

Institutional Ownership Concentration and Informational Efficiency

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Abstract

We study how the concentration of ownership among institutional investors influences price informativeness in financial markets. We find that an increase in institutional ownership concentration — whether measured by investors' assets under management or their firm-level holdings — reduces price informativeness and investment-to-price sensitivity. This negative effect is attributed to the learning and trading decisions of active, rather than passive, investors. To establish causality, we utilize a setting involving mergers between active investors, and our results remain consistent across international contexts.

Keywords: Ownership concentration, market power, active trading, price informativeness

JEL Classification: G14, G15, G23

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1 Introduction

Over the past decades, the U.S. industries have exhibited a trend toward increased concentration (e.g., [Autor et al., 2020](#); [Kwon et al., 2024](#)). The asset management industry is no exception to this pattern. As illustrated in Figure 1, the concentration among institutional investors within the growing asset management space has been on the rise since 1980, with a particularly pronounced increase observed among active institutional investors. In this paper, we examine the polarized ownership structure of institutional investors and its implications for financial markets. In particular, we focus on how this skewed structure affects price informativeness, an established measure in the literature with important implications for welfare and the real economy (e.g., [Bond et al., 2012](#); [Goldstein, 2023](#)).

To guide the empirical analysis, we begin by presenting a model that is based on [Kacperczyk et al. \(2025\)](#) to formalize the relationship between institutional ownership concentration and price informativeness. The model features heterogeneous assets and investors. Multiple risky assets of varying sizes are traded in the financial market. The market consists of two types of traders: atomless competitive traders (e.g., retail investors) who take prices as given when trading, and a number of oligopolistic institutional investors who recognize that their trades can move asset prices. The institutional investors differ in size, which determines the magnitude of their price impact. Additionally, the institutional investors can be classified as either active or passive. Active investors have the capacity to collect information and hence reduce uncertainty about asset payoffs when trading. In contrast, passive investors and retail investors do not possess any information-gathering capability. After active investors make their learning choices, all traders trade in the financial market.

Our theoretical contribution is not a new model framework per se; rather, we extend the model of [Kacperczyk et al. \(2025\)](#) to conduct two novel analyses, which better connects to our empirical analysis. First, we propose and explore a new institutional ownership concentration measure based on investors' asset demand. In [Kacperczyk et al. \(2025\)](#), ownership concentration is measured by the primitive size distribution among institutional investors, which we refer to

as *size*-based ownership concentration. This can be empirically proxied using institutional investors' assets under management (AUM). Our new measure, termed *trading*-based ownership concentration, focuses on the asset demand of institutional investors. This measure is closely connected to investors' firm-level equity holding data, allowing us to leverage this rich dataset to enhance the power of our subsequent empirical analysis.

We find that as the size of large institutional investors increases while that of small institutional investors decreases (i.e., indicating higher size-based ownership concentration), the large investors demand even more risky assets, whereas small investors do the opposite. This pattern suggests higher trading-based ownership concentration. Consequently, [Kacperczyk et al.](#)'s size-based ownership concentration measure is positively related to our trading-based ownership concentration measure. Together with [Kacperczyk et al. \(2025\)](#)'s finding that higher size-based ownership concentration leads to lower price informativeness (i.e., the extent to which current prices predict future cash flows), we can conclude that our higher trading-based ownership concentration is also negatively related to price informativeness.

Second, compared to [Kacperczyk et al. \(2025\)](#), we explicitly differentiate and examine ownership concentration among active and passive investors. While passive investors do not engage in information gathering or informed trading, and thus their presence does not directly impact price informativeness, changes in their ownership concentration may indirectly affect price informativeness by influencing the trading decisions of active investors. Our numerical analysis indicates that it is the increase in ownership concentration among active investors, rather than that among passive investors, that depresses price informativeness. Therefore, we focus on ownership concentration among active investors in our empirical analysis.

We begin our empirical analysis by investigating the impact of size-based active ownership concentration. To quantify this concentration, we employ two metrics: the Herfindahl-Hirschman Index (HHI) of AUM among active institutional investors, and the share of AUM held by the top five active institutional investors. Across various model specifications, we observe a statistically significant and economically meaningful negative correlation between size-

based active ownership concentration and price informativeness, aligning with the predictions of [Kacperczyk et al. \(2025\)](#). For instance, a one percentage point increase in active ownership concentration is associated with a 25.7% decrease in price informativeness relative to its mean level. Furthermore, we explore whether this diminished informativeness affects real firm decisions. Our findings indicate that as active ownership concentration increases and depresses price informativeness, the capacity of current prices to predict future firm investment also declines.

Despite their significance and robustness, the results derived from size-based ownership concentration can be limited by the small sample size. Therefore, we shift our focus to the new trading-based ownership concentration measure. This measure is defined similarly to the size-based one but is based on investors' holdings in each stock. We examine the relationship between active ownership concentration and price informativeness at the stock level. Our findings reveal that the price informativeness of stocks with the highest active ownership concentration is significantly lower than that of stocks with the lowest concentration. This effect is both statistically and economically significant across short and long horizons. Additionally, we also observe a decline in the predictive power of current stock prices for future investment.

Furthermore, the loadings of passive ownership concentration in our specifications are unstable — varying from positive to negative, and significant to insignificant. This instability indicates that ownership concentration among passive investors does not drive our results, which aligns with our model's implications.

The above regression results might be difficult to interpret economically given the endogenous ownership structure. To address this concern, we leverage a quasi-natural experiment involving financial institution mergers. Specifically, the merger of two active institutional investors can lead to a plausibly exogenous increase in the active ownership concentration of any stocks held by both the acquirer and the target financial institutions. We find that for these stocks, the subsequent decrease in their price informativeness is significantly greater relative to other stocks held by one of the two merging parties.

To further solidify our findings, we conduct a series of robustness tests. Notably, the negative

relationship between active ownership concentration and price informativeness persists when we employ alternative common measures of price informativeness, including post-earnings-announcement drift (Ball and Brown, 1968), conditional probability of an information event (Duarte et al., 2020), informed trading intensity (Bogousslavsky et al., 2024), variance ratio (Lo and MacKinlay, 1988), and relative price informativeness (Dávila and Parlato, 2025). Moreover, our results also hold in an international context, extending beyond the U.S. market.

Finally, we investigate how active ownership concentration can undermine price informativeness by examining the information pass-through and learning effects, as outlined by Kacperczyk et al. (2025). First, the information pass-through effect suggests that as active institutional ownership becomes more concentrated, large active investors adopt conservative trading strategies to minimize their price impact. This effect is supported by empirical evidence showing that lower portfolio turnover occurs when investors hold large shares in these portfolio companies. Additionally, there is reduced information content in earnings announcements for stocks with concentrated active institutional ownership.

Second, the learning effect posits that the polarization of investor sizes hampers small investors' ability to diversify their learning, leading them to focus on assets with the largest supply. Using downloads from the Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system as a proxy for information acquisition, we find empirical evidence supporting this channel: An increased imbalance in EDGAR downloads between large and small stocks as ownership concentration rises. Together, both the information pass-through and learning effects contribute to the negative impact of active ownership concentration on price informativeness.

Our paper contributes to the literature on ownership structure. The study most closely related to ours is Kacperczyk et al. (2025), which develop a general equilibrium model to analyze the joint impact of the size, concentration, and active/passive ownership share of large investors on price informativeness. We provide the first empirical evidence for their predicted negative effect of size-based ownership concentration. Additionally, we extend their analysis by proposing a new trading-based ownership concentration measure. We predict a negative effect of this measure

on price informativeness and present compelling empirical evidence to support this prediction. More recently, [Gleбкин et al. \(2025\)](#) construct a non-CARA-normal model to examine how asset concentration among a few large investors affects asset prices and liquidity. However, their model abstracts from asymmetric information among investors.

Various empirical research examines the implications of ownership concentration for financial markets. [Greenwood and Thesmar \(2011\)](#) find that stocks with concentrated ownership exhibit increased fragility, being more vulnerable to non-fundamental risk as indicated by stock return volatility. Consequently, managerial expectations of potential future misvaluation due to this price fragility lead to elevated precautionary cash holdings and reduced investment ([Friberg et al., 2024](#)). [Porrás Prado et al. \(2016\)](#) demonstrate that ownership concentration results in increased short-selling restrictions due to the reluctance of blockholders to lend shares, fearing a loss of monitoring control. This creates supply-side barriers that impede arbitrageurs from correcting mispricings, thereby inhibiting the injection of negative information. [Massa et al. \(2021\)](#) analyze the effects of an anticipated increase in ownership concentration following the merger of BlackRock and Barclays Global Investors. They report that the expected rise in concentration prompts selling by shareholders, leading to negative impacts on both price levels and liquidity. [Huang et al. \(2024\)](#) demonstrate that in the corporate bond market, higher mutual fund ownership concentration leads to increased bond volatility. [Kacperczyk et al. \(2005\)](#) and [Ivković et al. \(2008\)](#) show that investors with informational advantages tend to hold concentrated portfolios, which can encourage information acquisition about illiquid, information-sensitive assets ([Sialm and Xu, 2023](#)).

Different from the general focus on firm-level ownership concentration irrespective of the institution size, [Ben-David et al. \(2021\)](#) investigate the implications of ownership concentration among the top-10 largest institutional investors at the market level. They show that large institutions are granular, in the sense that capital flows and trading strategies are correlated across different entities within the same institution. Such granularity reduces diversification of idiosyncratic shocks and induces higher price volatility. Finally, rather than ownership concentration,

Cen et al. (2024) examine the concentration of data scientists across all institutional investors holding a stock. They find that this concentration negatively affects price informativeness via the competition effect.

We contribute to these prior studies by exploring the effect of ownership concentration, particularly among active investors, on price informativeness and investment-to-price sensitivity. Importantly, we document a distinct mechanism through the learning and trading decisions of active investors. This is distinct from other drivers such as the exposure to non-fundamental demand shocks (Greenwood and Thesmar, 2011; Friberg et al., 2024; Huang et al., 2024), the role of short selling (Porrás Prado et al., 2016), investors' responses to anticipated changes in ownership concentration (Massa et al., 2021), or the traits of granularity embedded in large institutions (Ben-David et al., 2021).

In addition to ownership concentration, other features of ownership structure affecting price informativeness have been studied, such as the total size of institutional ownership (Boehmer and Kelley, 2009), passive ownership (Bennett et al., 2020; Coles et al., 2022; Sammon, 2024), short-term ownership (Yan and Zhang, 2009), socially responsible institutional ownership (Cao et al., 2023), and intermediaries' liability structures (Coppola, 2024). Our research differs by focusing on ownership concentration and utilizing a welfare-based measure of price informativeness (Bai et al., 2016; Kacperczyk et al., 2021), which assesses the predictability of future earnings from current market prices. Unlike commonly used price-based efficiency measures, this approach aligns closely with our theoretical framework and facilitates examination of the real effect of price informativeness on investment decisions (Bond et al., 2012; Goldstein, 2023).

The rest of the paper is organized as follows. Section 2 presents a theoretical framework and hypotheses to guide the ensuing empirical investigation. Section 3 describes the data. Sections 4 and 5 present the main empirical findings using size- and trading-based ownership concentration measures, respectively. Section 6 delves into an analysis of the underlying mechanism. Section 7 concludes.

2 A Model of Ownership Concentration and Price Informativeness

In this section, we present a theoretical model based on [Kacperczyk, Nosal, and Sundaresan \(2025\)](#) to formalize the relationship between institutional ownership concentration and price informativeness. Our contribution is not the model per se, but rather a novel analysis conducted within the economy established by [Kacperczyk et al. \(2025\)](#), which more effectively informs our empirical analysis. First, we develop and explore a new *trading*-based ownership concentration measure, which is different from the *size*-based measure as defined by [Kacperczyk et al. \(2025\)](#). This trading-based concentration measure aligns closely with the firm-level investor holding data utilized in our empirical analysis. Second, to further explore the underlying mechanisms, we differentiate ownership concentration between active and passive investors and analyze their respective effects on price informativeness.

2.1 Setup

The model features a unit continuum of investors and multiple assets. There are three dates: $t = 0, 1$, and 2 . At date 0 , investors acquire private information about the assets. At date 1 , investors trade in the asset markets. At date 2 , the assets pay off and all investors consume.

Assets. There are one risk-free asset and $n \geq 1$ risky assets. The price of the risk-free asset is normalized to 1 and its gross return is r . It is in unlimited supply. Each risky asset is traded at an endogenous price $\tilde{p}_i$ per unit at date 1 and it pays an uncertain cash flow $\tilde{z}_i \sim N(\bar{z}, \sigma_i^2)$ at date 2, with $\bar{z} > 0$ and $\sigma_i > 0$. The total supply of risky asset i is $\tilde{x}_i \sim N(\bar{x}_i, \sigma_{xi}^2)$, with $\bar{x}_i > 0$ and $\sigma_{xi} > 0$, which is independent across assets and of all other random variables in the model.

Investors and trading. There is a continuum of investors, indexed by $j \in [0, 1]$. Investors allocate information capacity across assets at date 0, trade assets at date 1, and consume at date 2. All investors derive expected utility over their date-2 wealth according to a mean-variance

utility with a common risk-aversion coefficient $\rho > 0$. Without loss of generality, we normalize investors' initial wealth to be zero.

The continuum of investors is divided into two groups, retail and institutional investors, which differ in their price impacts. Specifically, a mass $\lambda_0 < 1$ of investors is competitive atomistic uninformed investors, i.e., retail investors, indexed collectively by $j = 0$. The others are oligopolists, i.e., institutional investors, who behave strategically and have price impacts. There are a number l of oligopolistic investors; each, indexed by $j \in \{1, \dots, l\}$, has information-gathering capacity K_j and size λ_j such that $\sum_{j=1}^l \lambda_j = 1 - \lambda_0$. The sizes of the oligopolistic investors, parameterized by λ s, are mapped monotonically to ownership, serving as proxies for ownership shares, which in turn influence investors' price impact.

Following [Kacperczyk et al. \(2025\)](#), within the institutional category, we further classify investors into the following four distinct types, based on their size and information-gathering capacity: (i) Large active investors (*LA*) who have large size λ_j and large capacity K_j ; (ii) large passive investors (*LP*) who have a large size but zero capacity; (iii) small active investors (*SA*) who have a small size and lower capacity than large active investors; and (iv) small passive investors (*SP*) who have a small size and zero capacity.

Prior to trading, at date 0, active investors ($j \in SA \cup LA$), who own positive information-gathering capacity, can acquire private signals about the risky asset payoffs. Investor j 's signal about the asset fundamental $\tilde{z}_i$ takes the form $\tilde{z}_i = \tilde{s}_{ji} + \tilde{\delta}_{ji}$, where $\tilde{\delta}_{ji}$ represents information loss due to the learning capacity constraint and is independent of the signal $\tilde{s}_{ji}$. For retail and passive investors, $\tilde{s}_{ji} = \bar{z}$.

