initial-stake ones. Alternatively, following Fich, Harford and Tran (2015), portfolio firms are sorted based on the dollar-value weights they represent in an institutional investor’s portfolio. The associated empirical evidence suggests that institutional investors’ RPI among firms they hold larger initial stakes in is 0.46 percentage points higher than that among firms they hold smaller initial stakes, indicating a 20.76% differential in RPI between large-initial-stake firms and small-initial-stake ones.

As with distracted investor attention, I follow KMS (2017) and construct the “institution-specific” component of their distraction measure and compare the RPI of portfolio firms facing distracted shareholders with that of portfolio firms experiencing “attention-grabbing”
events. Empirical evidence suggests that institutional investors, when adjusting their portfolios, tend to rely less on private information among the firms facing distracted shareholders by 0.14% (indicating a 6% RPI differential). This empirical evidence, together with the disciplining effects of shareholder monitoring pressure on corporate activities argued by KMS (2017), requires a framework where monitoring has beneficial effects on information acquisition and where exogenous changes in prior uncertainty lead to monitoring effort being re-allocated to those attention-grabbing industries.

This paper broadly relates to the literature on endogenous information acquisition. Grossman and Stiglitz (1980) build a competitive equilibrium framework where a continuum of investors choose to either pay a fixed information cost and get informed or not pay and stay uninformed. Verrecchia (1982) further allows investors to endogenously choose the precision level of private information and explores the relation between the informativeness of the pricing system and the cost of acquiring information. Recent theoretical work on endogenous information acquisition introduces the framework of “rational inattention”, or the constraint of limited learning capacity, to study optimal attention allocation across multiple risky assets or risk factors. Van Nieuwerburgh and Veldkamp (2009) address how endogenously acquired information enlarges informational asymmetry between home and foreign investors. Van Nieuwerburgh and Veldkamp (2010) focus on how investors with limited information processing capacity optimally allocate their attention across multiple risky assets. Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) provide a theoretical framework of attention allocation for mutual fund managers and present empirical evidence using business-cycle variations in aggregate uncertainty and risk aversion. My paper follows this line of research, focuses on how investors optimally allocate valuable resources in both monitoring and information among the firms that deserve such effort, and delivers predictions relating information acquisition to factors of exerting external governance.

My paper also relates to the empirical literature of costly monitoring activities conducted by US institutional investors and the literature documenting that institutional investors possess informational advantages and make better informed portfolio decisions. The beneficial outcomes of institutional monitoring are well documented in Brickley, Lease and Smith (1988), Agrawal and Mandelker (1990), Del Guercio and Hawkins (1999), Borokhovich et al.

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7Their model implicitly assumes a common single signal available to all at a homogeneous cost.
8His framework assumes informed traders independently observe “diverse signals”, each signal containing the true value plus a cross-sectionally uncorrelated error term.
9Feasibly, institutional investors either have their own research departments writing analyst reports or use their own networks to gather non-public information. An upper-bounded capacity of their research departments or networks results in the need for optimally allocating such resources.
The Investor Responsibility Research Center Institute (2011) widely surveyed US institutional investors and firms, suggesting that time and personnel considerations rank as the top two factors impeding effective engagement between institutional investors and portfolio firms. Institutional investors are also argued to possess informational advantages around dividend announcements (Amihud and Li (2006)), in seasonal equity offerings (Chemmanur, He and Hu (2009)), or in events of stock splits (Chemmanur, Hu and Huang (2015)), or hold both corporate debt and equity of the same firms as “dual holders” (Jiang, Li and Shao (2010), and Ivashina and Sun (2011)). The theoretical role of information acquisition as conducting independent research arises from the information acquisition literature that studies the learning role of institutional investors. These two streams of literature theoretically motivates a joint constraint of valuable resources for monitoring and information acquisition as set up in my paper, making it possible to further explore their within-firm and cross-firm interactions. Accordingly, my paper also presents empirical evidence that institutional investors optimally choose to be differentially informed about subgroups of portfolio firms that are sorted based on firm-investor determinants of exerting corporate governance.

Most importantly, my paper is closely related to Kempf, Manconi and Spalt (KMS onwards; 2017) where they propose a new empirical approach to identify the re-allocation pattern of monitoring attention for institutional investors. KMS argue that monitoring attention is re-allocated to firms whose industries are experiencing “attention-grabbing” events such that the other firms facing reduced monitoring pressure tend to announce value-destroying acquisitions, cut dividends, and so on. Additionally, they find that CEOs of firms facing reduced monitoring pressure are less likely to be fired for delivering bad performance. Since the major contributions of KMS are on the empirical side, their theoretical framework for empirical identification does not allow for a distinction between investor attention for monitoring and investor attention for information acquisition.

However, my paper theoretically distinguishes between attention for monitoring and attention for information acquisition, and reserves the flexibility to explore the within-firm and

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10Becht, Franks, Mayer and Rossi (2009) provide evidence of monitoring activities conducted by UK institutional investors.

11This paper does not touch the relation between stock market liquidity and the (opportunity) cost of monitoring portfolio firms. Maug (1998), Bolton and von Thadden (1998), Almazan, Hartzell and Starks (2005), and Back et al. (2016) consider stock market liquidity as a factor that impacts external governance.

12“Learning” in this paper refers to “active learning”, which is different from “passive learning”. Veldkamp (2011, p.4) provides clear discussions to distinguish between active and passive learning. “Learning” and “information acquisition” are exchangeable terms in this paper.
cross-firm interactions between monitoring and information acquisition. Strictly speaking, the attention-grabbing events constructed in KMS are supposed to directly grab investors’ attention for information acquisition rather than attention for monitoring. In particular, when motivating their empirical measure of investor distraction, it is still unclear why investors’ monitoring attention on certain firms will be distracted when other firms experiencing industry-wide extraordinarily volatile returns are highly worth more information acquisition. Their rationale is that firms whose industries are experiencing extraordinarily volatile returns (high $\sigma_i$) attract more attention from investors, leaving the other firms facing reduced monitoring pressure.

Clearly, KMS’s empirical identification strategy requires a framework where attention for monitoring is squeezed among certain firms when attention for information acquisition is attracted to other firms in response to shocks to other firms’ prior uncertainty. My model can deliver such features in terms of within-firm complementarity and cross-firm substitutability between monitoring and information acquisition. In my model, specifically, investors optimally make more effort to monitoring firms with higher prior uncertainty; in response to large (exogenous) increases in other firms’ prior uncertainty, investors optimally shift monitoring attention away towards other firms. Therefore, my paper focuses on the theoretical distinction between monitoring and information acquisition and their intrinsic connection, provides a supportive foundation for KMS’s empirical identification strategy, and delivers new predictions regarding information acquisition for empirical tests.

The rest of this paper proceeds as follows. Section 2 sets up the theoretical framework, develops propositions and the associated predictions, and provides model robustness checks for lemmas and propositions. Section 3 briefly describes data sources and provides (suggestive) empirical evidence to support model predictions. Section 4 conducts robustness checks with different specifications and alternatively defined variables, and Section 5 makes concluding remarks.

13Proposition 1 in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) states that attention for information acquisition is increasing in prior uncertainty; in other words, investors optimally allocate more attention for information acquisition to firms with more volatile returns. This proposition is cited in KMS as well.
2. The Model

2.1. Model Setup

There are $N$ firms. The value of firm $i$ is $\tilde{V}_i$, defined as the sum of fundamental value $\bar{V}_i$ and a firm-specific random component $\tilde{z}_i$, that is,

$$\tilde{V}_i = \bar{V}_i + \tilde{z}_i \tag{1}$$

where $\tilde{z}_i$ has zero mean with variance $\sigma_i$ for $i = 1, ..., N$. For simplicity and tractability, the firm-specific random component is assumed to be cross-sectionally independent. Assume there is a continuum of CARA investors with mass one and absolute risk aversion $\rho$. Investor $j \in [0, 1]$ is endowed with a fraction $\beta_{ij} \geq 0$ of firm $i$, and $\int_0^1 \beta_{ij} \, dj = 1$. Each investor $j$ faces a three-stage problem. In stage 1, investor $j$ decides how much monitoring effort to exert onto each firm. Let $b_{ij} \geq 0$ denote the monitoring effort allocated to firm $i$ by investor $j$. Initial wealth after monitoring is $W_0 = \sum_{i=1}^{N} (\beta_{ij} \bar{V}_i - b_{ij})$. In stage 2, based on the choice of monitoring effort $b_{ij}$, investor $j$ chooses how much (or how precise) private information to acquire about firm $i$ and reduces her uncertainty about $\tilde{V}_i$. In stage 3, investor $j$ makes an optimal portfolio choice given her monitoring effort and information acquisition decision. Specifically, in line with the literature of institutional ownership and corporate governance suggesting that institutional monitoring pressure enhances firm performance, the fundamental value of firm $i$ can be constructed as

$$\bar{V}_i = \int_0^1 \phi_{ij} \ln(1 + b_{ij}) \, dj \tag{2}$$

where $\phi_{ij}$ measures how effectively investors can exert external governance to improve firm fundamental values. Equation (2) can be considered as a variant of production function with monitoring effort being the input and firm fundamental value the output.

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$^{14}$Eigen-value decomposition may be applied to deal with cross-sectionally correlated error terms. Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) provide further detail regarding applying eigen-value decomposition to cross-sectional correlation.

$^{15}$One reason why CRRA preference is commonly used in rational expectations models is that there is no wealth effect and thus concerns about heterogeneous initial wealth are largely mitigated. Liu, Peleg, and Subrahmanyan (2010) build up a continuous-time framework with a CRRA agent who jointly solves the problem of portfolio choice and information acquisition.

$^{16}$Edmans and Manso (2011), in their base model, use a similar natural log functional form to express how monitoring effort exerted by investors can help enhance firm fundamental value, and they interpret the coefficient multiplied with the natural log of 1 plus effort as the “productivity” of effort. $\phi_{ij}$ here in (2) allows the productivity of monitoring effort to be cross-sectionally heterogeneous.
The role of information acquisition is to reduce the prior uncertainty of firm $i$, $\sigma_i$, down to the posterior uncertainty of firm $i$. All investors are assumed to observe $\bar{V}_i$ before stage 2 starts. Investor $j$ has an information processing capacity $K_j$ to be allocated to $N$ firms. The more of this information processing capacity allocated to firm $i$, the more precise the acquired information about $\tilde{z}_i$ in stage 2. Without the stage of monitoring, the attention allocation problem would be the same as that in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016): Investor $j$ optimally allocate her capacity to each firm, and $\sum_{i=1}^{N} K_{ij} \leq K_j$ where $K_{ij} \geq 0$ is the capacity of investor $j$ allocated to firm $i$. In their paper, allocating $K_{ij}$ to firm $i$ by investor $j$ is modelled as investor $j$ independently receiving a private signal of precision $K_{ij}$ about $\tilde{V}_i$. Following their work, this paper uses $K'_{ij}$ to denote the attention purposely allocated to firm $i$ by investor $j$ in stage 2, and $K_{ij} = \kappa(b_{ij}) + K'_{ij}$ denotes the sum of information precisions in stage 1 and in stage 2, respectively. Unlike Kyle (1985) modelling perfect information, rational expectations models normally assume the private signal is still a noisy signal taking the form:

$$\tilde{\theta}_{ij} = \tilde{V}_i + \epsilon_{ij}$$

where $\epsilon_{ij} \sim N\left(0, \frac{1}{K'_{ij}}\right)$, or put differently, $\tilde{\theta}_{ij}|\tilde{V}_i \sim N\left(\tilde{V}_i, \frac{1}{K'_{ij}}\right)$. 17 That is, $K'_{ij}$ measures how precise investor $j$’s purposely acquired private information about firm $i$.