Denote the vector of asset fundamental $\tilde{z} = (\tilde{z}_1, \dots, \tilde{z}_n)$, the vector of asset prices $\tilde{p} = (\tilde{p}_1, \dots, \tilde{p}_n)$, and investor j 's private signal about the assets $\tilde{s}_j = (\tilde{s}_{j1}, \dots, \tilde{s}_{jn})$. Investor j 's information set is $\mathcal{F}_j$. Following [Kacperczyk et al. \(2025\)](#), active and retail investors learn from prices, whereas passive investors do not.¹ Since only active investors can acquire private signals about assets, we have $\mathcal{F}_j = \{\tilde{p}, \bar{z}\}$ for $j = 0$, $\mathcal{F}_j = \{\tilde{p}, \tilde{s}_j\}$ for $j \in LA \cup SA$, and $\mathcal{F}_j = \{\bar{z}\}$ for

¹As in [Kacperczyk et al. \(2025\)](#), our model implications remain robust whether passive investors are allowed to update based on prices or are redefined as pure indexers trading the market portfolio.

$j \in LP \cup SP$. In the date-1 asset market, investor j chooses demand $\{q_{ji}\}_{i=1}^n$ for the risky assets to maximize the following mean-variance utility:

$$U_j = E \left[\sum_{i=1}^n q_{ji}(\tilde{z}_i - r\tilde{p}_i) \mid \mathcal{F}_j \right] - \frac{\rho}{2} \text{Var} \left[\sum_{i=1}^n q_{ji}(\tilde{z}_i - r\tilde{p}_i) \mid \mathcal{F}_j \right]. \quad (1)$$

Learning capacity. At date 0, active investors can acquire private signals about the risky assets. The quality of the private signals is constrained by each investor's capacity to process information, $K_j \geq 0$, which places a limit on the reduction of uncertainty about asset payoffs. Define $\alpha_{ji} \equiv \frac{\text{Var}[\tilde{z}_i]}{\text{Var}[\tilde{z}_i | \tilde{s}_{ji}]}$ as an investor j 's learning choice for asset i . Following [Kacperczyk et al. \(2016\)](#), we impose a linear capacity constraint such that the sum of the uncertainty reduction must not exceed the information capacity:

$$\sum_{i=1}^n \alpha_{ji} \leq n + 2K_j. \quad (2)$$

As evident in (2), higher capacity K_j implies more resources to gather and process information about different assets, and it translates into signals that track the realized payoffs with higher precision. For retail and passive investors who lack any information capacity ($K_j = 0$ for $j = 0$ or $j \in SP \cup LP$), it is immediate that $\alpha_{ji} = 1$. At date 0, given other active investors' information choices, active investor j chooses her capacity allocation $\{\alpha_{ji}\}_{i=1}^n$ to maximize the ex-ante expected utility $E[U_j]$.

2.2 Equilibrium

The economy is defined by a tuple of exogenous parameters $\mathcal{E} = \{n, l, r, \rho, \{\tilde{z}_i\}_{i=1}^n, \{\sigma_i\}_{i=1}^n, \{\bar{x}_i\}_{i=1}^n, \{\sigma_{xi}\}_{i=1}^n, \{K_j\}_{j=1}^l, \{\lambda_j\}_{j=0}^l\}$. An equilibrium consists of active investors' date-0 information allocation strategies, $\{\alpha_{ji}^*\}_{j=1, \dots, l; i=1, \dots, n}$, all investors' date-1 trading strategies $\{q_{ji}(\tilde{s}_{ji}, \tilde{p}_i)\}_{j=1, \dots, l; i=1, \dots, n}$, and date-2 price functions $\{\tilde{p}_i\}_{i=1}^n$ such that

- (i) Active investors' information allocation strategies $\{\alpha_{ji}^*\}_{j=1, \dots, l; i=1, \dots, n}$ form a Nash equilib-

rium: $\alpha_{ji}^* = \arg \max_{\alpha_{ji}} E[U_j(q_{ji}(\tilde{s}_{ji}, \tilde{p}_i), q_{j'i}(\tilde{s}_{j'i}, \tilde{p}_i))]$ where $j, j' \in LA \cup SA$ and $j' \neq j$, subject to the constraint (2);

(ii) The trading strategies $\{q_{ji}(\mathcal{F}_j)\}_{j=1}^l$ form a Bayesian-Nash equilibrium in the asset market:

$$q_{ji}(\mathcal{F}_j) = \arg \max_{q_{ji}} E[U_j(q_{ji}, q_{j'i}(\mathcal{F}_{j'})) \mid \mathcal{F}_j] \text{ for } \forall j, \text{ where } j' \neq j;$$

(iii) The price $\tilde{p}_i$ clears the market for asset i , where $i \in \{1, \dots, n\}$: $\sum_{j=0}^l \lambda_j q_{ji} = \tilde{x}_i$.

Trading decisions. As is standard in the literature (e.g., Kyle, 1989), we consider the following linear demand schedule of investor j for asset i in the date-1 financial market:

$$q_{ji} = \beta_{0ji} + \beta_{1ji} \tilde{s}_{ji} - \beta_{2ji} r \tilde{p}_i, \quad (3)$$

where the β -coefficients are endogenously determined in equilibrium. At date 1, investors choose their demand $\{q_{ji}\}$ to maximize the utility in equation (1). The solution to the problem depends on whether the investor is an oligopolistic or a retail investor, with their optimal demand respectively given as follows:

$$q_{ji} = \frac{\mu_{ji} - r \tilde{p}_i}{\rho \hat{\sigma}_{ji}^2 + r \frac{d\tilde{p}_i}{dq_{ji}}} \text{ for oligopolists and } q_{0i} = \frac{\mu_{0i} - r \tilde{p}_i}{\rho \hat{\sigma}_{0i}^2} \text{ for retail investors,} \quad (4)$$

where the conditional moments $\mu_{ji} \equiv E[\tilde{z}_i \mid \mathcal{F}_j]$ and $\hat{\sigma}_{ji}^2 \equiv Var[\tilde{z}_i \mid \mathcal{F}_j]$ are computed using Bayes' rule. Here, oligopolists internalize their price impact when making trading decisions, introducing a wedge $\frac{d\tilde{p}_i}{dq_{ji}}$ into the otherwise standard Constant Absolute Risk Aversion (CARA) demand function. Given the linear demand (3) and the market clearing condition, the price impact of oligopolist j on asset i is $\frac{d\tilde{p}_i}{dq_{ji}} = \frac{\lambda_j}{r \sum_{k=-j} \lambda_k \beta_{2ki}}$. Moreover, the demand by the retail investors does not move the price and thus takes the standard form.

Given (4) and the market-clearing condition, investors' demand schedules (3), conditional on

active investors' information choices at date 0, can be summarized by a fixed point of the system:

$$\begin{aligned}\beta_{0ji} &= \frac{-\frac{\gamma_{ji}}{\Delta_i} \left(-\bar{x}_i + \sum_{k=0}^l \lambda_k \beta_{0ki} + \sum_{k \neq j} \lambda_k \beta_{1ki} \frac{1}{\alpha_{ki}} \bar{z} \right)}{\rho \hat{\sigma}_{ji}^2 + r \frac{d\bar{p}_i}{dq_{ji}}}, \\ \beta_{1ji} &= \frac{1 - \frac{\gamma_{ji}}{\Delta_i} \left(\lambda_j \beta_{1ji} + \sum_{k \neq j} \lambda_k \beta_{1ki} \left(1 - \frac{1}{\alpha_{ki}} \right) \right)}{\rho \hat{\sigma}_{ji}^2 + r \frac{d\bar{p}_i}{dq_{ji}}}, \\ \beta_{2ji} &= \frac{1 - \frac{\gamma_{ji}}{r}}{\rho \hat{\sigma}_{ji}^2 + r \frac{d\bar{p}_i}{dq_{ji}}},\end{aligned}$$

where $\gamma_{ji} \equiv \frac{\text{Cov}_j(\bar{z}_i, \bar{p}_i)}{\text{Var}_j(\bar{p}_i)}$ is used by investors to update their beliefs after observing prices and $\Delta_i \equiv r \sum_{j=0}^l \lambda_j \beta_{2ji}$ is the size-weighted sensitivity of investor demand to prices. For retail investors, there is no price impact, i.e., $\frac{d\bar{p}_i}{dq_{0i}} = 0$. For passive investors, without any information, $\gamma_{ji} = 0$ and the system simplifies to:

$$\beta_{0ji} = 0 \text{ and } \beta_{1ji} = \beta_{2ji} = \frac{1}{\rho \hat{\sigma}_{ji}^2 + r \frac{d\bar{p}_i}{dq_{ji}}}. \quad (5)$$

Information-acquisition decisions. We move backward to date 0 to characterize active investors' information acquisition decisions (noting that $\alpha_{ji} = 1$ for $j \in SP \cup LP \cup \{0\}$). Given other active investors information choices $\{\alpha_{j'i}\}_{j' \neq j}$, active investor j chooses $\{\alpha_{ji}\}$ to maximize their expected utility $E[U_j]$, subject to the constraint (2). In other words, each active investor's information choice is a best response to the choices made by other active investors. The equilibrium information choices arise from the interplay of these best responses.

Informativeness and concentration. Our analysis centers on the relationship between ownership concentration and price informativeness. Price informativeness measures the amount of information incorporated into asset prices. Following [Bai et al. \(2016\)](#) and [Kacperczyk et al. \(2025\)](#), we measure it as the covariance of the price with the asset fundamental, normalized by the volatil-

ity of the price:

$$PI_i \equiv \frac{Cov(\tilde{p}_i, \tilde{z}_i)}{\sqrt{Var(\tilde{p}_i)}} = \frac{\sigma_i \sum_{j=0}^l \omega_{ji} (1 - \frac{1}{\alpha_{ji}})}{\sqrt{\frac{\sigma_{x_i}^2}{\sigma_i^2} + \left(\sum_{j=0}^l \omega_{ji} (1 - \frac{1}{\alpha_{ji}}) \right)^2 + \sum_{j=0}^l \omega_{ji}^2 \frac{\alpha_{ji}-1}{\alpha_{ji}^2}}}, \quad (6)$$

where $\omega_{ji} \equiv \frac{\partial \lambda_j q_{ji}}{\partial s_{ji}} = \lambda_j \beta_{1ji}$, capturing investors' trading aggressiveness on their signals. This measure of price informativeness maps well to our framework, since the square root of the reduction in the variance of posterior beliefs of a Bayesian agent captures their learning from the price. In addition, [Bai et al. \(2016\)](#) have shown that it can be derived as a welfare measure under the Q-theory.

Based on (6), price informativeness is shaped by two key variables. First, ω_{ji} captures how an oligopolist's total demand for asset i responds to her private signal s_{ji} , which is referred to as the information pass-through effect in [Kacperczyk et al. \(2025\)](#). Second, α_{ji} captures an oligopolist's learning choices, which is termed the learning effect by [Kacperczyk et al. \(2025\)](#).

Depending on the category of institutional investors, we can define ownership concentration among active, passive, or total institutional investors. As will be discussed in Section 2.3.4, it is the learning and trading of active investors that drive price informativeness; thus, we will focus on active investors. We explore two layers of ownership concentration. First, we follow [Kacperczyk et al. \(2025\)](#) to measure the concentration among active investors based on their size:

$$ActHHI_{size} = \sum_{j \in SAULA} \left(\frac{\lambda_j}{\sum_{k \in SAULA} \lambda_k} \right)^2. \quad (7)$$

Second, we introduce a new ownership concentration measure, which is constructed based on investors' endogenous asset demand $\{q_{ji}\}$:

$$ActHHI_{trading} = \sum_{j \in SAULA} \left(\frac{\lambda_j E[|q_{ji}|]}{\sum_{k \in SAULA} \lambda_k E[|q_{ki}|]} \right)^2. \quad (8)$$

Given the static nature of our model, investors' asset demand can also serve as a proxy for their

asset holdings. Consequently, this measure enables us to leverage the extensive firm-level holding data and the resulting variation in our empirical analysis.

2.3 Numerical Results

We follow [Kacperczyk et al. \(2025\)](#) and conduct numerical analysis to derive model implications of institutional ownership concentration for price informativeness. We will test these implications in the subsequent sections.

2.3.1 Parameter Choices

The values of parameters used in our numerical analysis are summarized in Table 1. Specifically, following [Kacperczyk et al. \(2025\)](#), we set the asset payoff distribution to $\bar{z}_i = 10$ and $\sigma_i = 1$ for all i , the number of assets to $n = 5$, and the number of oligopolists to $l = 20$. Moreover, the volatility of asset supply, σ_{xi} , is chosen with a target coefficient of variation of 0.2 for all i . The risk-free rate is set to match the real return of 2.5% on 3-month T-bills. The risk aversion coefficient ρ is 2.32, and the learning capacity is $K_j = 12.5$ for large active oligopolists and $K_j = 1.25$ for small oligopolists. The supply of risky assets, $\bar{x}_i$, is linearly distributed between 3 and 6, featuring a narrower range between the largest and smallest assets compared to that in [Kacperczyk et al. \(2025\)](#). This setup allows for the smallest asset to be learned.

In addition, our investor mass $\{\lambda_j\}_{j=0}^l$ is set to match the empirical ownership distribution. Specifically, we choose the retail ownership $\lambda_0 = 40\%$ to reflect the fact that institutional ownership has fluctuated between 55% and 65% over the past two decades based on the 13F holding data (note that our results are robust if this value is varied between 35% and 45%). The remaining 60% institutional holdings are allocated among 20 oligopolists.

As in [Kacperczyk et al. \(2025\)](#), half of the oligopolists are active and the other half are passive. Within the active or passive group, 2 oligopolists are assumed to be large, and the other 8 oligopolists are assumed to be small. That is, $LA = \{1, 2\}$, $LP = \{3, 4\}$, $SA = \{5, \dots, 12\}$, and $SP = \{13, \dots, 20\}$. Furthermore, the relative size within each small group is set to be linearly

distributed between 1 and 5. That is, the largest small active oligopolist is five times larger than the smallest one; the same is true for small passive oligopolists.

For passive ownership, [Kacperczyk et al. \(2025\)](#) assume that the size of the passive sector is 20% of total institutional ownership based on the index fund share published in the Investment Company Institute (ICI) Fact Book. However, index funds are not the only type of passive investor. Based on the closing volumes of index additions and deletions on the reconstitution days, [Chinco and Sammon \(2024\)](#) estimate that passive investors held around 30% of the U.S. stock market in the past decade. Thus, in our model, with 40% retail ownership, the passive sector is around 50% of total institutional ownership, that is, $\sum_{j \in SP \cup LP} \lambda_j / \sum_{j=1}^l \lambda_j = 30\% / 60\% = 50\%$ (note that our results remain robust if we vary the value between 20% and 60%).

Finally, to study the effect of institutional ownership concentration on price informativeness, we follow [Kacperczyk et al. \(2025\)](#) and generate different concentration levels by varying two sets of parameters to produce an increasing HHI index for oligopolistic ownership. First, we vary the relative size of the two large active oligopolists and the two large passive oligopolists by increasing the ratios λ_1/λ_2 and λ_3/λ_4 linearly from 1.1 to 10 across ten scenarios. Second, and simultaneously, we vary the relative size of the small sectors, given by $\sum_{j \in SA} \lambda_j / \sum_{j \in SA \cup LA} \lambda_j$ and $\sum_{j \in SP} \lambda_j / \sum_{j \in SP \cup LP} \lambda_j$, linearly from 10% to 3% across the same ten scenarios. These parameter changes mirror the empirical trend of an increasing relative size within the large sector and a concurrent decrease in the relative size of the small sector over time. The resulting distribution of λ_j across the ten calibration scenarios closely matches the data. For details, see Section [A](#) of the online appendix.

2.3.2 Ownership Concentration and Price Informativeness

To begin, in Figure [2](#), we plot the effect of size-based concentration $ActHHI_{size}$ among active oligopolists, as defined in equation (7), on price informativeness on an asset-by-asset basis. Consistent with Figure 10 of [Kacperczyk et al. \(2025\)](#), Panel (a) of Figure [2](#) shows that price informativeness of all assets decreases with higher size-based active ownership concentration. The

following hypothesis summarizes this result.

Hypothesis 1 (Size-based concentration). *Price informativeness is lower when the size-based active ownership concentration is higher.*

As large active investors increase in size, they tend to trade conservatively based on their private information, while smaller active investors exhibit the opposite behavior when they decrease in size. This shift in size distribution also influences how active investors allocate their capacity for information learning. Together, these factors shape price informativeness through their trading and learning decisions. We defer a detailed discussion of the underlying mechanisms to Section 2.3.4.

We next explore our new trading-based ownership concentration $ActHHI_{trading}$, as defined in equation (8), in Figure 3. This measure is specific to each asset. Analyzing all panels of Figure 3 for assets of varying sizes, we observe that higher trading-based ownership concentration is associated with a decline in individual price informativeness. Given the endogenous nature of this measure, i.e., calculated based on trading volume as shown in equation (8), the underlying driver of its effect on price informativeness must stem from the primitive investor size λ s.

To illustrate this point, Figure 4 plots the trading activity of the largest active investor alongside that of the other investors. Recall that the increase in $ActHHI_{size}$ is driven by the increase in the size λ_1 of the largest active institutional investor and the decrease in the sizes of other active institutional investors (see Table A1). Panel (a) shows that an increase in the size of the largest active investor leads to the investor's heightened trading activity across all risky assets, resulting in varying increases in the trading volume for different assets. Conversely, when the sizes of other active investors decrease, they exhibit a decline in trading volume across all assets, as illustrated in Panel (b) of Figure 4. So, as $ActHHI_{size}$ increases, more of the trades in each asset comes from the largest active investor, which implies that trading-based concentration $ActHHI_{trading}$ increases in size-based concentration $ActHHI_{size}$, as shown in Panel (c) of Figure 4. Combined with the negative price-informativeness effects of size-based ownership concentration, our findings suggest that trading-based ownership concentration is also negatively related to individual

price informativeness. This finding is summarized in the following hypothesis.

Hypothesis 2 (Trading-based concentration). *Price informativeness is lower when the trading-based active ownership concentration is higher.*

2.3.3 Active versus Passive Ownership Concentration

We have found that as active ownership concentration rises, price informativeness decreases. However, since we follow [Kacperczyk et al. \(2025\)](#) and increase ownership concentration for both active and passive investors in our numerical analysis, there is a concern that the observed decrease in price informativeness might be attributed to the increasing ownership concentration among passive investors, rather than active investors.

Although passive investors lack learning capacity, they can indirectly influence price informativeness by affecting the trading decisions of active investors. For example, as large passive investors become larger while small passive investors become smaller, the former group becomes less responsive to price changes, whereas the latter group exhibits greater responsiveness (as shown in equation (5), the coefficient β_2 decreases as price impact $d\tilde{p}_i/dq_{ji}$ increases). Due to the larger size of large passive investors, the overall passive sector tends to trade less aggressively in response to price changes. Consequently, active investors become increasingly concerned about their own price impact and hence, trade less aggressively based on their private information, which ultimately leads to a decrease in price informativeness.

To evaluate the effect of passive ownership concentration, we conduct two placebo tests by respectively fixing the size distribution for active and passive investors throughout the experiment. For the first placebo test (with a similar approach for the second), the relative size of the two large active investors, λ_1/λ_2 , is fixed at 1.1, as in the first scenario. Meanwhile, the relative size of the small active sector, $\sum_{j \in SA} \lambda_j / \sum_{j \in SA \cup LA} \lambda_j$, is fixed at 0.10. This ensures that ownership concentration among active investors remains constant across ten scenarios, while ownership concentration among passive investors increases.²

²Passive ownership concentration is defined similarly to equations (7) and (8), but with active investors replaced

Figures 5 and 6 illustrate the results of our placebo tests using size-based and trading-based ownership concentration, respectively. We find that as passive ownership concentration increases, either size-based or trading-based, price informativeness remains relatively unchanged. In contrast, when active ownership concentration increases, price informativeness decreases, following a pattern quantitatively similar to that observed in Figures 2 and 3. This indicates that it is indeed active ownership concentration that drives the observed results, rather than passive ownership concentration.

2.3.4 Mechanisms

Following Kacperczyk et al. (2025), we attribute the effect of ownership concentration on price informativeness to two forces pertaining to investors' trading and learning behaviors, respectively.

Information pass-through effect. We follow Kacperczyk et al. (2025) and decompose the overall effect into information pass-through effect and learning effect. The first effect refers to investors' trading aggressiveness on their private signals, represented by $\omega_{ji} \equiv \frac{\partial \lambda_j q_{ji}}{\partial s_{ji}} = \lambda_j \beta_{1ji}$. The second effect concerns investors' information acquisition choices, captured by parameter α_{ji} . We examine the information pass-through effect by fixing the degree of learning (α_{ji}) at the level in the first scenario of the concentration experiment and the learning effect by holding the information pass-through (ω_{ji}) fixed at values from the same first scenario. Panels (a) and (b) of Figure 7 present these results.

Firstly, as shown in Panel (a) of Figure 7, when learning (α_{ji}) is fixed, as large active investors grow in size, they trade more conservatively on their private signals (captured by β_1) due to the increasing price impact concern. On the other hand, small active investors may trade more aggressively on their private signals as their price impact concerns decrease. However, their economic importance diminishes as they shrink in size (captured by λ). Taken together, the dropping information pass-through drives the price informativeness down. These results are

by passive investors. Formally, $PaSHHI_{size} = \sum_{j \in SPULP} \left(\frac{\lambda_j}{\sum_{k \in SPULP} \lambda_k} \right)^2$.

summarized as follows:

Hypothesis 3 (Information pass-through effect). *When active ownership concentration is higher, large active investors tend to trade more conservatively based on their information, leading to a lower average trading intensity across all active investors.*

Learning effect. When information pass through (ω_{ji}) is fixed, large active investors diversify their learning as they grow in size. In contrast, small active investors, as they decrease in size, tend to specialize their learning in large assets. The pattern in Panel (b) of Figure 7 suggests that the specialized learning by small active investors dominate.

To further clarify why small active investors' specialized learning dominates in this learning effect, we compare the learning choices of the largest active investors with those of other active investors in Figure 8. As the largest active investor grows, she spreads her learning capacity across various assets. This increases the price informativeness of smaller assets (assets 1 and 2) and decreases the price informativeness of larger assets (assets 4 and 5). Conversely, other active investors shrink in size and thus focus their learning capacity on larger assets (assets 4 and 5). This reduces the price informativeness of smaller assets (assets 1 and 2) and increases the price informativeness of larger assets (assets 4 and 5). Overall, since the largest active investor has already diversified her learning in the beginning, her further diversification has a marginal impact on price informativeness. That is, the specialized learning by small active investors prevails, leading to the increasing price informativeness for large assets and decreasing price informativeness for small assets observed in Panel (b) of Figure 7. These results are summarized as follows:

Hypothesis 4 (Learning effect). *Higher active ownership concentration leads to increased learning in large assets and diminished learning in small assets, on average.*

2.3.5 Real Investment

Having established that price informativeness decreases as active ownership concentration increases, a natural follow-up question is whether this reduced informativeness extends to real

firm decisions, as discussed by [Bond et al. \(2012\)](#) and [Goldstein \(2023\)](#). Due to the complexity of our framework, we do not explicitly model how asset prices influence managers' investment decisions. Instead, we adopt the approach of [Subrahmanyam and Titman \(2001\)](#) and assume that as prices become less informative, they predict investment decisions less accurately.

Based on this assumption, along with Hypotheses 1 and 2, we anticipate that higher ownership concentration – whether size-based or trading-based – is likely associated with a lower association between prices and future investment. This leads us to the following hypothesis:

Hypothesis 5 (Real investment). *When active ownership concentration is higher, prices become less informative about future investment.*

3 Data and Measures

3.1 Sample Construction

Our main sample includes U.S.-listed companies with common stocks traded on the NYSE, NASDAQ, and AMEX. Firm-level financial statement data are sourced from Compustat, supplemented with the intangible capital estimates as defined in [Peters and Taylor \(2017\)](#) from WRDS. We obtain the stock price information from CRSP.

To construct measures of ownership concentration, we begin by extracting institutional holdings information from the Thomson Reuters 13F database. We then merge the 13F holdings data with the classification scheme by [Bushee \(1998\)](#) to identify active institutional investors. Following this, we construct ownership-related variables, such as active and passive institutional ownership concentration, for each firm-quarter or market-quarter.

For empirical tests regarding size-based ownership concentration, we construct ownership-related variables in the fourth quarter and merge them with price informativeness measures, which will be introduced shortly. For empirical tests regarding trading-based ownership concentration, we construct ownership-related variables that are most recent to the end of each firm's

fiscal year and merge them with the firm-level financial statement data. Our samples are all of annual frequency and cover the period from 1980 to 2022.

Our sampling criteria are as follows. We exclude observations with a stock price below 1 dollar and observations with a market capitalization below 5 million. We exclude firms within the financial industry and firms with less than four successive years of accounting data. Further, we require that sample firms have at least one active institutional investor. For those empirical tests using the trading-based concentration metrics, we tighten the requirement so that the sample firms have at least five active institutional investors to avoid extreme values of concentration, though our results persist if we relax the requirement to be one active institutional investor. Unless otherwise stated, our sample selection criterion is consistent throughout all following empirical analysis. Table 2 reports the summary statistics of the variables used in our main analysis. A comprehensive list of variable definitions is provided in Table B1 of the online appendix. All continuous variables are winsorized at the 1% and 99% levels to mitigate the influence of outliers.

3.2 Measures of Active Institutional Ownership Concentration

We follow the classification from Bushee (1998) to categorize institutions as active or passive investors, based on their historical investment behaviors.³ Specifically, there are three categories: (i) quasi-indexers, with low turnover and high diversification; (ii) transient investors, with high turnover and high diversification; and (iii) dedicated investors, with low turnover and low diversification. As in Kacperczyk et al. (2021), we classify transient and dedicated investors as active, while quasi-indexers as passive.

We first construct the size-based ownership concentration measure. In each quarter, we cal-

³Bushee’s classification has two versions, one is “permanent” and the other is “time-varying.” Following Appel, Gormley, and Keim (2016), we use the permanent version in our baseline results to avoid an institutional investor being classified as an active investor at some points but a passive investor at others. Our results remain if we use the time-varying classification, as shown in Table C3 in the online appendix. Moreover, institution here is at the management company level as recorded in 13F holdings data. This poses a challenge as a fund management company may oversee both passive and active mutual funds, potentially leading to measurement errors in the classification. To address this issue, we utilize fund-level holdings data from Thomson Reuters S12 as an alternative source to distinguish between active and passive mutual funds. The results are robust, as shown in Table C2 in the online appendix.

culate the asset under management (AUM) of each active institutional investor by adding up their holding value in their underlying securities. The first concentration measure refers to the Herfindahl-Hirschman Index of AUM among active institutional investors:

$$ActHHI_{size,q} = \frac{\sum_{j=1}^N (AUM_{j,q}^2)}{\left(\sum_{j=1}^N AUM_{j,q}\right)^2}, \quad (9)$$

where $AUM_{j,q}$ is the AUM of active institutional investor j in quarter q and N is the total number of active institutional investors. The second concentration measure calculates the proportion of AUM held by the top five active institutional investors relative to the total AUM of all active institutional investors:

$$ActTop5_{size,q} = \frac{\sum_{j=1}^{Top\ 5} AUM_{j,q}}{\sum_{j=1}^N AUM_{j,q}}. \quad (10)$$

We then construct the trading-based ownership concentration measure in a way similar to the size-based concentration measure, but using firm-level holding data:

$$ActHHI_{i,q} = \frac{\sum_{j=1}^{N_i} (S_{i,j,q}^2)}{\left(\sum_{j=1}^{N_i} S_{i,j,q}\right)^2} \text{ and } ActTop5_{i,q} = \frac{\sum_{j=1}^{Top\ 5} S_{i,j,q}}{\sum_{j=1}^{N_i} S_{i,j,q}}, \quad (11)$$

where $S_{i,j,q}$ denotes the equity shares of stock i owned by active institution j in quarter q and N_i is the number of active institutions holding stock i .

Both $ActHHI$ and $ActTop5$, whether size-based or trading-based, are designed to have values between 0 and 1, with 0 representing highly dispersed ownership and 1 representing highly concentrated ownership.

3.3 Measures of Price Informativeness

Our primary measure of price informativeness is based on [Bai, Philippon, and Savov \(2016\)](#), which is welfare-based and maps well to our theoretical framework. In Section C.1 of the online appendix, we also explore several alternative measures of price informativeness and demonstrate the robustness of our results. These measures include post-earnings-announcement drift ([Ball and](#)

Brown, 1968), conditional probability of an information event (Duarte et al., 2020), informed trading intensity (Bogousslavsky et al., 2024), variance ratio (Lo and MacKinlay, 1988), and relative price informativeness (Dávila and Parlato, 2025).