The intrinsic link between monitoring and information acquisition fundamentally originates from the non-separability of monitoring and information acquisition, because monitoring activities cannot really take place with zero information acquisition. 18 To model this link, investor $j$ is assumed to inevitably acquire a piece of private information when monitoring the firm in stage 1. This piece of private information is a private signal about $\tilde{V}_i$ and takes the form of $\tilde{\nu}_{ij} = \tilde{V}_i + \epsilon_{ij}'$ with $\tilde{\nu}_{ij}|\tilde{V}_i \sim N\left(\tilde{V}_i, \frac{1}{\kappa(b_{ij})}\right)$, where $\kappa'(b_{ij}) > 0$ and $\kappa''(b_{ij}) < 0$. Here $\kappa(b_{ij})$ measures the precision of firm-specific private information acquired during the process of investor $j$ monitoring firm $i$. This inevitably acquired information due to exerting monitoring effort is, in nature, independent of the purposely acquired information $\tilde{\theta}_{ij}$. For simplicity, a functional form has been assumed: $\kappa(b_{ij}) = \phi_b ln (1 + b_{ij})$, where $\phi_b > 0$ transforms (the log of) monitoring effort into acquired firm-specific information. One thing to be clear is that there is no “free-lunch”: The inevitably acquired information during the process of monitoring also occupies investor $j$’s information processing capacity. Thus, in

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17 $\epsilon_{ij}$’s are assumed to be cross-sectionally independent.
18 This setup can be alternatively interpreted as monitoring and information acquisition taking place at the same time in stage 1, while investors are allowed to (but do not have to) conduct independent research in stage 2. Conducting independent research purely serves the purpose of making portfolio choices.
this model, the constraint of information processing capacity takes the following form:

$$\sum_{i=1}^{N} K_{ij} \leq K_j$$  \hspace{1cm} (4)

where $K_{ij} = \kappa(b_{ij}) + K'_{ij}$. The “no-forgetting constraint” in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016) requires $K_{ij} \geq 0$. In the same spirit of their no-forgetting constraint but in the presence of monitoring effort, this constraint takes the form:

$$K_{ij} \geq \kappa(b_{ij})$$  \hspace{1cm} (5)

for $i = 1, \ldots, N$. Equivalently, (5) requires nonnegativity of $K'_{ij}$; that is, the precision of information acquired through conducting independent research is non-negative.

2.2. **Backward Induction**

Investor $j$ faces the aforementioned three-stage problem that can be solved using backward induction. In stage 3, investor $j$ makes her portfolio choice by choosing the quantities of firm shares to hold, denoted by the vector $q_j = (q_{1j}, \ldots, q_{Nj})'$. The vector of firm payoffs is $\tilde{f} = (\tilde{V}_1, \ldots, \tilde{V}_N)'$ and the vector of share prices is $\tilde{p} = (p_1, \ldots, p_N)'$. Let $W_j$ denote investor $j$’s terminal wealth, which takes the form:

$$W_j = rW_0 + q_j' (\tilde{f} - \tilde{p}r)$$  \hspace{1cm} (6)

where $r$ is the gross riskfree rate. In this stage, investor $j$ choose $q_j$ to maximize stage-3 expected utility $U_{3j}$:

$$U_{3j} = E_j(W_j) - \frac{\rho}{2} Var_j(W_j)$$  \hspace{1cm} (7)

where $E_j(W_j)$ and $Var_j(W_j)$ are the conditional expectation and variance conditioning on investor $j$’s information sources. Maximizing (7) subject to (6) delivers the demand for firm $i$ from investor $j$:

$$q_{ij} = \frac{E_j(\tilde{V}_i) - rp_i}{\rho Var_j(\tilde{V}_i)}$$  \hspace{1cm} (8)

Equilibrium prices are determined by equating supply and demand of firm shares. In this model, the number of shares outstanding of each firm is set to be one such that quantities
traded or held are actually the fractions of firms that are traded or held. As assumed
in standard noisy rational expectations models, noise traders (or liquidity traders) submit
random orders, which is denoted by the vector \( x = (x_1, \ldots, x_N)' \), where \( x_i \) has zero mean
with variance \( \sigma_x \) and \( x_i \)'s are cross-sectionally uncorrelated. Therefore, the market clearing
condition takes the form:

\[
\int_0^1 q_j dj = 1 + x
\] (9)

To simplify notations, define \( \alpha_i = \frac{1}{\sigma_i} \) for \( i = 1, \ldots, N \) and \( \gamma = \frac{1}{\sigma_x} \).

**Lemma 1.** The equilibrium price of firm \( i = 1, \ldots, n \) takes the form:

\[
p_i^* = \frac{1}{r} \left( \frac{\alpha_i \bar{V}_i + \left( \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma \right) \tilde{V}_i - \left( \frac{\bar{K}_i}{\rho} \gamma + \rho \right) (1 + x_i)}{\alpha_i + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2} \gamma} \right)
\] (10)

where \( \bar{K}_i = \int_0^1 K_{ij} dj \) is the average attention allocated to firm \( i \) across all investors \( j \in [0, 1] \).

A detailed derivation of Lemma 1 is in Appendix A. Consistent with Admati (1985), \( p_i^* \) is
conjectured and verified to be a linear function of \( \bar{V}_i, \tilde{V}_i, \) and supply shock \( x_i \).

Stage 2 and stage 3 are essentially the same problems as already solved in Kacperczyk,
Van Nieuwerburgh, and Veldkamp (2016). Given the optimal portfolio choice in stage 3,
investor \( j \) faces the following optimization problem when choosing signal precision \( K_{ij} \):

\[
\max_{K_{ij}} \sum_{i=1}^{N} \lambda_i K_{ij} + \text{constant}
\] (11)

subject to the constraints (4) and (5), where

\[
\lambda_i = \bar{\sigma}_i \left[ 1 + \left( \rho^2 \sigma_x + \bar{K}_i \right) \bar{\sigma}_i \right] + \rho^2 \bar{\sigma}_i^2
\] (12)

and \( \bar{\sigma}_i^{-1} = \sigma_i^{-1} + \bar{K}_i + \frac{\bar{K}_i^2}{\rho^2 \sigma_x} \) is the average posterior precision about firm \( i \). One big contribution
of Kacperczyk, Van Nieuwerburgh and Veldkamp (2016) is to transform \( U_{3j} (q_j (\tilde{p}^*)) \) into a
linear function of \( K_{ij} \)'s. The coefficient \( \lambda_i \) measures the relative importance of acquiring
information about firm \( i \). Let \( K_{ij}^* \) denote the optimal choice of \( K_{ij} \) given her monitoring
effort allocation \( b_{1j}, \ldots, b_{Nj} \). Detailed solutions to \( K_{ij}^* \) and derivation of the following lemma

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19This paper focuses on the linear-price equilibrium of rational expectations models.
are provided in Appendix B.

**Lemma 2.** For each investor $j \in [0, 1]$, $\frac{\partial K^*_ij}{\partial b_{ij}} \geq 0$, and $\frac{\partial K^*_ij}{\partial b_{kj}} \leq 0$ when $i \neq k$.

This lemma says that there is complementarity between monitoring and information acquisition decisions within the same firm and that there is substitutability across firms. The within-firm complementarity originates from the non-separability assumption that investors inevitably acquire some firm-specific information during the process of monitoring. Given an exogenous increase in monitoring effort on firm $i$ and everything else being equal, the total amount of private information about firm $i$ acquired by investor $j$ tends to be higher. The feature that both $K'_{ij}$ and $\kappa(b_{kj})$ take up investor $j$’s valuable resources gives rise to the cross-firm substitutability of information acquisition about firm $i$ and monitoring on firm $k$, $i \neq k$. Given an exogenous increase in monitoring effort on firm $k$ and everything else being equal, more resources are captured by $\kappa(b_{kj})$ out of the attention budget constraint (4), crowding out information acquisition about other firms. Lemma 2 also opens the opportunity to provide empirical evidence, at least suggestive, to support my model structure regarding monitoring and information acquisition.

After figuring out the within-firm complementarity and cross-firm substitutability between monitoring and information acquisition, we then need to solve for the cross-sectional allocation of monitoring effort. Given the optimal information acquisition decisions $K^*_ij(b_{ij})$ for $i = 1, ..., N$, investor $j$ faces the problem of optimally choosing $b_{ij}$ to maximize:

$$U_{1j} = r \left[ \sum_{i=1}^{N} (\beta_{ij} \tilde{V}_i - b_{ij}) \right] + \sum_{i=1}^{N} \lambda_i K^*_ij(b_{ij}) + \text{constant}$$

(13)

**Proposition 1.** The optimal monitoring effort on firm $i$ exerted by investor $j$ is

$$b^*_{ij} = \begin{cases} 
\max \left\{ 0, \beta_{ij} \phi_{ij} + \frac{(\lambda_i - \max_l \lambda_l) \phi_b}{r} - 1 \right\} & \lambda_i \neq \max_l \lambda_l \\
\max \left\{ 0, \beta_{ij} \phi_{ij} + \frac{(n-1) \lambda_i \phi_b}{nr} - 1 \right\} & \lambda_i = \max_l \lambda_l, n \geq 2
\end{cases}$$

where $n$ is the number of multiple firms with $\lambda_i = \max_l \lambda_l$, and $n = 1$ if there is a unique $\lambda_i = \max_l \lambda_l$.

A few interesting and important properties can be derived from this proposition. First, the optimal monitoring effort of investor $j$ on firm $i$, $b^*_{ij}$, is weakly increasing in her initial shares in this firm, $\beta_{ij}$. Everything else being equal, investor $j$ allocates more monitoring
effort to firm $i$ if she initially holds a larger fraction in this firm, because she will obtain more of the enhanced firm valuation due to her monitoring effort. This is consistent with Shleifer and Vishny (1986) and many others illustrating the value of external shareholder monitoring. The second property of optimal monitoring effort is that $b_{ij}^*$ is weakly increasing in $\phi_{ij}$, the engagement effectiveness measure. Intuitively, the marginal value of monitoring effort is higher if investors monitor the firms they can more effectively engage with. Since monitoring effort is assumed to enhance firm valuations and is costly, investors will select firms within which their monitoring effort can be effectively transformed into enhanced valuations, everything else being equal. This property of optimal monitoring effort is insightful and practical for empirical tests when forming the subsample of firms which institutional investors are more likely to exert monitoring effort on or allocate more monitoring attention to.

Finally, $b_{ij}^*$ is weakly increasing in $\sigma_i$ via $\lambda_i$ since $\frac{\partial \lambda_i}{\partial \sigma_i} > 0$ and $\frac{\partial b_{ij}^*}{\partial \lambda_i} \geq 0$. This property says that investors optimally allocate more monitoring effort to firms that have higher prior uncertainty. Put differently, since high-$\sigma_i$ firms are more valuable to learn about (i.e. high-$\lambda_i$), firms with high values of information acquisition deserve additional monitoring effort from investors. Although the first two properties of optimal monitoring effort are consistent with previous research, the last property provides a novel source of motivation for investors to exert costly monitoring effort beyond pure purposes of raising expected payoffs. Intuitively, given that investors would inevitably acquire some firm-specific information during the process of monitoring a firm and that the precision of this piece of firm-specific information, $\kappa(b_{ij})$, is monotonically increasing in monitoring effort $b_{ij}$, investors rationally take into account the beneficial effects of monitoring effort on total acquired information when making their monitoring decisions in stage 1. Derivations of Proposition 1 and the associated properties of $b_{ij}^*$ can be found in Appendix B.

Proposition 1 solves the optimal monitoring effort under the non-separability assumption that models the intrinsic link between monitoring and information acquisition. However, were there no such link, investors would exert monitoring effort purely for enhancing firm fundamental values, and the associated allocation of monitoring attention could be pinned down by directly equating marginal benefits and costs of monitoring. We may take this monitoring attention allocation pattern ($b_{ij}^{**}$ in the appendix) as the baseline allocation. Clearly, in the baseline case, there are no information-acquisition considerations when investors optimally choose monitoring effort.
Proposition 2. Let $b_{ij}^{**}$ denote the baseline-case allocation of optimal monitoring effort. Then, $b_{ij}^{*} \leq b_{ij}^{**}$ for $\lambda_i \neq \max_l \lambda_l$ and $b_{ij}^{*} \geq b_{ij}^{**}$ for $\lambda_i = \max_l \lambda_l$.

Proposition 2 provides cross-sectional comparisons for two different patterns of monitoring attention allocation. Cross-sectionally, the optimal monitoring effort for firms with high (low) importance of acquiring information is greater (smaller) than the baseline case assuming there is no link between monitoring and information acquisition at all. Considering the baseline-case allocation of monitoring effort as a benchmark, investors are actually re-allocating their monitoring effort from firms with low value of information acquisition to those with high value of information acquisition. Comparing these two different patterns of monitoring attention allocation formally formulates the “monitoring-for-learning” mechanism as follows. Taking into account the beneficial effects of monitoring effort on total acquired information, investors, compared to the baseline case, optimally make additional monitoring effort onto firms with high value of information acquisition and reduce their monitoring effort onto firms with low value of information acquisition. Therefore, apart from the determinants of exerting external governance as argued in previous research, this proposition theoretically emphasizes a novel motivation for investors to undertake costly monitoring activities: monitoring for learning. Derivations of Proposition 2 can be found in Appendix C.

Proposition 3. Investor $j$’s private information precision of firm $i$ ($K_{ij}$) is weakly increasing in the engagement effectiveness measure $\phi_{ij}$.

Proposition 4. Investor $j$’s private information precision of firm $i$ ($K_{ij}$) is weakly increasing in her initial holding $\beta_{ij}$.

Propositions 3 and 4 are extensions of the within-firm complementarity between monitoring and information acquisition. In other words, information acquisition decisions are expressed as increasing functions of factors that directly determine monitoring decisions. Proposition 3 suggests that investors acquire more precise information about some of their portfolio firms and less about other ones based on how effective it is to engage with corporate executives. Proposition 4 similarly suggests that investors acquire differentially more private information about the portfolio firms in which they have larger ex-ante holdings. Propositions 3 and 4 suggest empirical tests on the linkages between information acquisition and determinants of exerting external governance. These propositions enrich the set of feasible empirical tests of information acquisition theory, indicating that determinants of how much monitoring effort to exert matter for how much private information to acquire about certain
firms within an investor’s portfolio. Derivations of Propositions 3 and 4 can be found in Appendix D.

Proposition 5a. In response to a marginal exogenous increase in firm $k$’s ex-ante uncertainty, monitoring attention to firm $i$ ($i \neq k$) by investor $j$ is weakly increasing if $\lambda_i = \max_l \lambda_l$, or weakly decreasing if $\lambda_i \neq \max_l \lambda_l$; investor $j$’s private information precision of firm $i$ is weakly decreasing in the prior uncertainty of firm $k$, $\sigma_k$.

Proposition 5b. When the exogenous increase in $\sigma_k$ is large enough such that $\lambda_k$ becomes the unique $\max_l \lambda_l$ ex post, then $b_{ij}$ weakly decreases for all $i \neq k$, and $K_{ij}$ weakly decreases for all $i \neq k$ as well.

Propositions 5a and 5b show that monitoring and information acquisition activities do not always go hand in hand. Appendix C shows the detailed derivations of these two versions of Proposition 5. Depending on the situation in force, $K_{ij}$ either strictly or weakly decreases in response to a marginal increase in $\sigma_k$ ($k \neq i$); therefore, $K_{ij}$ is overall weakly decreasing in $\sigma_k$. Depending on the situation in force, $b_{ij}$ either weakly increases or decreases in response to a marginal increase in $\sigma_k$ ($k \neq i$); that is, $b_{ij}$ and $K_{ij}$ may go into opposite directions when the exogenous shock to $\sigma_k$ is marginal.

More importantly, Proposition 5b is closely related to the empirical identification strategy in KMS’s paper. KMS (2017) conjecture that investors’ monitoring attention is re-allocated to firms whose industry is experiencing “attention-grabbing” events. They label experiencing industry-wide extraordinarily volatile returns as attention-grabbing events. Their conjecture is consistent with conventional wisdom that it is more rewarding to learn about the more uncertain outcomes. Everything else being equal, firms with high prior uncertainty have high value of information acquisition. However, strictly speaking, since the direct role of monitoring is to enhance firm fundamental values, there still remains a question mark concerning through what channel monitoring attention should be attracted to firms experiencing industry-wide extraordinarily volatile returns. Again, my paper can lend a theoretical support by formally distinguishing between monitoring and information acquisition while maintaining the intrinsic link between them. In particular, the monitoring-for-learning mechanism underlines the theoretical motivation for investors to make extra monitoring effort onto firms with high value of information acquisition and reduce their monitoring effort onto firms with low value of information acquisition. The monitoring-for-learning story suggests that investors optimally re-allocate their monitoring effort to firms experiencing
industry-wide extraordinarily volatile returns as conjectured in KMS (2017).

2.3. Model Robustness

2.3.1. Informational Advantage from Monitoring

In section 2.1, the intrinsic link between monitoring and information acquisition is modelled in a way that exerting monitoring effort $b_{ij}$ brings investor $j$ with a signal about the firm-specific random component $\tilde{z}_i$ with precision $\kappa (b_{ij})$. The more monitoring effort exerted, the more precise the signal is. In terms of model robustness, other ways of modelling should be considered regarding the intrinsic link between monitoring and information acquisition.

In a realistic sense, during the process of monitoring a portfolio firm, institutional investors may, via board meetings or board members, acquire some “soft information” about CEO ability and internal operating conditions of that firm, which research analysts normally have little access to\(^{20}\). That is, in nature, this piece of private information acquired during the process of monitoring may be different from the piece of private information acquired by stock analysts in the research department of asset management companies. However, having obtained such soft information can help stock analysts more efficiently produce research reports, resulting in acquiring more precise information about that particular firm. Thus, access to soft information during the process of monitoring can be alternatively modelled as an informational advantage to enable more efficient information acquisition.

To model the private information acquired during the process of monitoring as an informational advantage, there are a few changes that need to be clarified. First, $\kappa (b_{ij})$ can no longer be directly used to form portfolio choices. Second, there is no “$K - prime$” anymore; instead, $K_{ij}$ is the signal precision of acquired private information in stage 2. Finally, the information processing capacity and the no-forgetting constraints need to be modified accordingly. Specifically, informational advantage $\kappa (b_{ij})$ can be incorporated into the information processing capacity constraint as follows:

$$\sum_{i=1}^{N} \frac{K_{ij}}{\kappa (b_{ij})} \leq K_j$$

(14)

where the scaling factor $\frac{1}{\kappa (b_{ij})}$ measures the relative cost of information acquisition across firms. This modified constraint allows acquiring private information about different firms to be differentially costly, and the relative costliness depends on investors’ monitoring activities.

\(^{20}\)Haresh Sapra is highly acknowledged for pointing this out.
If investor \( j \) chooses to make more effort to monitor firm \( i \) in stage 1, then she will rationally expect it less costly to acquire information about this firm in stage 2. For simplicity, \( \kappa (b_{ij}) \) can take the functional form: \( \kappa (b_{ij}) = 1 + \phi_b \ln (1 + b_{ij}) \). Appendix S1 provides the solutions to this modified model and propositions still hold.

2.3.2. Entropy Learning Capacity

In section 2.1, a linear constraint of information processing capacity is employed following Kacperczyk, Van Niewerburgh and Veldkamp (2016). In their online appendix, entropy learning capacity is also checked to ensure propositions to hold.\(^{21}\) Essentially, a linear learning capacity constrains the sum of signal precisions while an entropy learning capacity constrains the product of signal precisions (Veldkamp (2011, p.21)). This subsection considers the entropy learning capacity constraint and the associated no-forgetting constraint as follows. Let \( \kappa (b_{ij}) \) still denote the firm-specific private information acquired due to investor \( j \) exerting monitoring effort on firm \( i \) such that the scaling factor \( \frac{1}{\kappa (b_{ij})} \) still measures the relative costliness of information acquisition across firms, and let \( K_{ij} \) denote the signal precision of acquired private information in stage 2. Now, the entropy learning constraint takes the following form:

\[
\prod_{i=1}^{N} \frac{K_{ij}}{\kappa (b_{ij})} \leq K_j
\]  

(15)

and the associated no-forgetting constraint takes the form:

\[
K_{ij} \geq \kappa (b_{ij})
\]  

(16)

For simplicity, \( \kappa (b_{ij}) \) can still take the functional form \( \kappa (b_{ij}) = 1 + \phi_b \ln (1 + b_{ij}) \) as before. Appendix S2 provides the solutions to the 3-stage model where investors face entropy learning capacity constraints. Propositions still hold in this modified framework.

2.4. From Propositions to Predictions

Empirical measures of investors’ information acquisition activities are to be constructed in the next section. The key idea is to measure to what extent investors rely on private information when adjusting their holdings in portfolio firms relative to the previous quarter. In the model, percentage change in investor \( j \)'s holdings in firm \( i \) is \( \frac{q_{ij} - \beta_{ij}}{\beta_{ij}} \), and \( \bar{z}_i \) is the

\(^{21}\)Sims (2003), Mondria (2010), and Maćkowiak and Wiederholt (2009, 2015) provide the applications of entropy-based constraints in economics and finance.
firm-specific information investors want to learn. The $R^2$ value of regressing the empirical counterparts of $q_{ij} - \beta_{ij}$ on $\tilde{z}_i$ can serve as a proxy for how informed investor $j$ is when making portfolio adjustments based on her private information of $\tilde{z}_i$. This $R^2$ value serves as a proxy for $K_{ij}$ throughout the empirical section. Appendix S3 provides the theoretical rationale to use the $R^2$ value of regressing the empirical counterparts of $q_{ij} - \beta_{ij}$ on $\tilde{z}_i$.