Following Bai et al. (2016), we first run cross-sectional regressions of future earnings on current market prices for each year:

$$\frac{E_{i,t+h}}{A_{i,t}} = a_{t,h} + b_{t,h} \log \left(\frac{M_{i,t}}{A_{i,t}} \right) + c_{t,h} \left(\frac{E_{i,t}}{A_{i,t}} \right) + d_{t,h}^s \mathbf{1}_{i,t}^s + \epsilon_{i,t,h}, \quad (12)$$

where h denotes the prediction horizons, which equals 1 or 3 in our study; $\mathbf{1}_{i,t}^s$ is a sector indicator defined as the one-digit SIC code; $M_{i,t}/A_{i,t}$ denotes the market price of firm i in fiscal year t , computed as the market capitalization at the end of March after year t , scaled by total assets in year t ; $E_{i,t+h}/A_{i,t}$ ($E_{i,t}/A_{i,t}$) denotes future (current) earnings, computed as cash flow in year $t+h$ (t) scaled by total assets in year t . Following Bai et al. (2016), we use earnings before interest and taxes (*EBIT*), earnings before interest, taxes, depreciation and amortization (*EBITDA*), and net income (*NI*) to measure firm cash flows. The average price informativeness in year t at prediction horizon h is then calculated as the forecasting coefficient $b_{t,h}$ in equation (12) multiplied by $\sigma_t(\log(M/A))$, the cross-sectional standard deviation of the scaled market price $\log(M/A)$ in year t :

$$PI_{t,h} = b_{t,h} \times \sigma_t(\log(M/A)). \quad (13)$$

Similarly, we estimate the investment-to-price sensitivity by firstly running cross-sectional regressions of future investment rates on current market prices for each year, and then multiplying the forecasting coefficient by $\sigma_t(\log(M/A))$:

$$\frac{I_{i,t+h}}{K_{i,t}} = a_{t,h} + b_{t,h} \log \left(\frac{M_{i,t}}{A_{i,t}} \right) + c_{t,h} \left(\frac{E_{i,t}}{A_{i,t}} \right) + d_{t,h} \left(\frac{I_{i,t}}{K_{i,t}} \right) + e_{t,h}^s \mathbf{1}_{i,t}^s + \epsilon_{i,t,h}, \quad (14)$$

where $I_{i,t+h}/K_{i,t}$ denotes investment rates as in Peters and Taylor (2017), including intangible

investment rate ($Intangible/K$), physical investment rate ($Physical/K$), and total investment rate ($Invest/K$). Specifically, intangible investment rate ($Intangible/K$) is calculated as $R\&D + 0.3 \times SG\&A$ expenses,⁴ scaled by total capital (K), where total capital is defined as the sum of net property, plant and equipment (item PPENT from Compustat) and intangible capital (item K_INT from Peters and Taylor (2017)). Physical investment rate ($Physical/K$) is calculated by dividing capital expenditures (CAPX) by total capital. Finally, the total investment rate ($Invest/K$) is the aggregate of intangible and physical investment rates. The predicted variation of real investment from prices in year t at prediction horizon h is then calculated as the forecasting coefficient $b_{t,h}$ in equation (14) multiplied by $\sigma_t(\log(M/A))$.

By conducting the cross-sectional regressions for each year, we are able to estimate a time-series set of price informativeness and investment-to-price sensitivity, and examine their relation with the size-based active institutional ownership concentration. However, the cross-sectional nature of this estimation makes it unsuitable for utilizing investors' firm-level equity holding data, as this holding data is panel data while price informativeness is time-series data. Kacperczyk et al. (2021) address this issue by modifying the cross-sectional regression into a pooled regression. Taken together, we use the cross-sectional regression model to estimate price informativeness when studying the effect of size-based concentration on price informativeness, and use the modified pooled regression model as detailed in Section 5.1 when studying the effect of trading-based concentration.

4 Size-based Ownership Concentration

In this section, we follow the approach developed by Bai et al. (2016) and Farboodi et al. (2022) to test Hypotheses 1 and 5. Specifically, we investigate the effect of size-based active ownership concentration on price informativeness and how current prices predict future investment. This analysis directly tests the implications from Kacperczyk et al. (2025).

⁴Only a small proportion of SG&A is related to investment in intangible organization capital, while the rest of SG&A is related to operating costs that support the current period's profits. The 30% is a rule of thumb used in prior studies (Eisfeldt and Papanikolaou, 2014; Peters and Taylor, 2017; Jha et al., 2024).

Firstly, we visually inspect the relationship between size-based active ownership concentration and price informativeness estimated from equation (13), using a one-year prediction horizon.⁵ Figure 9 presents scatter plots along with the fitted lines and the 95% confidence intervals. Panels (a1)-(a3) use $ActHHI_{size}$ in equation (9) to measure concentration, while Panels (b1)-(b3) use $ActTop5_{size}$ in equation (10) as an alternative measure. We observe a significantly negative correlation between size-based active ownership concentration and price informativeness across different specifications, consistent with Hypothesis 1 and its numerical analysis in Figure 2. Moreover, the effect is economically meaningful. For example, the correlation coefficient is -0.18 in Panel (a2) of Figure 9, suggesting that a one percentage point increase in $ActHHI_{size}$ is associated with a 25.7% decrease in price informativeness relative to its mean level of 0.007.

Secondly, we divide the sample firms into five groups based on their market capitalization, and estimate price informativeness for each group. Figure 10 presents the scatter plots along with the fitted lines. Two observations are worth noting. First, larger firms enjoy higher price informativeness on average, consistent with our numerical results in Figure 2. This is also consistent with Farboodi et al. (2022), which shows that data processing efforts in large firms are much higher than those in small firms. Second, the negative correlation between size-based ownership concentration and price informativeness holds for all size groups, suggesting that our results are not driven by any specific group of firms.

In addition, we examine how size-based active ownership concentration affects investment-to-price sensitivity. Consistent with Hypothesis 5, we observe a negative correlation between the concentration and investment-to-price sensitivity in all specifications in Figure 11, which is generally statistically significant except for Panel (b1). This implies that as active ownership concentration depresses price informativeness, the ability of prices to predict investment diminishes.

Finally, despite the significance and robustness of these results, we are aware of their limitations. For instance, the sample size is small due to the low data frequency (42 for $h = 1$ and 40 for $h = 3$), indicating that the point estimates might be sensitive to different empirical setups.

⁵This negative relation remains robust when we change the prediction horizon from one year to three years, as shown in Figures B1 and B2 in the online appendix.

In addition, some estimates of price informativeness in Figures 9 and 10 are negative, which is also observed in previous studies using the similar estimation process (e.g. Farboodi et al., 2022; Dávila and Parlato, 2025). These limitations thereby motivate and justify our further intensive exploration at the firm level, as will be presented in the next section.

5 Trading-based Ownership Concentration

In this section, we investigate the effect of our new trading-based active ownership concentration using the method developed by Kacperczyk et al. (2021). Specifically, Section 5.1 conducts baseline regressions. Section 5.2 addresses the endogeneity issue by examining the context of mergers among active financial institutions. Section 5.3 expands the sample to an international setting. Section C of the online appendix provides additional robustness analyses.

5.1 Baseline Regressions

To examine the effect of trading-based active ownership concentration on price informativeness as stated in Hypothesis 2, we follow Kacperczyk et al. (2021) and estimate the following pooled regression model using firm-level data at the annual frequency:

$$\begin{aligned} \frac{E_{i,t+h}}{A_{i,t}} = & a_h + b_h \log \left(\frac{M_{i,t}}{A_{i,t}} \right) + c_h \log \left(\frac{M_{i,t}}{A_{i,t}} \right) \times Concentration_{i,t} + d_h Concentration_{i,t} \\ & + e_h \frac{E_{i,t}}{A_{i,t}} + f_h \chi_{i,t} + g_h \log \left(\frac{M_{i,t}}{A_{i,t}} \right) \times \chi_{i,t} + F E_{i,t} + \varepsilon_{i,t+h}, \end{aligned} \quad (15)$$

where h denotes the prediction horizons, equaling 1 or 3 in this paper. $Concentration_{i,t}$ denotes the trading-based ownership concentration among active institutional investors, measured by $ActHHI$ or $ActTop5$ as defined in equation (11). $E_{i,t}/A_{i,t}$ is one of the three measures of earnings ($EBIT$, $EBITDA$, and NI), scaled by total assets. $\chi_{i,t}$ is a saturated set of control variables: passive ownership concentration ($PasHHI$ or $PasTop5$), calculated in the same way as active ownership concentration except that we use the holding information from passive institutional

investors; institutional ownership (*IO*), calculated as the total share holdings by institutional investors divided by the market capitalization; firm leverage (*Leverage*), defined as book debt divided by total assets; firms' total sales scaled by total assets (*Sale*); firms' cash holdings scaled by total assets (*Cash*). We include firm fixed effects to control for unobserved omitted firm characteristics correlated with both ownership concentration and price informativeness measures. We also include industry-year fixed effects to absorb time-varying economic or regulatory shocks at the industry level (Antón et al., 2023), defined based on the first two digits of SIC codes. $\varepsilon_{i,t+h}$ is the error term, double clustered at both firm and year levels to account for possible dependence along those two dimensions. The coefficients c_h are of interest, which measure the average price informativeness, defined as the sensitivity of future earnings to current stock prices, conditional on the active institutional ownership concentration.

Panel A of Table 3 uses *ActHHI* to measure the active institutional ownership concentration. In Columns (1)-(3), we use the scaled *EBIT*, *EBITDA*, and *NI* to measure earnings, respectively. The coefficient of interest, $c_{h=1}$, is statistically significantly negative at the 1% level. The effect is also economically significant. For example, $c_{h=1} = -0.030$ in Column (2), indicating that when *ActHHI* increases from the 25th to the 75th quantiles while other control variables stay constant at their mean levels, price informativeness decreases by 24.2%. In Columns (4)-(6), we perform the same estimation regression for price informativeness but at a 3-year prediction horizon. The coefficients $c_{h=3}$ remain significantly negative, and somewhat larger in magnitude. For example, the coefficient $c_{h=3} = -0.059$ implies that when *ActHHI* increases from the 25th to 75th quantiles, conditional on other control variables staying constant at their mean levels, price informativeness decreases by 40.6%.

Panel B of Table 3 replicates the results in Panel A, but employs *ActTop5* to measure active institutional ownership concentration. We continue to observe a significantly negative effect of trading-based active ownership concentration on price informativeness. The economic magnitude is comparable to that in Panel A. For instance, the coefficients $c_{h=1} = -0.040$ and $c_{h=3} = -0.063$ suggest that an interquartile range move in *ActHHI*, with other control vari-

ables held constant at their mean levels, corresponds to a decrease of 27.8% and 45.2% in price informativeness at the 1-year and 3-year prediction horizons, respectively. These results are consistent with Hypothesis 2 in Section 2.3.

We then estimate the effect of active institutional ownership concentration on investment-to-price sensitivity in a similar fashion to regression (15), but with the scaled earnings E/A replaced by investment rate I/K . Panel A of Table 4 uses $ActHHI$ to measure active institutional ownership concentration, while Panel B uses $ActTop5$ instead. The coefficients on the interaction term, $\log(M/A) \times Concentration$, are negative and statistically and economically significant across different specifications. Take the results related to physical investment in Columns (2) and (5) of Panel A in Table 4 for example. The coefficients $c_{h=1} = -0.023$ and $c_{h=3} = -0.025$ suggest that when $ActHHI$ rises from the 25th to the 75th quantiles, with other control variables held constant at their mean levels, investment-to-price sensitivity decreases by 10.7% and 12.6% at the 1-year and 3-year prediction horizons, respectively. The results suggest that the predictive power of the current stock price for future investment decisions is poorer for firms with more concentrated active institutional ownership, consistent with Hypothesis 5 in Section 2.3.

Finally, we have controlled for passive ownership concentration in all specifications. This control does not alter the negative effect of active ownership concentration on price informativeness. Additionally, the effect of passive ownership concentration on price informativeness is empirically inconsistent across specifications. For example, using post-earnings-announcement drift as an alternative measure of price informativeness (Table C1 in the online appendix), we find that passive ownership concentration is associated with increased price informativeness, contrary to the results presented in Table 3. Similarly, when utilizing S12 mutual fund holdings to construct the concentration measure (Table C2 in the online appendix), the coefficients on the interaction terms $\log(M/A) \times PasHHI$ and $\log(M/A) \times PasTop5$ are unstable, fluctuating between positive and negative and varying from significant to insignificant. These inconsistent results largely align with our model, indicating that passive ownership concentration does not exert a meaningful impact on price informativeness.

5.2 Identification

One potential concern is that the observed negative effect of active ownership concentration might be attributable to unobservable economic forces correlated with both ownership concentration and its price informativeness. Another concern suggests that firms with lower price informativeness and, consequently, greater exploitable mispricing opportunities may attract more institutional blockholders. We address these potential endogeneity issues utilizing a quasi-natural experiment of financial institution mergers, generating plausibly exogenous variation in a firm’s ownership structure. Our DiD estimation methodology not only attenuates the endogeneity issue, but also addresses the measurement error concern in concentration measures, since the estimation of $b_{3,h}$ does not rely on the ownership concentration measures.

As [He and Huang \(2017\)](#) elucidated, the experiment of institutional mergers hinges on the premise that the reasons for mergers are often unrelated to the fundamentals of their portfolio holdings. Upon merging, the acquirer typically assumes control of the target’s existing portfolios and retains these acquired holdings for an extended duration, owing to liquidity and transaction cost considerations. Consequently, if a firm is held by both an active acquirer and an active target prior to the merger, we anticipate an exogenous surge in its active institutional ownership concentration immediately following the merger.

We assemble a sample of financial institution mergers, adhering broadly to the criteria delineated in the literature on cross-ownership (e.g., [He and Huang, 2017](#); [Lewellen and Lowry, 2021](#); [Levonyan and Mengano, 2024](#)). First, we retrieve all mergers announced between 1980 and 2021 from the SDC mergers and acquisitions database. Second, we require that (i) the target firm is incorporated in the U.S.; (ii) both the acquirer and target are in the finance industry; (iii) firm names are accessible for both merger participants. Third, for each target and acquirer firm across these deals, we employ text-matching algorithms to align firm names with the 13F data.⁶ Upon merging the SDC and 13F data, we further mandate that either the target firm ceases filing 13F

⁶SDC provides firm names in three forms: the Company, the Immediate Parent Company, and the Ultimate Parent Company. While the three names are largely identical for most companies, discrepancies may arise for some. We utilize all three names in matching SDC mergers with 13F data.

statements within 15 months of the merger’s completion date, or the target’s AUM diminish by over 80% from quarter–6 to quarter 6 relative to the completion quarter.

In addition to the above data cleaning procedures, we implement several modifications to align the setting more closely with our research focus. We require the acquirer’s AUM to exceed 100 million dollars and increase by at least 1.5 times from quarter–6 to quarter 6 relative to the completion quarter. Also, we require both merger partners to be active according to Bushee’s classification. This process yields a sample of 11 active financial institution mergers, as detailed in Table B2 in the online appendix.

For each of the 11 mergers, we define treated firms as those held by both partners prior to the merger announcement.⁷ To preclude trivial holding positions, we also require that each partner’s holding value exceeds 0.01% of the stock’s market capitalization. We define control firms as those held by either the acquirer or the target, amounting to at least 0.01% of the market capitalization before the merger announcement. This strategy for selecting control firms accounts for institutional heterogeneity, such as managerial styles or abilities (Kini et al., 2024).⁸ To mitigate potential estimation bias stemming from the “bad comparisons” problem, as discussed by Baker et al. (2022), we exclude firms in the control group that had been treated by any of the other merger events. The final sample includes 700 unique treated firms and 2130 unique control firms. To zoom in on the merger shock, we restrict our analysis to the window of 2 years before and 2 years after mergers.⁹

We first check the validity of our DiD design by examining whether active financial institution mergers induce significant increases in active institutional ownership concentration. Specifically,

⁷We utilize the announcement date, rather than the completion date, to ensure that the treatment and control samples are defined using only ex-ante information (Lewellen and Lowry, 2021).