Although heterogeneity in initial holding is straightforward to measure using previous-quarter holdings, heterogeneity in engagement effectiveness is far more challenging to measure. Briefly, this paper exploits the heterogeneity of firm-level equity-based awards to firm managers (i.e. stock/option grants) to gather evidence regarding institutional investors’ monitoring effort. Normally, firm managers are willing to listen carefully to suggestions or different voices from external shareholders if their compensations are highly linked to share prices. In their recent paper based on surveys among institutional investors, McCahery, Sautner and Starks (2016) suggests managerial ownership is an important factor when fund managers consider active engagement with firm management via directly voicing their opinions to executives and the board of directors. Thus, it is feasible to argue that engagement with firm management is more effective among firms with stock/option grants to firm managers.

To sum up, $K_{ij}$ is motivated and measured by reliance on private information when making portfolio adjustments, initial holdings is measured using firm-level holdings in the previous quarter, and heterogeneity in engagement effectiveness is exploited through records of managerial equity-based awards in the previous quarter. The associated predictions are as follows.

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22 Hartzell and Starks (2003) empirically reject the hypothesis that the monitoring mechanism of institutional investors is a substitute for managerial equity-based compensation. Their work indicates that monitoring pressure from institutional investors and equity-based compensation tend to be jointly used to mitigate agency costs, suggesting the complementarity between institutional investor monitoring and equity-based incentive compensation.

23 Carleton, Nelson and Weisbach (1998) provide evidence of monitoring activities from one specific institutional investor, while McCahery, Sautner and Starks (2016) explore the usage of different channels to exercise external governance among institutional managers.

24 Managerial equity-based awards, as a form of internal governance, help mitigate the principal-agent problem because awarding firm shares to managers helps align their interests with shareholders. Institutional monitoring, as a form of external governance, can enhance firm values by limiting the scope of excessive executive pays and many forms of extracting private benefits via credible threats (private conversations, proxy fight, dumping shares) to corporate executives. My paper views these two forms of corporate governance as complementary. Edmans and Manso (2011) assumes independence between managerial effort and monitoring effort by blockholders in their core model for simplicity but provide a detailed discussion on the substitutability and complementarity between managerial effort and institution’s monitoring effort in their extended model.
Prediction 1. When adjusting holdings in portfolio firms, investors rely more on private information among firms with managerial equity-based awards.

Prediction 2. When adjusting holdings in portfolio firms, investors rely more on private information among firms with large initial holdings.

Prediction 3. When adjusting holdings in portfolio firms, investors rely less on private information if investor attention is distracted to other firms.

3. Empirical Evidence

3.1. Data Description

Datasets from several sources are employed in the empirical section. First, data of stock holdings by institutional investors at the quarterly frequency is obtained from Thomson Reuters’ institutional holdings (which used to be known as the CDA/Spectrum holdings database). Institutional investors are required to file 13f forms with the Securities and Exchange Commission (SEC) to report their equity holdings if their asset under management exceeds $100m or if other conditions are triggered. Complementary data of institutional investors includes investment types (namely, Large Value, Large Growth, Small Value, Small Growth) and the reclassified legal types (namely, bank trust, insurance company, investment company, independent investment advisor, corporate and public pension fund, university and foundation endowments, and others). This complementary data also classifies institutional investors into three groups: transient, dedicated, and quasi-index tracking.

Further detailed information about Form 13f with the SEC can be found via: https://www.sec.gov/fast-answers/answers-form13fhtm.html

There is an ongoing concern regarding the legal type classifications of institutional investors originally available from Thomson Reuters, especially for the recent sample period. Brian Bushee, Professor of Accounting at the Wharton School, University of Pennsylvania, shares his work of legal type reclassifications, investment styles, and other institution-level characteristics via his personal website: https://accounting.wharton.upenn.edu/profile/bushee/.

The methodology of classifying institutional investors as transient, dedicated, and quasi-index tracking can be found in Bushee (1998) and is further developed in Bushee and Noe (2000) and Bushee (2001). As described in these papers, briefly, transient institutional investors hold relatively well-diversified portfolios but actively trade, aiming at short-run gains; dedicated institutional investors hold relatively concentrated portfolios but do not often trade, aiming at long-run gains; quasi-index tracking institutional investors largely replicate the returns of market-level or industry-level indices. Dedicated and quasi-index tracking institutional investors do not trade very often, resulting in a vast majority of zeros for \( \frac{\Delta n_{ij,t+1}}{n_{ij,t}} \), the percentage change in portfolio firm holdings as shown below. In order to generate valid RPI measures, the empirical findings of this paper focus on transient institutional investors.
Second, information of managerial equity-based awards is obtained from Thomson Reuters’ insiders trading data. With proper filings with the SEC, corporate insiders can legally make transactions in stocks and derivatives of the firms under their management. Common transaction types include, but not limited to, open-market purchases and sales, and stock/option grants. This dataset includes not only executives but non-executives in record as well. Finally, information of stock price, shares outstanding, and so on is obtained from CRSP. Accounting information is obtained from Compustat at the quarterly frequency. Since institutional holdings data is at the quarterly frequency, information from all sources is organized at the quarterly frequency. The sample period spans 1980-2012.

3.2. Measures Construction

The empirical challenges to test the model’s predictions are reflected in the difficulty in empirically measuring information acquisition effort made by institutional investors and exploiting the heterogeneity in the determinants of monitoring effort. This paper takes the following approach. In the same spirit of Kacperczyk and Seru (2015), a measure of reliance on private information (RPI) is constructed through regressions of quarterly portfolio changes on the standardized unexpected earnings (SUE).\footnote{Kacperczyk and Seru (2007) generate a measure of reliance on public information following the rationale that mutual fund managers with better private information are expected to react less sensitively to new releases of public information.} Institutional investors may adjust their portfolios from time $t$ to time $t + 1$, which can be measured by $\Delta n_{ij,t+1} / n_{ij,t}$, where $n_{ij,t}$ is investor $j$’s time-$t$ holding in firm $i$ and $\Delta$ takes time-series first order difference. Kacperczyk and Seru (2015) regress holdings changes from time $t$ to time $t + 1$ onto SUE($t + 1$), and the resulting $R^2$ obtained from this OLS regression is the reliance on private information of investor $j$ at time $t$. Appendix F links RPI with the OLS $R^2$ value of regressing $q_{i,t} - \beta_{ij}$ on $\tilde{z}_i$, where $q_{i,t} - \beta_{ij}$ and $\tilde{z}_i$ are the model counterparts of $\Delta n_{ij,t+1} / n_{ij,t}$ and SUE($t + 1$). Following the literature on post earnings announcement drift, SUE is constructed based on the seasonal time-trend assumption of corporate earnings as in Bernard and Thomas (1990), Ke and Ramalingegowda (2005), and many others. The summary statistics of RPI can be found in Table 0.

In order to generate cross-sectional variations in RPI, specifically, for the same institutional investor at each quarter, all portfolio firms are sorted into two groups, with one RPI value

\footnote{Kacperczyk and Seru (2015) argue that SUE($t + 1$) may serve as a proxy for private information at time $t$. In other words, institutional investors with precise private information ought to make portfolio changes prior to the realization of such private information.}
Propositions 3 and 4 suggest two dimensions to consider for sorting firms into two groups. First, $\phi_{ij}$ measures the effectiveness of investor intervention when exerting costly effort to enhance firm fundamental values. As aforementioned, firm managers care more about voices from external shareholders among firms with managerial equity-based awards; therefore, institutional investors are argued to engage more effectively with firms that grant stock/options to managers. Along this dimension, portfolio firms can be sorted into “Equity Grant” and “Non-Equity Grant” groups based on whether there are equity-based awards to firm managers in the previous quarter.\footnote{Ideally, a quarterly RPI value should be generated for each portfolio firm held by each institutional investor. However, since an RPI value has to be obtained through a OLS regression, one RPI value has been generated, instead, for a group of portfolio firms held by each institutional investor.} Consistent with McCahery, Sautner and Starks (2016), institutional investors are expected to take managerial equity awards as an important consideration regarding to what extent to exercise external corporate governance.

Along the second dimension, portfolio firms can be sorted into “High Initial % Holding” and “Low Initial % Holding” groups based on an institution’s initial percentage holdings in these firms.\footnote{Hartzell and Starks (2003) extensively discuss the usage of one-period flow rather than cumulative equity-based awards. While admitting the evidence that firm managers, according to their compensation packages, do purchase or sell correspondingly (Ofek and Yermack (2000)), Hartzell and Starks argue that such “hedging transactions” are largely beyond the direct control of the board of directors and institutional investors, and that the current flow of equity-based compensation should be used when considering the monitoring pressure from institutional investors.} An investor’s initial percentage stake in a portfolio firm is an important factor determining her monitoring effort (Proposition 1) and influences her information activities as well (Proposition 3). Prediction 4 illustrates the differential reliance on private information when investors adjust their portfolios among large-initial-stake firms and small-initial-stake ones. An alternative way of sorting firms along this dimension may follow Fich, Harford and Tran (2015) and emphasize the importance of portfolio weights represented by individual firms. They argue that institutional investors, intuitively, tend to exert much effort to monitor the firms into which they have allocated much of their wealth. Accordingly, portfolio firms can be sorted into “High Initial Weight” and “Low Initial Weight” groups based on the initial weight represented by a portfolio firm out of an institution’s overall portfolio.

Indicator variables are generated to represent these sortings. In particular, $Equity~Grant$ equals 1 if RPI is generated among firms with managerial equity-based awards and 0 otherwise; $High~Initial~\%~Holding$ is an indicator variable that equals 1 if RPI is generated among
firms in which an institution has high initial % holdings and 0 otherwise; \textit{High Initial Weight} is an indicator variable that equals 1 if RPI is generated among firms in which an institution has high initial portfolio weight and 0 otherwise. Accordingly, the coefficients before these indicator variables can be interpreted as the RPI differentials for these sortings.

Controls variables include the following characteristics of institutional investors. \textit{Age} is the natural log of the number of quarters since a given institution was recorded in SEC 13f filings for the first time. \textit{Manager Size} is the natural log of market capitalization of an institution’s stock holdings. \textit{Holding Concentration} is the Herfindahl-Herschman index of holdings in portfolio firms at the institution-quarter level. \textit{Portfolio Turnover} is defined as the minimum of stocks bought and stocks sold scaled by the market capitalization of an institution’s stock holdings. \textit{Portfolio Turnover Alt} is alternatively defined as the average of stocks bought and stocks sold scaled by the market capitalization of an institution’s stock holdings. Section 4 employs \textit{Portfolio Turnover Alt} in robustness checks. \textit{Equity Grant}, \textit{High Initial % Holding}, \textit{High Initial Weight}, \textit{Age}, and \textit{Manager Size} are then multiplied by 0.01 for reporting purposes. All right-hand side variables are lagged one quarter except for \textit{Age}. Fixed effects and clustered standard errors are carefully dealt throughout. \textit{Legal Type Dummies} refers to the classifications of institutional investors based on their fiduciary duties and \textit{Investment Type Dummies} refers to the classifications of institutional investors based on their investment styles.\footnote{Abarbanell, Bushee, Raedy (2003) provides further information about the classifications of institutional investors based on their investment styles.}

3.3. \textit{Summary Statistics and Empirical Results}

When focusing on transient institutional investors only, Figures 1 and 2 further look into compositions of transient institutional investors over time classified by legal types and investment styles. In terms of number count, independent investment advisors are the vast majority of transient institutional investors, while the numbers of bank trusts, insurance companies and investment companies have been steadily decreasing over time. Most of these transient investors commit to small firms while a relatively steady portion of them commit to large firms. In terms of market capitalization, independent investment advisors are still the vast majority of transient institutional investors, dominating the sum of bank trusts, insurance companies and investment companies. The beginning part of the sample witnesses transient institutional investors’ commitment to small firms with growth potential. The commitment to small growth firms peaked around 1992, 2000, and 2006, while the
commitment to small value firms has been steadily growing since 1995 and peaked around 2010.

For those interested in looking into the compositions of all institutional investors over time, Figures S1 and S2 present various sortings along different classification dimensions. Figure S1 presents the composition of institutional investors by number count. Figure S1a classifies institutional investors as transient, dedicated, or index-tracking based on their portfolio diversification and investment horizon. Figures S1b and S1c classify institutional investors according to their legal types and investment styles, respectively. One interesting feature of Figure S1c is that roughly equal numbers of institutional investors commit to the four investment styles, especially in the recent sample period (from 2000 on). Figure S2 presents the composition of institutional investor by market capitalization, following similar patterns. From these figures, it is not difficult to find that transient institutional investors make up a substantial portion of the overall US equity market both by number count and by market capitalization.

Several data filtering criteria have been applied before running regressions. First, in order to be sorted based on an institution’s initial % holding in portfolio firms, an included portfolio firm should have non-missing values for the number of shares outstanding and the number of shares held by this institution. Similarly, in order to be sorted based on portfolio weight represented by a portfolio firm, an included portfolio firm should have no-missing values for share price and the number of shares held by this institution. Second, portfolio firms are required to have a valid SUE for the next quarter, because an institution’s portfolio firm holding changes within the same group are regressed on the next-quarter SUEs in order to generate the RPI of this institution for the current quarter. Next, a minimum of 20 portfolio firms in each firm group of an institution at a quarter is required in order to generate a feasible OLS \( R^2 \) as the RPI measure; otherwise, a missing value for RPI will be generated for this firm group of this institution at the current quarter. This data filtering process results in four different sample sizes for the empirical tests of Tables I, II, III and IV. Therefore, Table S0 provides four sets of summary statistics at the “quarter-institution-firm group” level.

[Insert Table S0 near here]

\(^{34}\)Supplementary Appendix contains the figures that summarize the compositions of all institutional investors over time.
The baseline OLS regression equation is

\[ RPI_{ijt} = \beta_1 \text{Indicator}_{ijt} + \beta_2' X_{jt} + \delta_t + \mu_j + \epsilon_{ijt} \]  

(17)

where \( t \) indexes quarter, \( j \) indexes institutional investor, and \( i \) indexes a portfolio firm group. The coefficient of interest is \( \beta_1 \), which is expected to be positive and statistically significant. The four indicator variables, \( \text{Equity Grant} \), \( \text{High Initial \% Holding} \), \( \text{High Initial Weight} \) and \( \text{Distraction} \) are the main regressors in Tables I, II, III and IV, respectively. Throughout these four tables, robust standard errors are reported in Columns (1)-(3), and standard errors clustered at the institution level are reported in Columns (4)-(6). Time- and institution-fixed effects are further included in Columns (4)-(6).

Table I shows that the coefficient of \( \text{Equity Grant} \) is stable and remains statistically significant across different model specifications. Specifically, institutional investors’ RPI among firms with managerial equity-based awards is 1.32 percentage points higher than RPI among firms without managerial equity-based awards. The economic significance of this coefficient can be evaluated if compared with the sample mean of RPI among firms without managerial equity-based awards, which is 2.10 percentage points. This indicates a 62.69\% differential in RPI between firms with and without managerial equity-based awards. The coefficient of \( \text{Age} \) is statistically insignificant across all columns. The negative coefficient of \( \text{Manager Size} \) indicates that, everything else being equal, larger institutions tend to rely less on private information when adjusting their portfolios. This negative association is consistent with a stream of the mutual fund literature arguing that larger funds, compared with funds of smaller sizes, are less able to outperform due to the diseconomies of scale.\(^{35}\) The positive and statistically significant coefficient of \( \text{Holding Concentration} \) indicates that institutional investors holding more concentrated portfolios tend to rely more on private information, everything else being equal, when adjusting their portfolios. Although not a key finding of this paper, this positive association between RPI and \( \text{Holding Concentration} \) is consistent in spirit with the major argument of Kacperczyk, Sialm and Zheng (2005).\(^{36}\) There is some week evidence that portfolio turnover is negatively related to information acquisition, while

\(^{35}\)Berk and Green (2004) provide a rational model to accommodate the diseconomies of scale in mutual funds and many other features in the data considered as anomalous.

\(^{36}\)Multiple performance measures are adopted in their work, and mutual funds holding concentrated portfolios at the industry level are argued to be related to outperformance after adjusting risks and investment styles.
the negative coefficient of Portfolio Turnover turns statistically insignificant once time- and institution-fixed effects are included.

[Insert Table II near here]

Along the second dimension, two ways of measuring initial stakes are adopted. The first one follows the model and uses the percentage of a firm an institutional investor holds in the previous quarter. Empirical evidence in Table II suggests that institutional investors’ RPI among large-initial-stake firms is 0.17 percentage points higher than RPI among small-initial-stake firms. The economic significance of this coefficient can be evaluated if compared with the sample mean of RPI among small-initial-stake firms, which is 2.36 percentage points. This indicates a 7.07% differential in RPI between large-initial-stake firms and small-initial-stake ones. While there is some weak evidence suggesting that younger institutions tend to rely more on private information when adjusting their portfolios, the coefficient of Age turns statistically insignificant once time- and institution-fixed effects are included. The negative coefficient of Manager Size again indicates that, everything else being equal, larger institutions tend to rely less on private information when adjusting their portfolios. This negative association is consistent with the argument that larger funds are less able to outperform due to the diseconomies of scale. The coefficient of Holding Concentration remains positive and statistically significant and again indicates that institutional investors holding highly concentrated portfolios tend to highly rely on private information when adjusting their portfolios. Similar with Table I, the negative coefficient of Portfolio Turnover turns statistically insignificant once time- and institution-fixed effects are included.

[Insert Table III near here]

Alternatively, following Fich, Harford and Tran (2015), portfolio firms of an institutional investor in a quarter are sorted based on the weights they represent in the institutional investor’s overall portfolio. The associated empirical evidence in Table III suggests that institutional investors’ RPI among large-initial-stake firms is 0.46 percentage points higher than RPI among small-initial-stake firms, of which the sample mean is 2.23 percentage points. This indicates a 20.76% differential in RPI between large-initial-stake firms and small-initial-stake ones. The coefficient of Age, again, turns statistically insignificant once time- and institution-fixed effects are included. The negative and statistically significant coefficient of Manager Size indicates that, everything else being equal, larger institutions tend to rely less on private information when adjusting their portfolios. Again, this evidence is
consistent with the argument that larger funds, due to the diseconomies of scale, are less able to outperform compared with funds of smaller sizes. The coefficient of Holding Concentration remains persistently positive and statistically significant, indicating that institutional investors holding highly concentrated portfolios tend to highly rely on private information when adjusting their portfolios. Similar with Tables I and II, the negative coefficient of Portfolio Turnover turns statistically insignificant once time- and institution-fixed effects are included.

Table IV shows that there is an RPI differential for institutional investors among firms whose industries were experiencing extraordinary returns in the previous quarter and among firms whose industries were experiencing moderate returns in the previous quarter. KMS have confirmed that institutional investors shift attention to firms whose industries were experiencing extraordinarily volatile returns, leaving less attention allocated to the rest firms. In consequence, firms facing reduced monitoring pressure are involved with value-reducing corporate activities. Results in Table IV further confirm this story of attention re-allocation but from the perspective of information acquisition by institutional investors. Specifically, institutional investors, when adjusting portfolios, tend to rely less on private information by 0.14% among firms to which investor attention has been shifted relative to firms experiencing attention-grabbing events. This corresponds to a 6.0% differential in RPI between these two groups of portfolio firms. Manager Size is persistently statistically significant, which is consistent with the diseconomies-of-scale argument.

4. Robustness Checks

4.1. Alternatively Defined Variables

This subsection presents the regression results for alternatively defined variables. The complementary data of institutional investors obtained from Professor Brian Bushee’s personal website provides an alternative classification of investment styles is provided in this complementary data. Furthermore, Portfolio Turnover Alt is an alternative to Portfolio Turnover as defined in the previous section. Tables Alternative I, II, III and IV present the OLS regression results using these alternatively defined variables. These tables keep similar patterns wherever possible.
Table Alternative I shows that the coefficient of *Equity Grant* is stable and remains statistically significant across different model specifications. Specifically, institutional investors’ RPI among firms with managerial equity-based awards is 1.32 percentage points higher than RPI among firms without managerial equity-based awards. Considering the sample mean of RPI among firms without managerial equity-based awards being 2.10 percentage points, this indicates a 62.7% differential in RPI between firms with and without managerial equity-based awards. Empirical evidence in Table Alternative II, using the percentage of a firm an institutional investor holds in the previous quarter to measure “initial stake”, suggests that institutional investors RPI among large-initial-stake firms is 0.17 percentage points higher than RPI among small-initial-stake firms, of which the sample mean is 2.4 percentage points. This indicates a 7.0% differential in RPI between large-initial-stake firms and small-initial-stake ones. Alternatively, following the “portfolio weight” argument of Fich, Harford and Tran (2015), Table Alternative III suggests that institutional investors’ RPI among large-initial-stake firms is 0.46 percentage points higher than RPI among small-initial-stake firms, of which the sample mean is 2.2 percentage points. This indicates a 20.7% differential in RPI between large-initial-stake firms and small-initial-stake ones. Table Alternative VI shows that the coefficient of *Distraction* is negative and statistically significant at 5% significance level. Specifically, institutional investors’ RPI is 0.14 percentage points higher among firms whose industries are experiencing attention-grabbing events than firms facing distracted investors. Accounting for the sample mean of RPI among firms facing distracted investors being 2.3 percentage points, this indicates a 6.0% RPI differential between attention firms and distraction firms.

For the control variables across Tables Alternative I, II, III and IV, there is some weak evidence for *Age* suggesting that younger institutions tend to rely more on private information when adjusting their portfolios, while the coefficient for *Age* largely turns statistically insignificant once time- and institution-fixed effects are included. The negative coefficient of *Manager Size* confirms the less capability of larger institutions to deliver outperformance in comparison with institutions of smaller sizes, which is persistently consistent with the “diseconomies of scale” argument in the mutual fund literature. The positive and statistically significant coefficient of *Holding Concentration*, consistent with the main results in Tables I, II and III, indicates that institutional investors holding highly concentrated portfolios tend to rely more on private information when adjusting their portfolios. This coefficient turns statistically insignificant in Table Alternative IV. There is no strong evidence that the coefficient of *Portfolio Turnover Alt* persistently remains statistically significant.
4.2. Nonlinear Models

The main empirical results in Tables I, II, III and IV are reported using OLS specifications with fixed effects and robust or clustered standard errors adopted where appropriate. This subsection considers nonlinear model specifications with robust or bootstrapped standard errors adopted where appropriate as robustness check. There may be concern that the dependent variable, RPI, essentially the OLS $R^2$ value, is known to be bounded between 0 and 1, inclusive. OLS specifications may not be able to accommodate this bounded dependent variable. To illustrate this concern, fractional response models are considered. This subsection presents the regression results for both fractional probit and fractional logit specifications. Briefly, both specifications confirm that there is a statistically significant RPI differential along each of the three dimensions (engagement effectiveness, initial holding stake, and allocation re-allocation), qualitatively similar as in Tables I, II, III and IV.