⁸We consider an alternative strategy for selecting control firms in Table B3 in the online appendix, where control firms are defined as those held by the acquirer but not the target, with a 0.01% or greater ownership prior to the merger announcement. The results remain virtually identical.

⁹Table B4 in the online appendix shows that our results are robust to an alternative estimation window from 3 years before to 3 years after mergers.

we run the following regression model on the quarterly basis:¹⁰

$$Concentration_{i,q} = \alpha + \beta Post_q \times Treat_i + Merger \times FE_{i,q} + \epsilon_{i,q},$$

where $Concentration_{i,q}$ denotes the trading-based ownership concentration among active institutional investors, measured by $ActHHI$ and $ActTop5$; $Treat$ is a dummy variable equal to 1 for treated firms and zero for control firms; $Post$ is, for any given merger event, a dummy variable equal to one for the merger completion quarter and all quarters after and zero for the quarters before; $Merger \times FE_{i,q}$ denotes the merger-firm and merger-quarter fixed effects, as per [He and Huang \(2017\)](#). Our regression model, with the “never-treated” requirement on the control group, aligns with the stacked regression estimator approach discussed by [Baker et al. \(2022\)](#) and adopted in recent studies (e.g., [Cengiz et al., 2019](#); [Hollingsworth et al., 2024](#)). Standard errors, $\epsilon_{i,q}$, are clustered two ways at the firm and quarter levels.

Panels A of Table 5 reports the results on post-merger changes in the two concentration measures, $ActHHI$ and $ActTop5$. We document that both concentration measures significantly increase following active financial institution mergers across different event windows, specifically $(-8, +8)$ and $(-12, +12)$ quarters. We conclude that active financial institution mergers provide a valid quasi-natural experiment, creating an exogenous and positive shock to ownership concentration among active institutional investors.

Next, we investigate the merger shock’s impact on price informativeness by estimating the subsequent regression model based on annual accounting information:

$$\begin{aligned} E_{i,t+h}/A_{i,t} = & a + b_{1,h} \log(M/A)_{i,t} + b_{2,h} Treat_i \times Post_t + b_{3,h} \log(M/A)_{i,t} \times Treat_i \times Post_t \\ & + b_{4,h} \log(M/A)_{i,t} \times Treat_i + b_{5,h} \log(M/A)_{i,t} \times Post_t \\ & + b_{6,h} \chi_{i,t} + b_{7,h} \log(M/A)_{i,t} \times \chi_{i,t} + Merger \times FE_{i,t} + \varepsilon_{i,t+h}. \end{aligned}$$

¹⁰The results remain robust if we calculate the mean values of $Concentration_{i,q}$ within each firm-year and re-run the regression model on an annual basis.

$Post$ is, for any given merger event, a dummy variable equal to one for the merger completion year and all years after and zero for the years before. We include merger-firm and merger-year fixed effects to absorb time-invariant characteristics across firms within the same merger as well as time-varying common time trends across mergers. We cluster standard errors by firm and year. The regression model for estimating the shock’s effect on investment-to-price sensitivity is similar, except that we replace the cash flow variables E/A with the investment variables I/K . Our coefficient of interest is $b_{3,h}$, which measures this sensitivity around the treatment group’s shock relative to the control group.

Panels B and C of Table 5 present the results. We find that the price informativeness of treatment firms diminishes significantly following the shock, along with a reduction in the predictive power of the current stock price for future investment decisions. Additionally, the effect is generally larger for the 3-year horizon compared to the 1-year short-run horizon.

Figure 12 plots the estimated effect of the merger shock over time in an extended window of $(-3, +3)$ years, with year-0 denoting the merger completion year. Panel (a) measures price informativeness based on the earnings variable $EBITDA/A$ at the 1-year prediction horizon, while Panel (b) measures investment-to-price sensitivity based on $Invest/K$ at the same horizon. Notably, the negative effect of active financial institution mergers is absent prior to the merger shock, as the estimated coefficients are indistinguishable from zero before the merger completion year. This observation supports the plausibility of the parallel trend assumption. Additionally, it is worth noting that the negative effect is gradual, increasing in magnitude over time following the merger completion year without exhibiting any reversal. Overall, our DiD estimation results suggest that the negative effect of firms’ active institutional ownership concentration is causal.

5.3 International Evidence

In this subsection, we examine whether the negative impact of active institutional ownership concentration on price informativeness prevails in other countries.

We construct the international sample by combining data on global institutional ownership

from FactSet, accounting data from Worldscope, and stock market data from DataStream. The international sample has an annual frequency and spans from 2000 to 2022. We exclude firms within the financial industry and require a firm to possess a market capitalization above \$1 million and have a minimum of five active institutional investors. We further restrict our sample to countries with at least 20 firms possessing adequate financial information. The final sample includes 22,887 unique firms across 63 countries.

Descriptive statistics are given in Table B5 in the online appendix. Figure B3 in the online appendix displays the time-series average trading-based *ActTop5* values for the largest equity markets globally. It is noteworthy that the average *ActTop5* value in the U.S. hovers around 50%, yet it remains the lowest among the nine markets examined. Conversely, markets like China, Japan, and Australia exhibit higher average *ActTop5* values, approximately around 80% over the last decade. This observation underscores the significance of active institutional ownership concentration on a global scale. We also notice that *ActTop5* was notably high at the onset of the sample period. This could be attributed to the relatively limited coverage of institutional holdings in FactSet in the early 2000s.

We follow the classification criteria in Kacperczyk et al. (2021) to identify active and passive institutional investors in the international sample. Specifically, active investors cover mutual funds, investment advisors, and hedge funds, while passive investors include the remaining types, namely, bank trusts, insurance companies, pension funds, endowments, index funds, and ETFs. The regression model closely mirrors that of the U.S. sample, with the difference being the incorporation of country-year fixed effects in lieu of industry-year fixed effects. This adjustment aims to better absorb country-level economic or regulatory fluctuations across time periods, though our results remain unchanged when using industry-year fixed effects.

Table 6 presents the results. The coefficients on the interaction term are significantly negative in all specifications, suggesting that the negative impact of active institutional ownership concentration on price informativeness, as well as investment-to-price sensitivity, persists in the international setting. Moreover, to assuage the concern that the observed negative effect is purely

driven by firms located in the U.S., we exclude the U.S. firms and present the consistent negative impact in Table B6 of the online appendix.

6 Mechanisms

In Section 2.3, we discuss two underlying channels through which active ownership concentration might undermine price informativeness, which we explore in this section.¹¹ The first effect, the “information pass-through effect” (Hypothesis 3), suggests that larger investors trade more conservatively on their private information due to the heightened price impact, leading to a decrease in average trading intensity as active ownership concentration increases. We use two settings in Section 6.1 to test this effect. The second effect, the “learning effect” (Hypothesis 4), posits that increased ownership concentration leads larger investors to diversify their learning, while smaller investors specialize. We provide suggestive evidence in Section 6.2.

6.1 Information Pass-through Effect

Portfolio turnover. If the information pass-through channel is valid, we expect smaller position adjustments in stocks for an active institutional investor when the investor is among the top 5 largest shareholders compared to the case when the investor holds a minor stake.

To test this hypothesis, we categorize the holding portfolio of each institutional investor into two subgroups: the Top5 subgroup and the Non-Top5 subgroup. The Top5 subgroup includes stocks where the investor is one of the top 5 largest shareholders, while the Non-Top5 subgroup includes her remaining stocks. We then construct the portfolio turnover measures following Yan and Zhang (2009). For each investor k in each quarter q , we first calculate the aggregate purchase

¹¹In the online appendix, we rule out several alternative explanations in Section D and explore competing hypotheses in Section E.

and sale for each subgroup g as follows:

$$AgBuy_{k,g,q} = \sum_{i \in N_{k,g}} |S_{k,g,i,q}P_{i,q} - S_{k,g,i,q-1}P_{i,q-1} - S_{k,g,i,q-1}\Delta P_{i,q}|, \text{ where } S_{k,g,i,q} > S_{k,g,i,q-1},$$

$$AgSell_{k,g,q} = \sum_{i \in N_{k,g}} |S_{k,g,i,q}P_{i,q} - S_{k,g,i,q-1}P_{i,q-1} - S_{k,g,i,q-1}\Delta P_{i,q}|, \text{ where } S_{k,g,i,q} \leq S_{k,g,i,q-1}.$$

$S_{k,g,i,q}$ is the number of shares held by investor k in firm i in quarter q classified into subgroup g ; $P_{i,q}$ is the share price of firm i in quarter q . The investor's portfolio turnover for each subgroup is then defined as $PTR_{k,g,q} = \frac{\min(AgBuy_{k,g,q}, AgSell_{k,g,q})}{\sum_{i \in N_{k,g}} (S_{k,g,i,q}P_{i,q} + S_{k,g,i,q-1}P_{i,q-1})/2}$.

We limit the sample to investors with available holding information in either subgroup. Specifically, we exclude investors whose holdings are consistently ranked among the top 5 largest across all underlying securities, as well as those whose holdings are minor in all securities. The final sample consists of 69,261 investor-quarter pairs and 138,522 observations, covering the sample period 1980-2022.

Panel A of Table 7 compares the distribution of portfolio turnover (PTR) between the Top5 subgroup and the Non-Top5 subgroup. We find that portfolio turnovers of the Top5 group are substantially smaller than those of the Non-Top5 subgroup in every percentile. For instance, the median value of PTR is 0.230 in the Non-Top5 subgroup, nearly four times the median PTR in the Top5 subgroup. For robustness, we alter the threshold to be the top 10 ranking. Once again, we observe a significant discrepancy in PTR across the Top10 and Non-Top10 subgroups, as demonstrated at the bottom of Panel A.

Furthermore, to mitigate the omitted variable concern, we estimate the following multi-variable regression model:

$$PTR_{k,g,q} = a + b_1 DumTop5_{k,g,q} + b_2 \chi_{k,g,q} + FE_{k,q} + \varepsilon_{k,g,q},$$

where $DumTop5$ equals 1 for the Top5 subgroup and 0 for the Non-Top5 subgroup. χ denotes a list of portfolio-level control variables: (i) PIO , the portfolio institution ownership calculated

as the holding-weighted average of stock-level institution ownership; (ii) $PRet$, the portfolio quarterly return; (iii) $PRetStd$, the portfolio volatility, calculated as the standard deviation of the quarterly returns in the past two years; and (iv) $PSize$, the portfolio size, computed as the logarithm of holding amount in million dollars. We also include the investor-quarter fixed effects to account for trends in PTR that are investor specific and may change over time. That said, the coefficient on $DumTop5$ should be interpreted as the within-investor-quarter difference in portfolio turnover between the Top5 and the Non-Top5 subgroups.

Panel B of Table 7 reports the regression result. The coefficient on $DumTop5$ is significantly negative at -0.143 in Column (1), indicating that the portfolio turnover of the Top5 subgroup is, on average, 14.3% lower than that of the Non-Top5 subgroup. The results hold when we relax the threshold to the top 10 ranking, as shown in Column (2).

Information content of earnings announcements. In the case of information shock, the price of a security with more concentrated ownership is expected to reflect the new information more slowly because large investors refrain from trading aggressively. Hence, another hypothesis underlying the information pass-through channel is that the information content of the stock price surrounding an information shock is lower for firms with more concentrated active institutional ownership.

To test this hypothesis, we utilize quarterly earnings announcements to capture the information shock. Following Landsman et al. (2012), we employ abnormal trading volume ($AVOL$) and abnormal return volatility ($AVAR$) to measure the information content of earnings announcements. $AVOL$ is calculated as the average trading volume in the event window, scaled by the counterparts in the non-event window: $AVOL = \ln \left(\frac{\overline{Volume}_{i,t \in [0,1]}}{\overline{Volume}_{i,t \in [-40,-6]}} \right)$, where $Volume_{i,t}$ denotes the daily trading volume in shares. Similarly, $AVAR$ is calculated as the mean square of adjusted returns in the event window, scaled by the counterparts in the non-event window: $AVAR = \ln \left(\frac{\overline{u^2}_{i,t \in [0,1]}}{\overline{u^2}_{i,t \in [-40,-6]}} \right)$, where $u_{i,t} = R_{i,t} - (\alpha_i + \beta_i R_{mkt,t})$ is calculated as daily stock returns subtracted by expected returns, with expected returns estimated based on the market model over

40 trading days before the announcement date to 6 trading days before the announcement date.

We apply the same rule introduced in Section C of the online appendix to pin down the effective earnings announcement date. We choose a two-day event window as per Pevzner, Xie, and Xin (2015), because newswire information is typically available on the next trading day. We commence the estimation window at $t-40$ to avoid overlapping the previous quarterly announcement date and conclude it at $t-6$ to prevent contaminating the parameter estimates with pre-leaked earnings information.

We then conduct the following regression model to investigate the effect of active institutional ownership concentration on the information content of earnings announcements:

$$InformContent_{i,q} = a + b_1 Concentration_{i,q} + b_2 \chi_{i,q} + FE_{i,q} + \varepsilon_{i,q},$$

where *InformContent* denotes the aforementioned two measures, *AVAR* and *AVOL*; $\chi_{i,q}$ is the same list of control variables as in the baseline regression model but on a quarterly basis; $FE_{i,q}$ captures the firm fixed effect and quarter-industry two-way fixed effects.

Table 8 reports the results. In Panel A, the coefficients of interest, b_1 , are significantly negative in all specifications, suggesting that less information is incorporated into the stock price for firms with more concentrated ownership. In Panel B, we further control for a saturated set of characteristics as in Pevzner, Xie, and Xin (2015) and demonstrate the robust negative relation between the information content and active institutional ownership concentration.¹²

6.2 Learning Effect

The “learning channel” posits that the polarization of investor sizes impedes small investors from diversifying their learning. Consequently, small investors allocate their learning capacity to a

¹²We include the following control variables as per Pevzner et al. (2015): *FirmSize* denotes the natural logarithm of the market capitalization at the fiscal quarter end; $|UE|$ is the absolute value of unexpected earnings, computed as actual annual earnings minus the most recent median analyst forecast scaled by the quarter-end stock price; *ReportLag* is the number of days from the fiscal quarter-end to the earnings announcement date; *ForeDisp* is the standard deviation of analysts’ earnings forecasts scaled by the fiscal quarter-end stock price, and *ForeNum* is the number of annual earnings forecasts reported by LSEG IBES.

specific portfolio, favoring assets with the largest supply. While large investors may diversify their learning, the impact of this diversification can be limited since their learning is already well-diversified. Thus, a testable hypothesis is that greater concentration leads to increased learning in large stocks and diminished learning in small stocks.