[Insert Tables Nonlinear I, II, III and IV near here]

The coefficients of control variables largely preserve the results in previous tables. Specifically, Manager Size is negatively associated with RPI (except for Nonlinear IV), confirming the diseconomies of scale: larger institutions tend to rely less on private information when adjusting their portfolios. Holding Concentration, again, persistently remains positive and statistically significant. This positive association with RPI suggests that institutions holding highly concentrated portfolios tend to highly rely on private information when adjusting their portfolios. There is some evidence for Age to play a role, while the coefficient of Age turns insignificant in Tables Nolinear I, II and III once time-fixed effects are included. The coefficient of Portfolio Turnover in these nonlinear models persistently remains negative. In spite of the need to avoid over-interpreting these results, the negative association of Portfolio Turnover with RPI indicates that institutions with higher portfolio turnovers tend to rely less on private information. Recall that the sample only covers transient institutional investors, who are relatively well-diversified and actively trade for short-run gains. Thus, the negative association of Portfolio Turnover could be interpreted, if not over-interpreted, as excessive portfolio turnovers are associated with less informed portfolio adjustments among transient institutional investors. Due to using nonlinear specifications, however, the magnitudes of coefficients are different from those of OLS specifications, and the interpretations of these coefficients using nonlinear specifications are different as well. Furthermore, it is

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37 Bootstrapped standard errors of average partial effects are suggested in Wooldridge (2010, pp.768-769) for fractional response models. Time-fixed effects are included in nonlinear models while institution-fixed effects are not due to calculation capacity.
understandable that the magnitudes of coefficients are different when employing different nonlinear models (fractional probit or fractional logit).

5. Conclusion

Investor attention may be considered as the attention for monitoring or monitoring pressure on firms as in Kempf, Manconi and Spalt (2017) while considered as the attention for information acquisition as in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). However, monitoring and information acquisition are conceptually different, and how they are related in terms of within-firm and cross-firm interactions is largely unexplored, both empirically and theoretically. My paper formally models both monitoring and information acquisition in a rational expectations framework where investors can choose how much effort to exert in each activity. Specifically, this paper theoretically distinguishes monitoring and information acquisition, explores their intrinsic link, delivers empirically testable predictions regarding information acquisition, and provides empirical evidence to support these predictions. Within-firm complementarity and cross-firm substitutability between monitoring and information acquisition are developed as the implications of the non-separability assumption. Most importantly, my paper emphasizes one novel source of motivation for investors to exert external governance on portfolio firms via the monitoring-for-learning channel: Investors optimally re-allocate monitoring effort from firms with low value of information acquisition to those with high value of information acquisition. This cross-sectional feature of optimal monitoring effort can lend theoretical support to the attention re-allocation story of investor monitoring in Kempf, Manconi and Spalt (2017).

My paper also enriches the set of empirical tests regarding information acquisition theory. In particular, my paper has developed a few predictions linking information acquisition with determinants of exerting external governance for institutional investors. Institutional investors are predicted, on average, to acquire more private information about the firms they can more effectively engage with and about those they initially hold larger stakes in. Another prediction is about the distracted attention story in the context of information acquisition. In addition to the empirical findings in KMS, my paper further hypothesizes that attention for information acquisition is distracted from firms experiencing industry-wide moderate returns to firms experiencing industry-wide extraordinarily volatile returns. Empirical evidence supports these hypotheses.
The empirical section looks into the heterogeneous patterns of adjusting holdings in portfolio firms using reliance on private information (RPI) as a proxy for private information, and provides supportive evidence for model predictions. Specifically, I find that institutional investors, when adjusting their portfolios, rely more on private information among firms with managerial equity-based awards than without. I also find that institutional investors, when adjusting their portfolios, differentially rely on private information between large-initial-stake firms and small-initial-stake ones, relying more on private information among large-initial-stake firms. By defining attention-grabbing events following KMS, I find a significant differential of reliance on private information by institutional investors among firms experiencing attention-grabbing events and those facing distracted investor attention. These differentials in RPI further confirm the feasibility of the intrinsic link between monitoring and information acquisition coined as the non-separability assumption that enables the determinants of exerting monitoring effort to play important roles in the information acquisition activities of institutional investors.

Due to construction requirements of the RPI measure, the empirical evidence in this paper focuses on how transient institutional investors differentially adjust their holdings in portfolio firms based on firm-level heterogeneous determinants of exerting external governance. Another interesting and important type of investors are dedicated institutional investors who hold concentrated portfolios but do not trade very often. Because dedicated investors do not trade very often, RPI cannot serve as a proxy for the amount of private information among these investors. Although usually without in-house research departments, dedicated institutional investors gather private information through proactive and close engagement with corporate executives and can themselves serve as a rationale for their concentrated portfolios with infrequent trades. That is, dedicated investors are very likely to have low $K'_{ij}$ (i.e. low independent research) but very high $b_{ij}$ (i.e. high monitoring), still resulting in high $K_{ij}$. Future empirical studies can explore how dedicated institutional investors make infrequent but well-informed portfolio adjustments, especially right before extremely negative news, for further evidence.
Appendix A.

Lemma 1

Equilibrium price of firm $i$ is conjectured to take the linear form, for $i=1,...,n$:

$$p_i = \mu_1 \bar{V}_i + \mu_2 \tilde{V}_i + \mu_3 (1 + x_i)$$ (18)

Rescaling the price signal into:

$$\tilde{s}_i = \frac{p_i - \mu_1}{\mu_2} = \tilde{V}_i + \frac{\mu_3}{\mu_2} (1 + x_i)$$ (19)

Please note that $p_i$ and $\tilde{s}_i$ contains the same information. The precision of this rescaled price signal is $\frac{\mu_2^2}{\mu_3^2} \gamma$. Then applying Bayesian updating to form investor $j$’s posterior beliefs:

$$E_j (\tilde{V}_i) = \frac{\alpha_i \tilde{V}_i + \kappa (b_{ij}) \left( \tilde{V}_i + \epsilon_{ij}^\nu \right) + K'_{ij} \left( \tilde{V}_i + \epsilon_{ij}^\theta \right) + \frac{\mu_2^2}{\mu_3^2} \gamma \tilde{s}_i}{\alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3^2} \gamma}$$ (20)

$$Var_j (\tilde{V}_i) = \frac{1}{\alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3^2} \gamma}$$ (21)

Plugging (20) and (21) into (8) gives:

$$q_{ij} = \frac{1}{\rho} \left( \alpha_i \tilde{V}_i + \kappa (b_{ij}) \left( \tilde{V}_i + \epsilon_{ij}^\nu \right) + K'_{ij} \left( \tilde{V}_i + \epsilon_{ij}^\theta \right) + \frac{\mu_2^2}{\mu_3^2} \gamma \tilde{s}_i - rp_i \left( \alpha_i + K_{ij} + \frac{\mu_2^2}{\mu_3^2} \gamma \right) \right)$$ (22)

Equilibrium price of firm $i$ can be obtained by equating demand and supply of firm $i$’s shares in (9):

$$\int_0^1 q_{ij} dj = 1 + x_i$$ (23)

Rearranging the terms delivers the equilibrium price of firm $i$ as a linear function of $\tilde{V}_i$, $\bar{V}_i$, $\tilde{s}_i$.
and $x_i$:

$$p_i = \frac{\alpha_i \bar{V}_i + \left(K_{ij} + \frac{\mu_1^2}{\mu_3^2} \gamma \right) \tilde{V}_i + \left(\frac{\mu_2}{\mu_3} \gamma - \rho \right) (1 + x_i)}{\alpha_i + \bar{K}_i + \frac{\mu_1^2}{\mu_3^2} \gamma}
$$

(24)

The coefficients of $\bar{V}_i$, $\tilde{V}_i$, and $x_i$ in (24) contain $\mu_1$, $\mu_2$, and $\mu_3$, which can be solved by matching the coefficients in (18) and (24). Specifically,

$$\mu_1 = \frac{\alpha_i}{r \left(\alpha_i + \bar{K}_i + \frac{K_i^2}{\rho^2} \gamma \right)}$$

(25)

$$\mu_2 = \frac{\bar{K}_i + \frac{K_i^2}{\rho^2} \gamma}{r \left(\alpha_i + \bar{K}_i + \frac{K_i^2}{\rho^2} \gamma \right)}$$

(26)

$$\mu_3 = -\frac{\left(\frac{K_i}{\rho} \gamma + \rho \right) (1 + x_i)}{r \left(\alpha_i + \bar{K}_i + \frac{K_i^2}{\rho^2} \gamma \right)}$$

(27)

This is Lemma 1.

Appendix B.

Lemma 2, Proposition 1 and Properties 1-3

Solutions to stage 2 and stage 3 problems are readily established in Kacperczyk, Van Nieuwerburgh, and Veldkamp (2016). For investor $j$ choosing $K_{ij}$, the objective function to maximize is

$$\sum_{i=1}^{n} \lambda_i K_{ij} + \text{constant}
$$

(28)

subject to the constraints (4) and (5), which can be rewritten as:

$$\sum_{i=1}^{n} K'_{ij} \leq K_j - \sum_{i=1}^{n} \kappa (b_{ij})
$$

(29)

$^{38}$One useful result to mention is $\int_{0}^{1} K'_{ij} \epsilon_{ij}^\theta dj = \int_{0}^{1} K_{ij} dj \int_{0}^{\theta} \epsilon_{ij}^\theta dj = 0$. This is due to the fact that $K'_{ij}$ and $\epsilon_{ij}^\theta$ are linearly uncorrelated. Similarly, we have $\int_{0}^{1} \kappa (b_{ij}) \epsilon_{ij}^\nu dj = \int_{0}^{1} \kappa (b_{ij}) dj \int_{0}^{\nu} \epsilon_{ij}^\nu dj = 0$. 

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where $K'_{ij} = K_{ij} - \kappa(b_{ij})$. Since $b_{ij}$’s are monitoring effort readily chosen in stage 1, the maximization problem above regards all $b_{ij}$’s and thus all $\kappa(b_{ij})$’s as constant; the objective function can also be rewritten as:

$$
\sum_{i=1}^{n} \lambda_i K'_{ij} + \sum_{i=1}^{n} \lambda_i \kappa(b_{ij}) + \text{constant}
$$

Therefore, the original optimization problem is equivalent to maximizing (32) subject to the constraints (30) and (31). With the rewritten objective function and constraints, we can apply the solutions in Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). Since $\lambda_i$, as indicated in (12), is composed of aggregate variables and each investor in this model is atomic on a continuum of mass one, investor $j$ regards $\lambda_i$ as a constant when making choices of $K_{ij}$. Further, all investors face the same $\lambda_i$’s for $i = 1, \ldots, n$ in their own optimization problem. Van Nieuwerburgh and Veldkamp (2010) also formally prove that the solution of such optimization problem when there is a unique $\lambda_i = \max_l \lambda_l$ is: $K'_{ij} = K_j - \sum_{i=1}^{n} \kappa(b_{ij})$ if $\lambda_i = \max_l \lambda_l$ and $K'_{ij} = 0$ otherwise. That is, $K_{ij} = (K_j - \sum_{i=1}^{n} \kappa(b_{ij})) + \kappa(b_{ij})$ if $\lambda_i = \max_l \lambda_l$ and $K_{ij} = \kappa(b_{ij})$ otherwise. Naturally, we cannot rule out the possibility that there may be multiple firms with the same level of $\lambda = \max_l \lambda_l$. This can happen when $K_j$ is large enough. In this situation, investor $j$ will be indifferent to allocating $K_j - \sum_{i=1}^{n} \kappa(b_{ij})$, her remaining capacity after monitoring, to the firms with the same level of $\lambda = \max_l \lambda_l$. For simplicity, we may assume that equal fractions of her remaining capacity are allocated to each firm with $\lambda = \max_l \lambda_l$. That is, $K_{ij} = \frac{1}{n}(K_j - \sum_{i=1}^{n} \kappa(b_{ij})) + \kappa(b_{ij})$ if $\lambda_i = \max_l \lambda_l$ and $K_{ij} = \kappa(b_{ij})$ otherwise, where $n$ is the number of firms with $\lambda = \max_l \lambda_l$. Overall, $K_{ij}$, information acquisition of firm $i$ by investor $j$, is weakly increasing in monitoring effort of the same firm, $b_{ij}$. The cross-firm relation between information acquisition and monitoring is that $K_{ij}$ is weakly decreasing in $b_{kj}$ where $i \neq k$. This is Lemma 2.

After solving the stage 2 and stage 3 problems in this model, we can use backward induction to work on the stage 1 problem: optimally choose $b_{ij}$. The stage 1 utility of investor $j$ takes the following form:

$$
U_{1j} = r \left( \sum_{i=1}^{n} (\beta_{ij} \bar{V}_i - b_{ij}) \right) + \sum_{i=1}^{n} \lambda_i K_{ij} + \text{constant}
$$

(32)
For firms with $\lambda_i \neq \max_l \lambda_l$, assuming interior solutions and setting the FOC w.r.t. $b_{ij}$ equal to zero gives:

$$\frac{\partial U_{ij}}{\partial b_{ij}} = r \left( \beta_{ij} \phi_{bij} \frac{1}{1 + b_{ij}} - 1 \right) + (\lambda_i - \max_l \lambda_l) \phi_b \frac{1}{1 + b_{ij}} = 0$$ (33)

Rearranging terms in (34) gives:

$$b_{ij} = \beta_{ij} \phi_{ij} + \left( \frac{\lambda_i - \max_l \lambda_l}{r} \right) \phi_b - 1$$ (34)

For firms with multiple $\lambda_i = \max_l \lambda_l$, assuming interior solutions and setting the FOC w.r.t. $b_{ij}$ equal to zero gives:

$$\frac{\partial U_{ij}}{\partial b_{ij}} = r \left( \beta_{ij} \phi_{bij} \frac{1}{1 + b_{ij}} - 1 \right) + \lambda_i \left( \frac{n - 1}{n} \right) \phi_b \frac{1}{1 + b_{ij}} = 0$$ (35)

where $n$ is the number of multiple firms with the highest $\lambda_i$. Rearranging terms in (36) gives:

$$b_{ij} = \beta_{ij} \phi_{ij} + \left( \frac{n - 1}{nr} \lambda_i \phi_b - 1 \right)$$ (36)

(37) can also accommodates the case that investor $j$ has one and only one firm with $\lambda_i = \max_l \lambda_l$ by setting $n = 1$. To sum up, according to $b_{ij} \geq 0$, the optimal monitoring effort can be expressed as

$$b_{ij}^* = \begin{cases} 
\max \left\{ 0, \beta_{ij} \phi_{ij} + \left( \frac{\lambda_i - \max_l \lambda_l}{r} \right) \phi_b - 1 \right\} & \lambda_i \neq \max_l \lambda_l \\
\max \left\{ 0, \beta_{ij} \phi_{ij} + \left( \frac{n - 1}{nr} \lambda_i \phi_b - 1 \right) \right\} & \lambda_i = \max_l \lambda_l 
\end{cases}$$

Here is Proposition 1. There are a few properties associated with this proposition.

**Property 1** If assuming interior solution, differentiaing $b_{ij}^*$ w.r.t. $\beta_{ij}$ gives

$$\frac{\partial b_{ij}^*}{\partial \beta_{ij}} = \phi_{ij} > 0$$ (37)

Taking into account the possible corner solution $b_{ij}^* = 0$, it is claimed that $b_{ij}$ is weakly increasing in $\beta_{ij}$. 

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Property 2  If assuming interior solution, differentiating $b_{ij}^*$ w.r.t. $\phi_{ij}$ gives

$$\frac{\partial b_{ij}^*}{\partial \phi_{ij}} = \beta_{ij} > 0 \quad (38)$$

Taking into account the possible corner solution $b_{ij}^* = 0$, it is claimed that $b_{ij}$ is weakly increasing in $\phi_{ij}$.

Property 3  This property can be derivd using the chain rule. Assuming interior solution, $\frac{\partial b_{ij}^*}{\partial \lambda_i} \geq 0$ is straightforward from Lemma 2. Using the chain rule and given that $\frac{\partial \lambda_i}{\partial \sigma_i} = \left(1 + 2\bar{\sigma}_i \left(\rho^2 (\sigma_x + 1) + \bar{K}_i \right) \left(\frac{\sigma_i}{\bar{\sigma}_i}\right)^2 \right) > 0$, we can claim that $b_{ij}^*$ is weakly increasing in $\sigma_i$ via $\lambda_i$. This is also true after considering the possible corner solution.

Appendix C.

Proposition 2

Were there no link between monitoring and information acquisition, investor $j$’s monitoring decision would only depend on the stage 1 problem: maximize her initial wealth after monitoring $W_0 = \sum_{i=1}^{n} (\beta_{ij} \bar{V}_i - b_{ij})$. Assuming interior solution, taking the first order derivative w.r.t. $b_{ij}$ gives:

$$\beta_{ij} \phi_{ij} \frac{1}{1 + b_{ij}} - 1 = 0 \quad (39)$$

That is,

$$b_{ij} = \beta_{ij} \phi_{ij} - 1 \quad (40)$$

Considering $b_{ij} \geq 0$, optimal monitoring effort in this situation is

$$b_{ij}^{**} = \max \{0, \beta_{ij} \phi_{ij} - 1\} \quad (41)$$

We use $b_{ij}^{**}$ to denote the baseline-case allocation of monitoring effort. Comparing $b_{ij}^*$ and $b_{ij}^{**}$, there are several cases to consider as follows.

Case 1: For firms with $\lambda_i \neq \max \lambda_i$,  

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If \( \beta_{ij} \phi_{ij} + \frac{\lambda_i - \max(\lambda_i) \phi_b}{r} > 1 \), then \( b_{ij}' = \beta_{ij} \phi_{ij} + \frac{(\lambda_i - \max(\lambda_i) \phi_b)}{r} - 1 \) and \( b_{ij}^{**} = \beta_{ij} \phi_{ij} - 1 \); that is, \( b_{ij}' - b_{ij}^{**} = \frac{(\lambda_i - \max(\lambda_i) \phi_b)}{r} < 0 \).

If \( \beta_{ij} \phi_{ij} + \frac{\lambda_i - \max(\lambda_i) \phi_b}{r} \leq 1 < \beta_{ij} \phi_{ij} \), then \( b_{ij}' = 0 \) and \( b_{ij}^{**} = \beta_{ij} \phi_{ij} - 1 > 0 \); that is, \( b_{ij}' - b_{ij}^{**} < 0 \).

If \( \beta_{ij} \phi_{ij} \leq 1 \), then \( b_{ij}' = 0 \) and \( b_{ij}^{**} = 0 \); that is, \( b_{ij}' - b_{ij}^{**} = 0 \).

To sum up Case 1, \( b_{ij}' \leq b_{ij}^{**} \) for firms with \( \lambda_i \neq \max_i \lambda_i \).

Case 2: For firms with \( \lambda_i = \max_i \lambda_i \),

- If \( \beta_{ij} \phi_{ij} > 1 \), then \( b_{ij}' = \beta_{ij} \phi_{ij} + \frac{(n-1)\lambda_i \phi_b}{nr} - 1 \) and \( b_{ij}^{**} = \beta_{ij} \phi_{ij} - 1 \); that is, \( b_{ij}' - b_{ij}^{**} = \frac{(n-1)\lambda_i \phi_b}{nr} \geq 0 \).
- If \( \beta_{ij} \phi_{ij} \leq 1 < \beta_{ij} \phi_{ij} \), then \( b_{ij}' = \beta_{ij} \phi_{ij} + \frac{(n-1)\lambda_i \phi_b}{nr} - 1 > 0 \) and \( b_{ij}^{**} = 0 \); that is, \( b_{ij}' - b_{ij}^{**} > 0 \).
- If \( \beta_{ij} \phi_{ij} + \frac{(n-1)\lambda_i \phi_b}{nr} \leq 1 \), then \( b_{ij}' = 0 \) and \( b_{ij}^{**} = 0 \); that is, \( b_{ij}' - b_{ij}^{**} = 0 \).

To sum up Case 2, \( b_{ij}' \geq b_{ij}^{**} \) for firms with \( \lambda_i = \max_i \lambda_i \). Clearly, comparing the results in Case 1 and Case 2, we can find that there is a re-allocation pattern of monitoring attention relative to the baseline case: Monitoring attention is re-allocated to firms with \( \lambda_i = \max_i \lambda_i \) from firms with \( \lambda_i \neq \max_i \lambda_i \).

**Appendix D.**

**Propositions 3 and 4**

The investors’ attention allocation problem has been illustrated in Appendix A. For detailed solutions, please refer to Kacperczyk, Van Nieuwerburgh and Veldkamp (2016). One useful and important feature is that since \( K_{ij}' \) is determined by \( \lambda_i \) and other given parameters, variations in \( b_{ij}, \phi_{ij} \), or \( \beta_{ij} \) will not change \( \lambda_i \). Therefore, variations in \( b_{ij}, \phi_{ij} \), or \( \beta_{ij} \) will not change \( K_{ij}' \), either. Specifically, when taking partial derivative of \( K_{ij} \) w.r.t. \( b_{ij} \),

\[
\frac{\partial K_{ij}}{\partial b_{ij}} = \frac{\phi_b}{1 + b_{ij}} \geq 0,
\]

where \( \phi_b = \phi_b \) for firms with \( \lambda_i \neq \max_i \lambda_i \); \( \phi_b = \frac{(n-1)\phi_b}{n} \) for multiple firms with \( \lambda_i = \max_i \lambda_i \); and \( \phi_b = 0 \) if there is one and only one firm with \( \lambda_i = \max_i \lambda_i \). Based on the first two properties of optimal monitoring effort solved in Appendix B, we may get:

\[
\frac{\partial K_{ij}}{\partial \phi_{ij}} = \frac{\partial K_{ij}}{\partial b_{ij}} \frac{\partial b_{ij}}{\partial \phi_{ij}} \geq 0
\]  

(42)
where both $\partial K_{ij}$ and $\partial b_{ij}$ are weakly positive. Similarly,

$$\frac{\partial K_{ij}}{\partial \beta_{ij}} = \frac{\partial K_{ij}}{\partial b_{ij}} \frac{\partial b_{ij}}{\partial \beta_{ij}} \geq 0$$  \hspace{1cm} (43)

where both $\partial K_{ij}$ and $\partial b_{ij}$ are weakly positive.