To examine this hypothesis, we employ the download records of company filings from the SEC EDGAR as an indicator of institutional investors' learning choices. We follow the data cleaning process outlined by Ryans (2017).¹³ Next, we differentiate EDGAR downloads by active financial institutions from other market participants through two steps. First, we identify IP addresses of active financial institutions by matching 13F active investors with two geolocation datasets, MaxMind and IPinfo, which provide information about IP addresses and their associated organizations. Second, we identify active investors' use of EDGAR. We employ the mapping table from Chen et al. (2020) to de-anonymize the IP addresses in the SEC EDGAR downloads and match 13F active investors to the EDGAR downloads data based on the IP addresses.

To capture active institutional investors' learning choices across various size groups, we categorize firms into five size groups based on their market capitalization and compute the size-weighted average EDGAR downloads for each group in each quarter. We normalize the downloads in each group by the total downloads to account for the time-varying trends in overall learning capacity. The sample period spans from the first quarter of 2003 to the first quarter of 2017.

Panel (a) of Figure 13 illustrates the EDGAR downloads by active investors for each size group. Aligned with our theoretical implications, we discern a water-filling pattern in learning choices. Over 60% of download activities occur in the largest group, while merely around 4% in the smallest group. There is a concern that this pattern might primarily reflect the learning decisions of large investors, rather than small investors. Due to strategic substitutability in learning, small investors

¹³First, we retain records where the EDGAR server successfully delivered the requested document (code = 200). Second, we remove index page observations (idx = 1), as these pages provide the viewer a link to a filing, not the filing itself. Third, we exclude downloads identified as web crawlers by the EDGAR server (crawler = 1). Lastly, we filter out downloads by robots using three criteria: (1) an IP address downloads more than 25 items in one minute; (2) an IP address downloads items from more than three different companies in one minute; (3) an IP address downloads more than 500 items in a single day.

might prefer to learn about different assets than large investors. If this effect is strong, small investors might allocate more learning capacity to smaller assets as concentration increases. To attenuate this concern, Panels (b) and (c) separate downloads by large and small active investors. Large investors are defined as those with AUM above the sample median each quarter. We find that the water-filling pattern exists in both large and small investor groups, indicating that the strategic substitutability effect, if present, does not significantly alter small investors’ learning choices.

In Figure 14, we explore the impact of size-based ownership concentration among active institutional investors on their learning choices. In Panel (a1), we identify a significantly positive correlation between size-based *ActHHI* and EDGAR downloads in the largest group. This implies that more investor attention is allocated to large stocks as size-based concentration increases. The pattern reverses in the smallest group, as depicted in Panel (a2). This indicates that small stocks are poorly learned when active institutional ownership is concentrated. In Panel (a3), we measure the learning imbalance by calculating the difference in EDGAR downloads between the largest and smallest groups. Consistent with our hypotheses and numerical results in Figure 7, Panel (b), we observe a positive correlation between size-based concentration and learning imbalance. The results remain robust when using *ActTop5* as an alternative measure of ownership concentration, as shown in Panels (b1)-(b3) of Figure 14.

7 Conclusion

Over the past few decades, equity ownership has increasingly concentrated in the hands of large investors. As analyzed in the theoretical work of [Kacperczyk et al. \(2025\)](#), this skewed ownership structure can lower the informational efficiency of stock prices. In this paper, we provide the first empirical evidence for this negative effect of institutional ownership concentration on price informativeness.

To better inform our empirical analysis, we extend the theoretical framework of [Kacperczyk](#)

et al. (2025) and conduct two novel analyses. First, we propose a new trading-based ownership concentration measure. This measure leverages rich firm-level investor holding data, enhancing the power of our empirical analysis. We find that an increase in Kacperczyk et al.'s size-based ownership concentration can lead to an increase in our trading-based ownership concentration. This implies a negative effect of trading-based ownership concentration on price informativeness, which we robustly support with extensive empirical evidence.

Second, we explicitly differentiate between active and passive investors, revealing that it is the ownership concentration among active investors that depresses price informativeness.

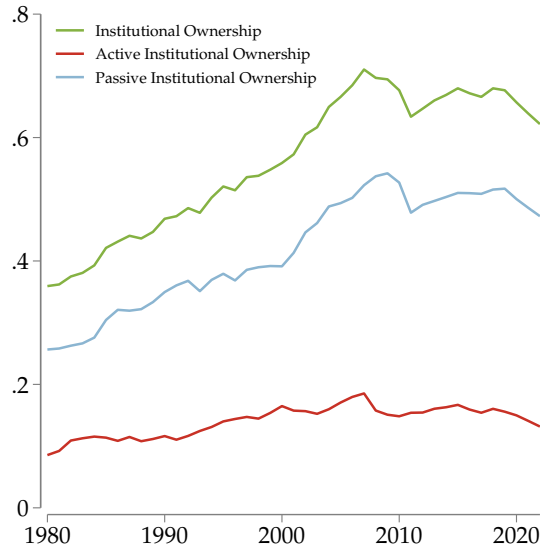
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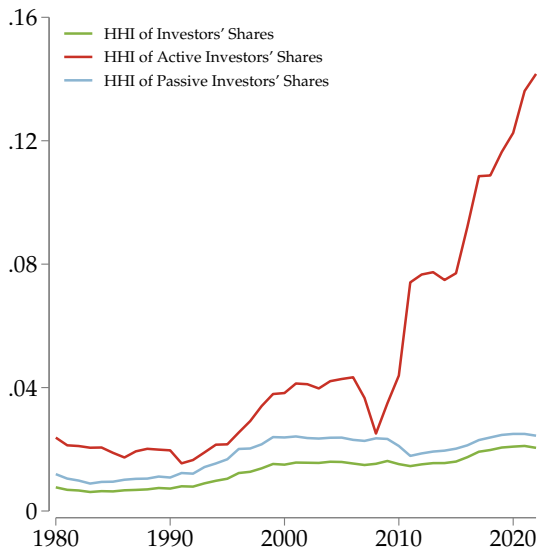
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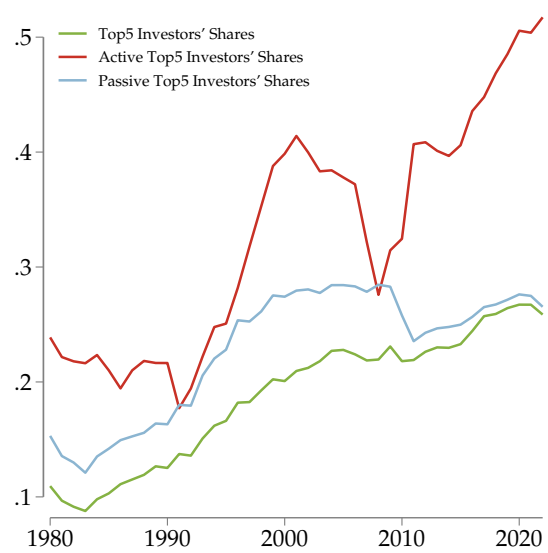
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(a) Ownership



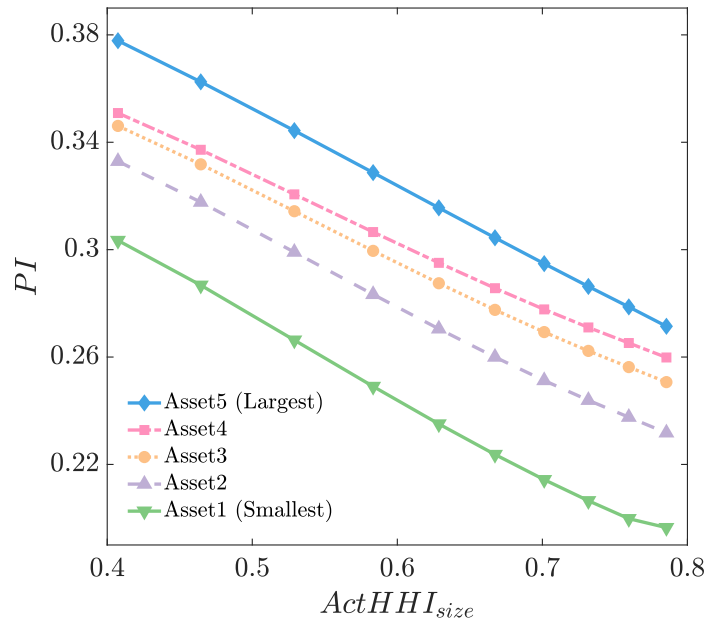
(b) Concentration: HHI



(c) Concentration: Top 5 Investor Shares

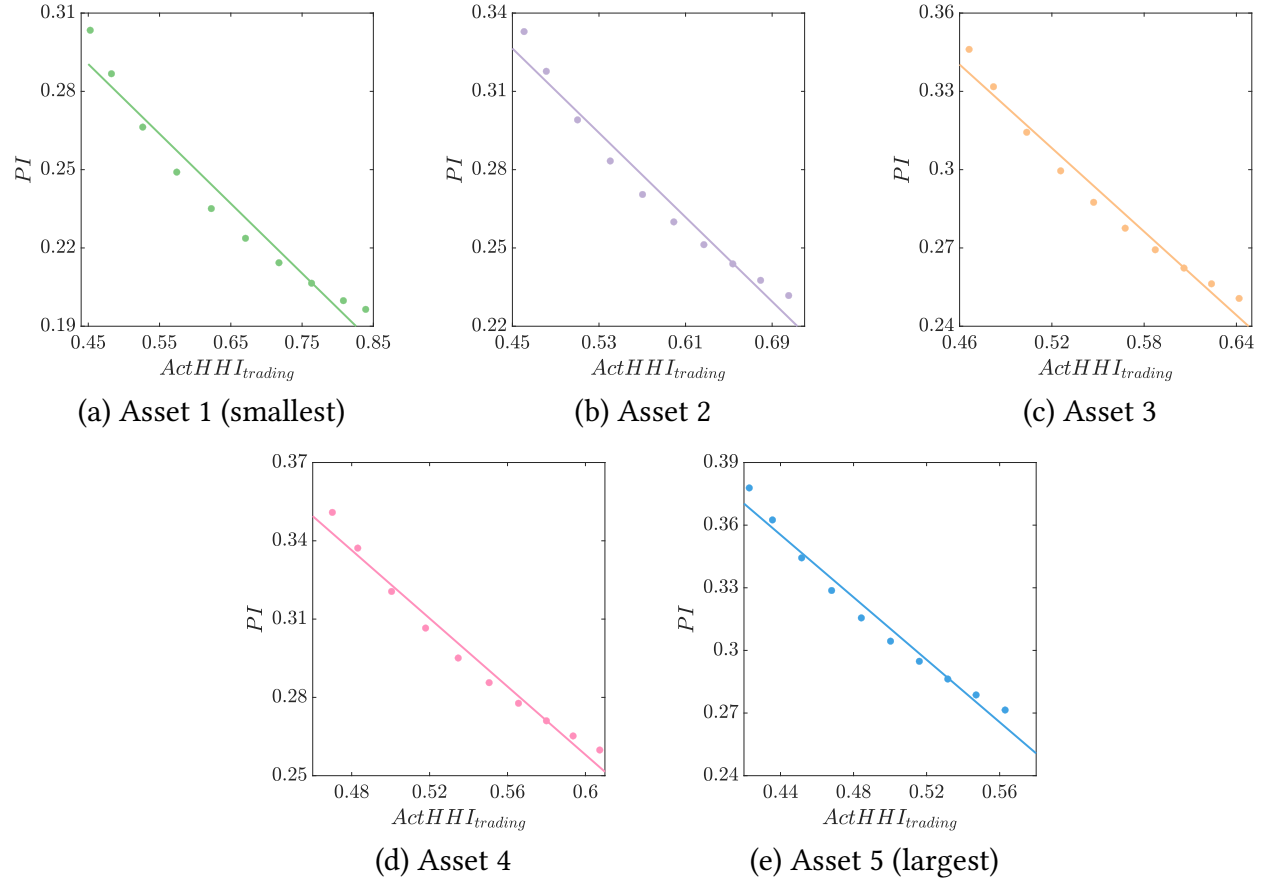
Panel (a) of this figure plots the total institutional equity ownership as well as the breakdown into active and passive ownership. Panels (b) and (c) present measures of the concentration of institutional investors within each group, specifically the Herfindahl-Hirschman Index (HHI) of investors' assets under management (AUM) and the share of AUM held by the top five investors.

Figure 1: The Time Trend of Institutional Ownership and Its Concentration



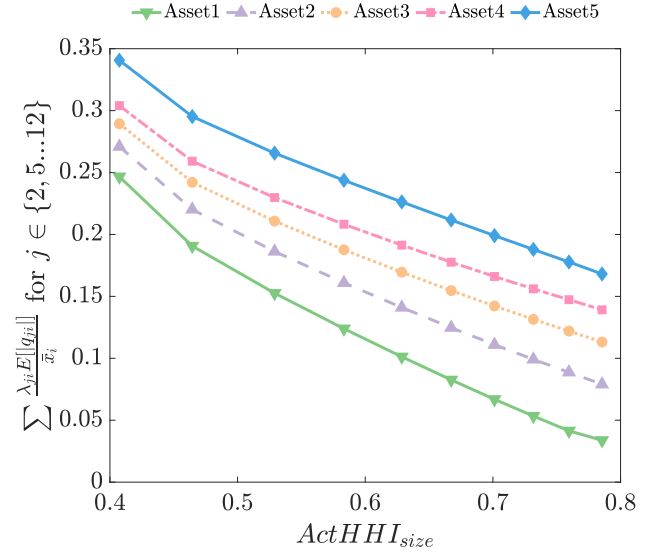
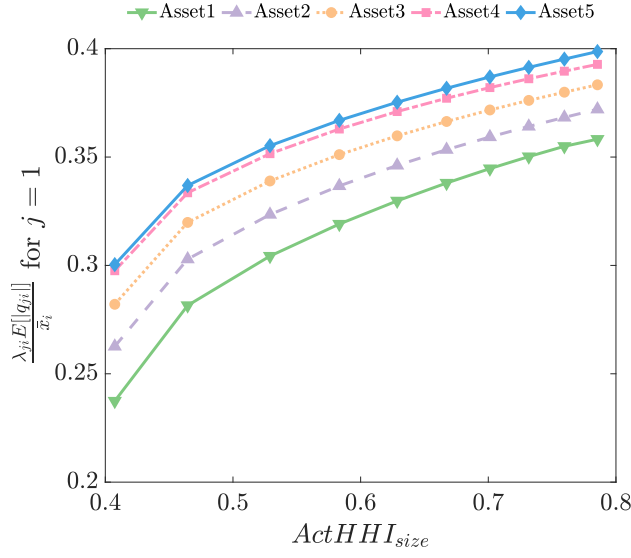
This figure plots the individual price informativeness against different values of size-based ownership concentration. Price informativeness and size-based ownership concentration are defined in equations (6) and (7) respectively. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5).