**Appendix E.**

**Proposition 5a: Marginal Shock to Prior Uncertainty**

According to Lemma 2, there are two cases to consider when exploring how $b^*_ij$ and $K_{ij}$, in Proposition 2 and Proposition 5, respectively, respond to an exogenous marginal increase in $\sigma_k$ ($k \neq i$).

**Case 1:** For firms with $\lambda_i \neq max_l \lambda_l$, $b^*_ij = max\{0, \beta_{ij} \phi_{ij} + \frac{(\lambda_i - max_l \lambda_l) \phi_b}{\tau} - 1\}$; an exogenous increase in $\sigma_k$ ($k \neq i$) weakly increases $max_l \lambda_l$ and thus weakly decreases $b^*_ij$. In terms of information acquisition, firms with $\lambda_i \neq max_l \lambda_l$ have $K_{ij} = \kappa(b_{ij})$, an increasing function of $b^*_ij$. Thus, an exogenous increase in $\sigma_k$ ($k \neq i$) weakly decreases $K_{ij}$ for these firms.

**Case 2:** For firms with $\lambda_i = max_l \lambda_l$, $b^*_ij = max\{0, \beta_{ij} \phi_{ij} + \frac{(n-1) \lambda_i \phi_b}{nr} - 1\}$; there are two situations to consider regarding an exogenous marginal increase in $\sigma_k$ ($k \neq i$).

- If $\lambda_k < \lambda = max_l \lambda_l$ before the exogenous increase in $\sigma_k$ happens, then $\lambda_k < \lambda = max_l \lambda_l$ still holds after that exogenous increase. This is because an exogenous marginal increase in $\sigma_k$ only increases $\lambda_k$ marginally while $\lambda_k < \lambda = max_l \lambda_l$ in a discrete manner. In this situation, $b^*_ij$ with $\lambda_i = max_l \lambda_l$ is not affected. Since neither the level nor the relative ranking of $\lambda$’s with $\lambda = max_l \lambda_l$ has changed, $K_{ij}$ with $\lambda = max_l \lambda_l$ is not affected, either.

- If $\lambda_k$ is one of the multiple $\lambda = max_l \lambda_l$, then $\lambda_k$ becomes the unique $\lambda = max_l \lambda_l$ after this exogenous increase, holding attention allocation constant. However, this exogenous increase in $\sigma_k$ affects all investors and the $\lambda$’s as well. When all investors allocate more attention (for information acquisition) to firm $k$ in response to this exogenous marginal increase in $\sigma_k$, $\lambda_k$ starts facing downward pressure.\footnote{Cover and Thomas (1991) provide a “waterfilling” solution to this type of question in information theory.} This is because when all investors acquire more information about the same firm, the value of obtaining an incremental unit of information about this firm will decrease. Grossman
and Stiglitz (1980) recognize this strategic substitutability of information acquisition. Such attention re-allocation to firm $k$ continues until firm $k$ joins the other firms having $\lambda = \max_l \lambda_l$ in the new equilibrium. Specifically, $\lambda_k$ in the new equilibrium is marginally bigger than before, so are all the other $\lambda$'s since $\lambda_k = \lambda = \max_l \lambda_l$ holds in the new equilibrium. From Lemma 2, we can see that monitoring effort $b_{ij}^*$ increases among firms with $\lambda_i = \max_l \lambda_l$ via the associated increase in $\lambda_i$. However, all investors re-allocate attention for information acquisition to firm $k$ right after the exogenous increase in $\sigma_k$ and the new equilibrium is reached where all $\lambda = \max_l \lambda_l$ strictly increase. An increased $\lambda_i$ means attention for information acquisition $K_{ij}$ ($i \neq k$) decreases in the first place for all investors.

To sum up, in the new equilibrium, $b_{ij}^*$ weakly decreases in response to an exogenous marginal increase in $\sigma_k$ ($k \neq i$) if $\lambda_i \neq \max_l \lambda_l$; and $b_{ij}^*$ strictly increases in response to an exogenous marginal increase in $\sigma_k$ ($k \neq i$) if $\lambda_i = \max_l \lambda_l$. Information acquisition in the new equilibrium takes the following form. In response to an exogenous marginal increase in $\sigma_k$ ($k \neq i$), $K_{ij}$ weakly decreases if $\lambda_i \neq \max_l \lambda_l$; and $K_{ij}$ strictly decreases if $\lambda_i = \max_l \lambda_l$.

**Proposition 5b: Large Shock to Prior Uncertainty**

When the exogenous increase in $\sigma_k$ is large enough such that $\lambda_k$ becomes the unique $\max_l \lambda_l$ ex post, then from Proposition 1, it is clear that $b_{ij}$ weakly decreases for any $i \neq k$. This indicates $\kappa(b_{ij})$ weakly decreases for any $i \neq k$. Since $\lambda_i$ governs how much independent research investor $j$ will conduct about firm $i$ (i.e. $K'_{ij}$) conditional on the choice of $b_{ij}$, then $K'_{ij}$ weakly decreases for any $i \neq k$. Therefore, $K_{ij} = \kappa(b_{ij}) + K'_{ij}$ ($i \neq k$) weakly decreases for any $i \neq k$ as well.
References


Table I. The Differential Reliance of Institutional Investors on Private Information: Managerial Stock/Option Grants

This table presents the differential reliance of institutional investors on private information (RPI) among firms with and without managerial equity-based awards. The dependent variable, RPI, is measured by the R-square value of regressing quarterly portfolio changes on standardized unexpected earnings. Equity Grant is an indicator variable that equals 1 if RPI is generated among firms with managerial equity-based awards and 0 otherwise. Age is the natural log of the number of quarters that a given institution has been recorded in SEC 13f filings. Manager Size is the natural log of the market capitalization of an institution’s stock holdings. Holding Concentration is the Herfindahl-Hirschman index of holdings in portfolio firms at institution-quarter level. Portfolio Turnover is defined as the ratio of the minimum of stocks bought and stocks sold over the market capitalization of an institution’s stock holdings. Investment Style Dummies include four categories: Large Value, Large Growth, Small Value, Small Growth. Legal Type Dummies include bank trust, insurance company, investment company, independent investment advisor, corporate (private) pension fund, public pension fund, university and foundation endowments, and miscellaneous. Equity Grant, Age, and Manager Size are then scaled by 0.01 for reporting purposes. All right-hand side variables are lagged one quarter except for Age. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. Standard errors are reported in parentheses. Columns (1)-(3) report robust standard errors, and Columns (4)-(6) report clustered standard errors at the institution level.

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Table II. The Differential Reliance of Institutional Investors on Private Information: High and Low Initial % Holdings

This table presents the differential reliance of institutional investors on private information (RPI) among firms in which an institution has high and low initial % holdings. The dependent variable, RPI, is measured by the R-square value of regressing quarterly portfolio changes on standardized unexpected earnings. High Initial % Holding is an indicator variable that equals 1 if RPI is generated among firms in which an institution has high initial % holdings and 0 otherwise. Age is the natural log of the number of quarters that a given institution has been recorded in SEC 13f filings. Manager Size is the natural log of the market capitalization of an institution’s stock holdings. Holding Concentration is the Herfindahl-Herschman index of holdings in portfolio firms at institution-quarter level. Portfolio Turnover is defined as the ratio of the minimum of stocks bought and stocks sold over the market capitalization of an institution’s stock holdings. Investment Style Dummies include four categories: Large Value, Large Growth, Small Value, Small Growth. Legal Type Dummies include bank trust, insurance company, investment company, independent investment advisor, corporate (private) pension fund, public pension fund, university and foundation endowments, and miscellaneous. High Initial % Holding, Age, and Manager Size are then scaled by 0.01 for reporting purposes. All right-hand side variables are lagged one quarter except for Age. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. Standard errors are reported in parentheses. Columns (1)-(3) report robust standard errors, and Columns (4)-(6) report clustered standard errors at the institution level.

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43
Table III. The Differential Reliance of Institutional Investors on Private Information: High and Low Initial Portfolio Weight

This table presents the differential reliance of institutional investors on private information (RPI) among firms in which an institution has high and low initial portfolio weight. The dependent variable, RPI, is measured by the R-square value of regressing quarterly portfolio changes on standardized unexpected earnings. High Initial Weight is an indicator variable that equals 1 if RPI is generated among firms in which an institution has high initial portfolio weight and 0 otherwise. Age is the natural log of the number of quarters that a given institution has been recorded in SEC 13f filings. Manager Size is the natural log of the market capitalization of an institution’s stock holdings. Holding Concentration is the Herfindahl-Herschman index of holdings in portfolio firms at institution-quarter level. Portfolio Turnover is defined as the ratio of the minimum of stocks bought and stocks sold over the market capitalization of an institution’s stock holdings. Investment Style Dummies include four categories: Large Value, Large Growth, Small Value, Small Growth. Legal Type Dummies include bank trust, insurance company, investment company, independent investment advisor, corporate (private) pension fund, public pension fund, university and foundation endowments, and miscellaneous. High Initial Weight, Age, and Manager Size are then scaled by 0.01 for reporting purposes. All right-hand side variables are lagged one quarter except for Age. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. Standard errors are reported in parentheses. Columns (1)-(3) report robust standard errors, and Columns (4)-(6) report clustered standard errors at the institution level.

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Table IV. The Differential Reliance of Institutional Investors on Private Information: Attention and Distraction

This table presents the differential reliance of institutional investors on private information (RPI) between firms whose industries are experiencing attention-grabbing events and those experiencing distracted investor attention. The dependent variable, RPI, is measured by the R-square value of regressing quarterly portfolio changes on standardized unexpected earnings. Distraction is an indicator variable that equals 1 if RPI is generated among firms experiencing distracted investor attention and 0 otherwise. Age is the natural log of the number of quarters that a given institution has been recorded in SEC 13f filings. Manager Size is the natural log of the market capitalization of an institution’s stock holdings. Holding Concentration is the Herfindahl-Herschman index of holdings in portfolio firms at institution-quarter level. Portfolio Turnover is defined as the ratio of the minimum of stocks bought and stocks sold over the market capitalization of an institution’s stock holdings. Investment Type Dummies include four categories: Large Value, Large Growth, Small Value, Small Growth. Legal Type Dummies include bank trust, insurance company, investment company, independent investment advisor, corporate (private) pension fund, public pension fund, university and foundation endowments, and miscellaneous. Distraction, Age, and Manager Size are then scaled by 0.01 for reporting purposes. All right-hand side variables are lagged one quarter except for Age. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively. Standard errors are reported in parentheses. Columns (1)-(3) report robust standard errors, and Columns (4)-(6) report clustered standard errors at the institution level.

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45
Figure 1. Composition of Transient Institutional Investors: Number Count

This figure presents the composition of institutional investors based on Bushee’s classifications of institutional investors. This figure shows the composition for transient institutional investors only. Institutional investors are classified in Figure 3a and Figure 3b based on their fiduciary duties and their investment styles, respectively.
**Figure 2. Composition of Transient Institutional Investors: Market Capitalization**

This figure presents the composition of institutional investors based on Bushee’s classifications of institutional investors. This figure shows the composition for transient institutional investors only. Institutional investors are classified in Figure 4a and Figure 4b based on their fiduciary duties and their investment styles, respectively.