Figure 2: The Effect of Size-based Ownership Concentration



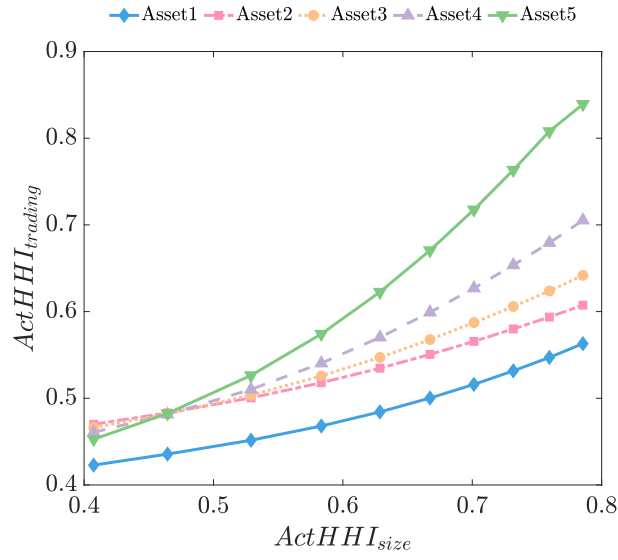
This figure plots individual price informativeness against different values of trading-based ownership concentration at the asset level. Price informativeness and trading-based ownership concentration are defined in equations (6) and (8) respectively. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5).

Figure 3: The Effect of Trading-based Ownership Concentration



(a) Trading Percentage by the Largest Active Investors

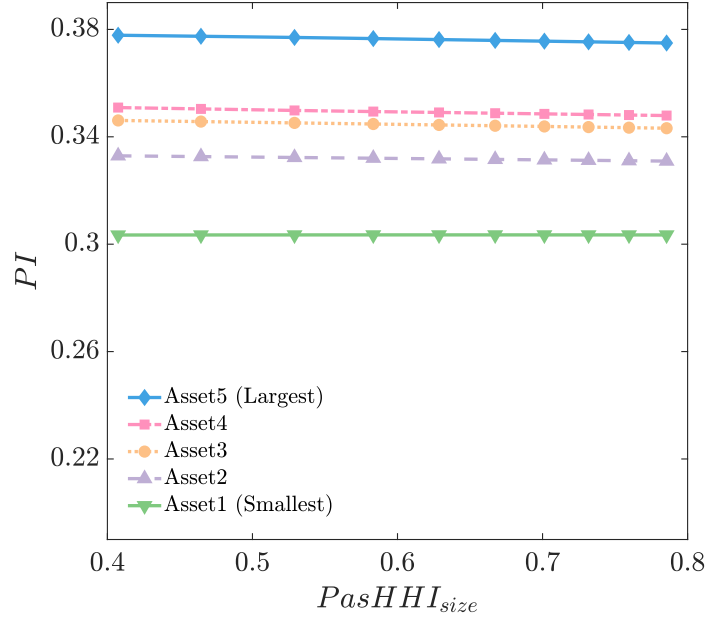
(b) Trading Percentage by Other Active Investors



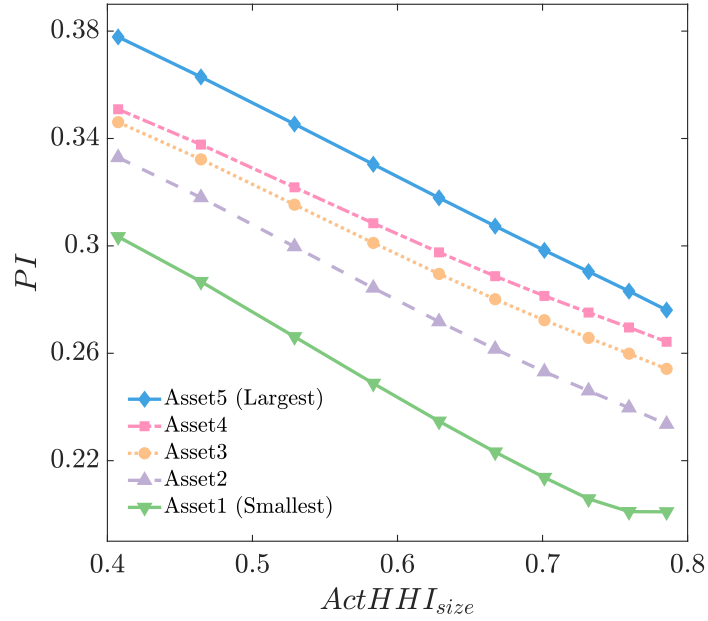
(c) $ActHHI_{size}$ and $ActHHI_{trading}$

Panels (a) and (b) plot active investors' trading choices against different values of size-based ownership concentration. Panel (c) plots the trading-based ownership concentration values against the size-based ownership concentration values. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5).

Figure 4: Trading Choices by Active Investors



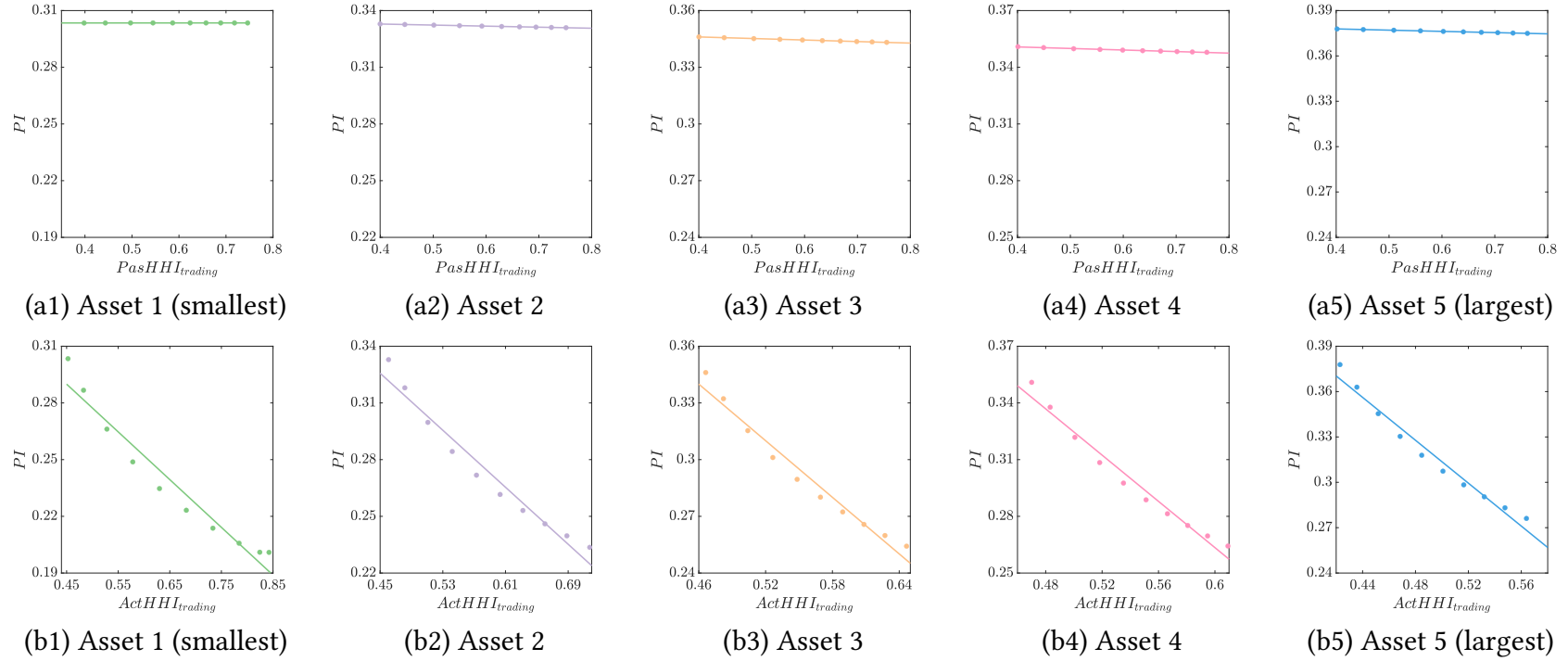
(a) Sized-based Ownership Concentration among Passive Investors



(b) Sized-based Ownership Concentration among Active Investors

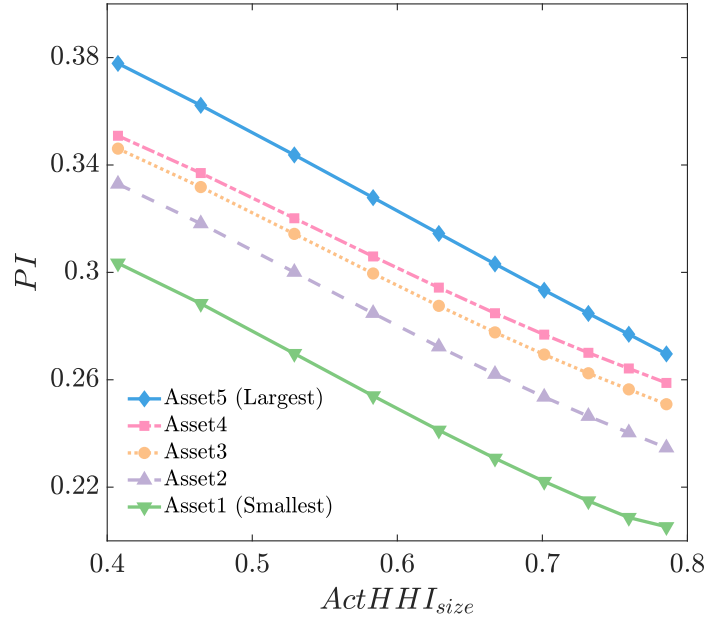
This figure illustrates the effect of size-based ownership concentration among passive investors in Panel (a) and that among active investors in Panel (b). In Panel (a), the size distribution of active investors is fixed ($\lambda_1/\lambda_2 = 1.1$ and $\sum_{j \in SA} \lambda_j / \sum_{j \in SA \cup LA} \lambda_j = 0.10$), while in Panel (b), the size distribution of passive investors is fixed ($\lambda_3/\lambda_4 = 1.1$ and $\sum_{j \in SP} \lambda_j / \sum_{j \in SP \cup LP} \lambda_j = 0.10$).

Figure 5: Size-based Ownership Concentration among Passive/Active Investors

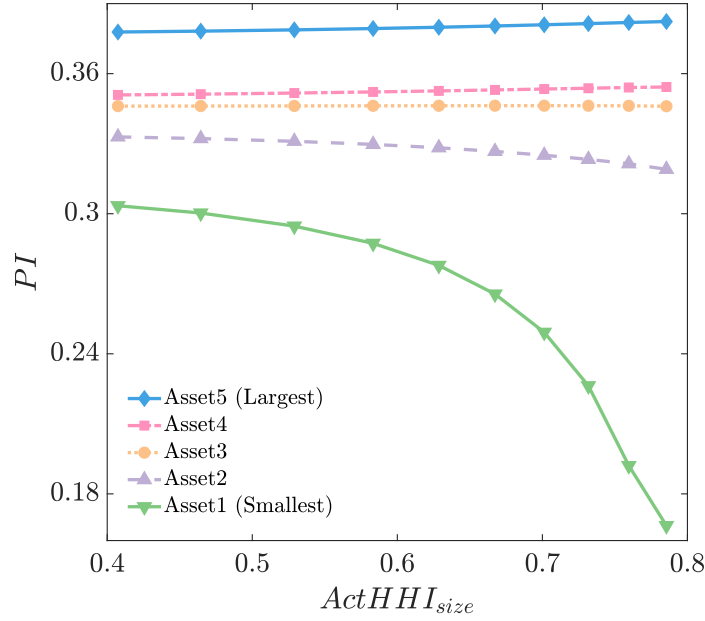


This figure illustrates the effect of trading-based ownership concentration among passive investors in Panels (a1)-(a5) and that among active investors in Panels (b1)-(b5). In Panels (a1)-(a5), the size distribution of active investors is fixed ($\lambda_1/\lambda_2 = 1.1$ and $\sum_{j \in SA} \lambda_j / \sum_{j \in SA \cup LA} \lambda_j = 0.10$), while in Panels (b1)-(b5), the size distribution of passive investors is fixed ($\lambda_3/\lambda_4 = 1.1$ and $\sum_{j \in SP} \lambda_j / \sum_{j \in SP \cup LP} \lambda_j = 0.10$).

Figure 6: Trading-based Ownership Concentration among Passive/Active Investors



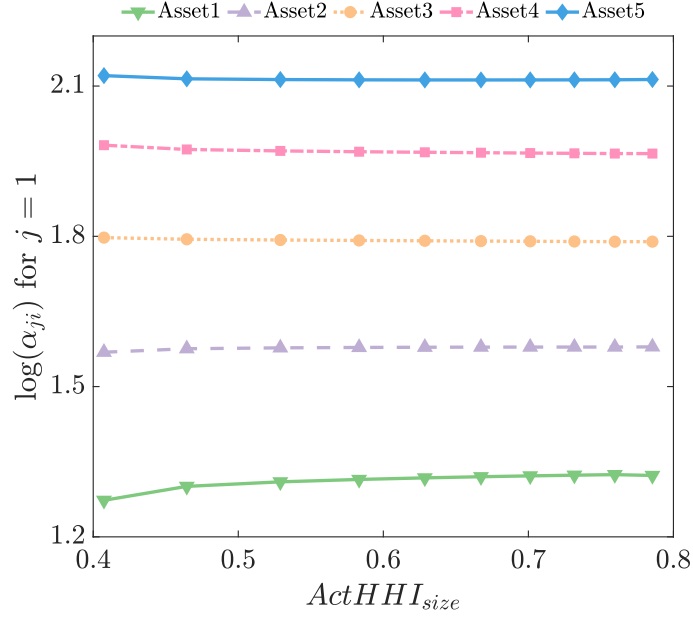
(a) Information Pass-through Effect



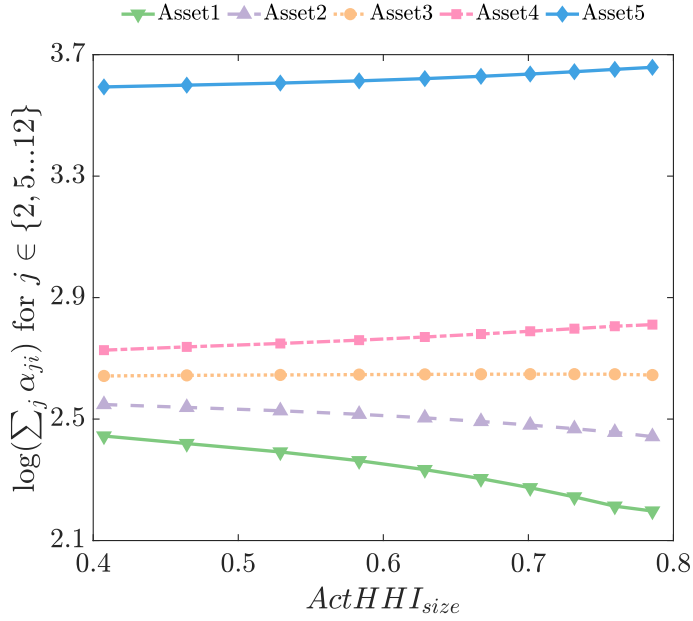
(b) Learning Effect

Panels (a) and (b) decompose the overall effect of ownership concentration documented in Figure 2 by respectively fixing the degree of learning (α_{ji}) and fixing the information pass-through (ω_{ji}). Price informativeness and size-based ownership concentration are defined in equations (6) and (7) respectively. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5).

Figure 7: Decomposition of the Effect of Ownership Concentration



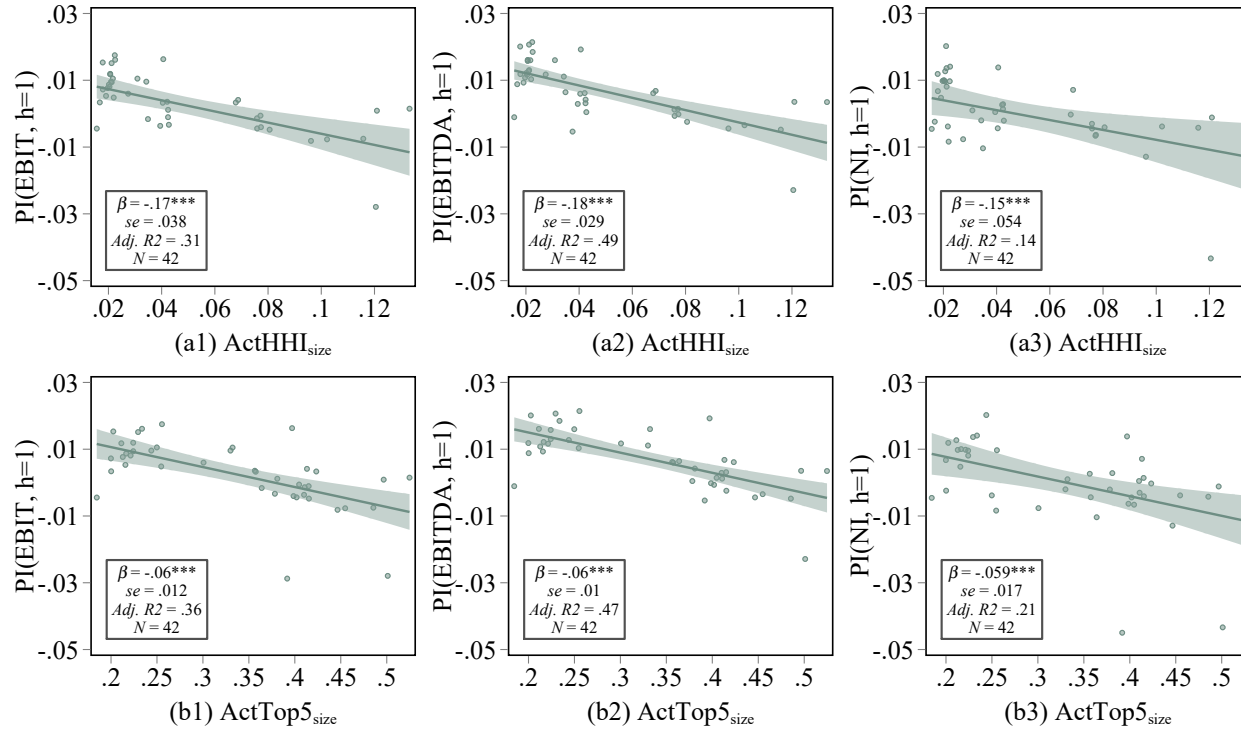
(a) Learning by the Largest Active Investors



(b) Learning by All Other Active Investors

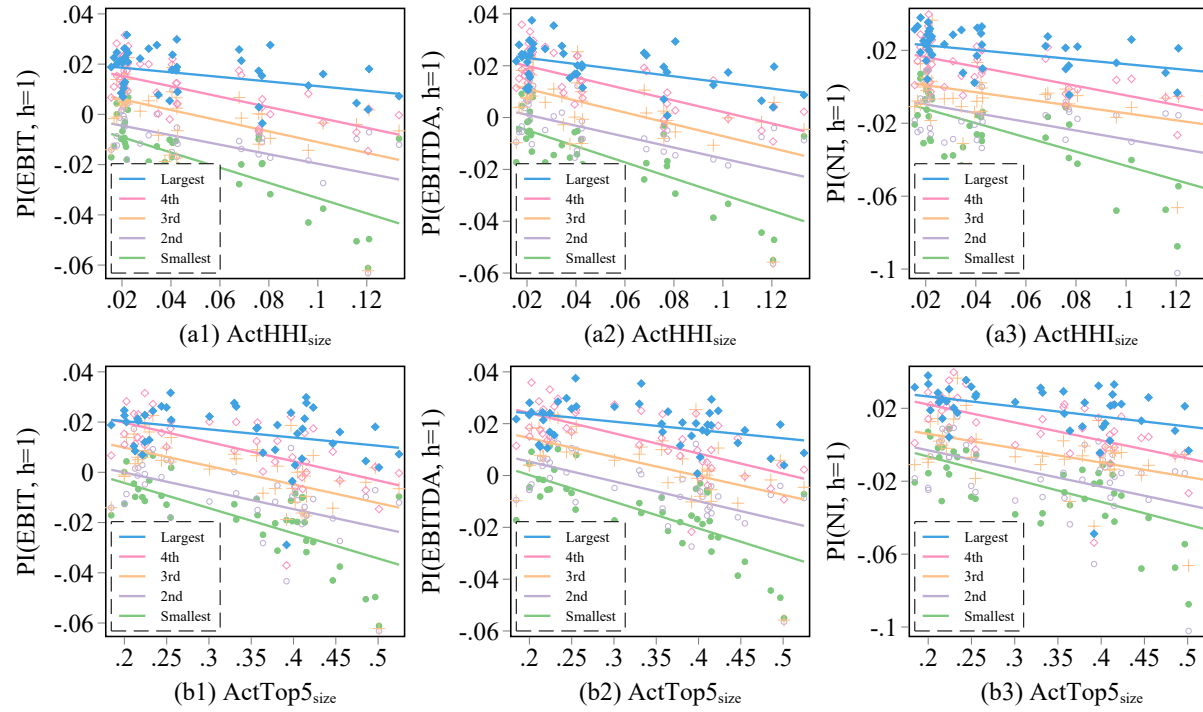
This figure plots active investors' learning choices against different values of size-based ownership concentration. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5).

Figure 8: Learning Choices by Active Investors



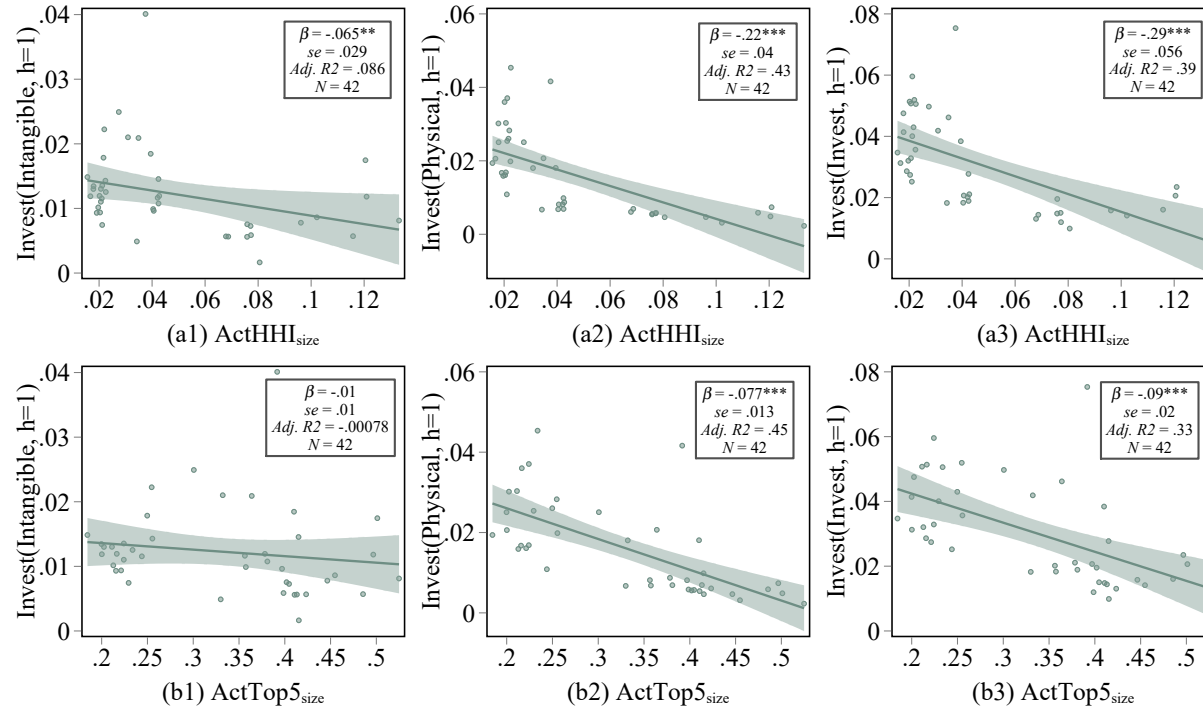
This figure presents scatter plots illustrating the relation between price informativeness and size-based ownership concentration. The plots include fitted lines and 95% confidence intervals. Size-based ownership concentration is quantified using two metrics: (i) $ActHHI_{size}$: the Herfindahl-Hirschman Index of Assets Under Management (AUM) among active institutional investors, shown in Panels (a1)-(a3), and (ii) $ActTop5_{size}$: the proportion of AUM held by the top five active institutional investors relative to the total AUM of all active institutional investors, depicted in Panels (b1)-(b3). PI is derived from equations (12) and (13) and measures the predictability of future cash flows based on current market prices, with future cash flows represented by one of the three variables ($EBIT$, $EBITDA$, or NI) calculated as of year $t + h$, scaled by total assets in year t . The prediction horizon, denoted by h , is set at 1 year. The sample has an annual frequency and spans from 1980 to 2022. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure 9: Price Informativeness and Size-based Ownership Concentration



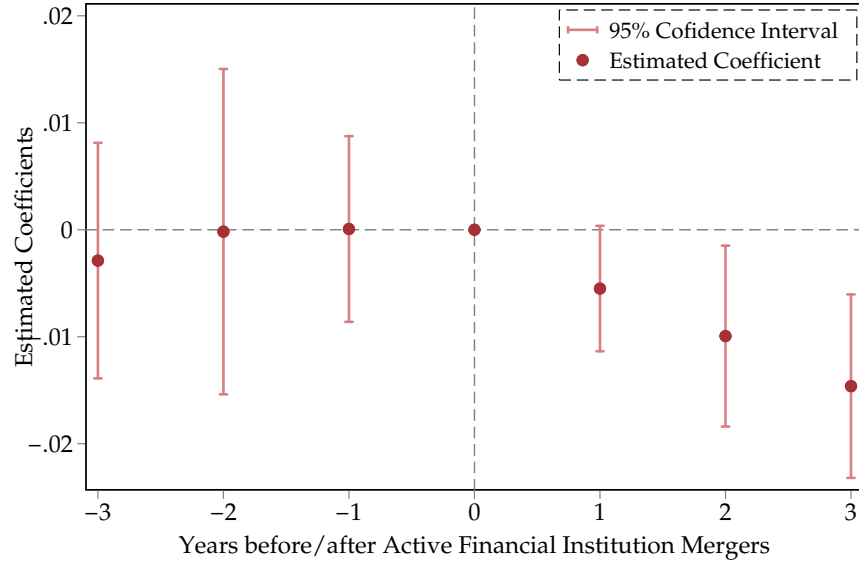
This figure presents scatter plots with fitted lines illustrating the relation between price informativeness by size group and size-based ownership concentration. Size-based ownership concentration is quantified using two metrics: (i) $ActHHI_{size}$: the Herfindahl-Hirschman Index of Assets Under Management (AUM) among active institutional investors, shown in Panels (a1)-(a3), and (ii) $ActTop5_{size}$: the proportion of AUM held by the top five active institutional investors relative to the total AUM of all active institutional investors, depicted in Panels (b1)-(b3). We divide the sample firms into quintiles based on each security's market capitalization, and estimate PI for each group according to equations (12) and (13). Future cash flows in equation (12) are represented by one of the three variables ($EBIT$, $EBITDA$, or NI) calculated as of year $t + h$, scaled by total assets in year t . The prediction horizon, denoted by h , is set at 1 year. The sample has an annual frequency and spans from 1980 to 2022.

Figure 10: Price Informativeness by Size Group and Size-based Ownership Concentration

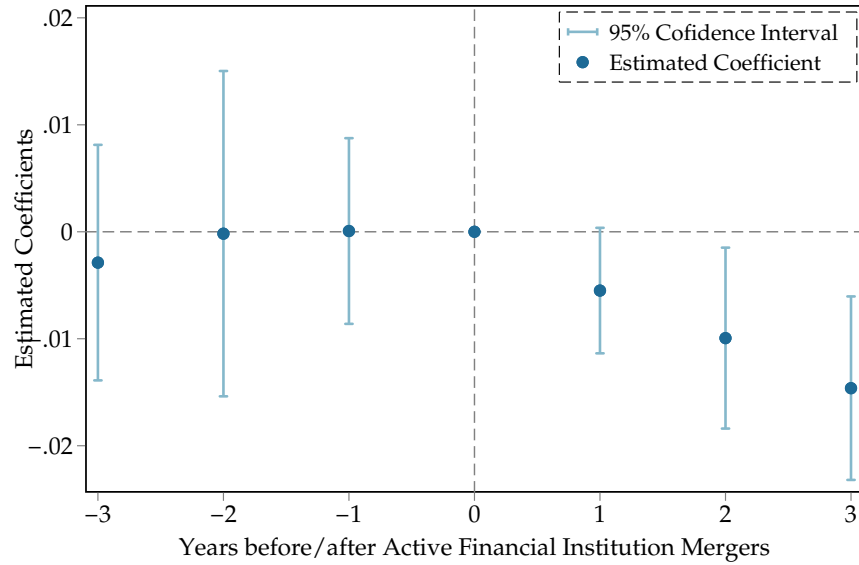


This figure presents scatter plots illustrating the relation between investment-to-price sensitivity and size-based ownership concentration. The plots include fitted lines and 95% confidence intervals. Size-based ownership concentration is quantified using two metrics: (i) $ActHHI_{size}$: the Herfindahl-Hirschman Index of Assets Under Management (AUM) among active institutional investors, shown in Panels (a1)-(a3), and (ii) $ActTop5_{size}$: the proportion of AUM held by the top five active institutional investors relative to the total AUM of all active institutional investors, depicted in Panels (b1)-(b3). Investment-to-price sensitivity is derived from equation (14) and measures the extent to which current market prices reveal the information necessary for future investment decisions, with future investments represented by one of the three variables (*Intangible*, *Physical*, or *Invest*) calculated as of year $t + h$, scaled by total capital in year t . The prediction horizon, denoted by h , is set at 1 year. The sample has an annual frequency and spans from 1980 to 2022. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure 11: Investment-to-Price Sensitivity and Size-based Ownership Concentration



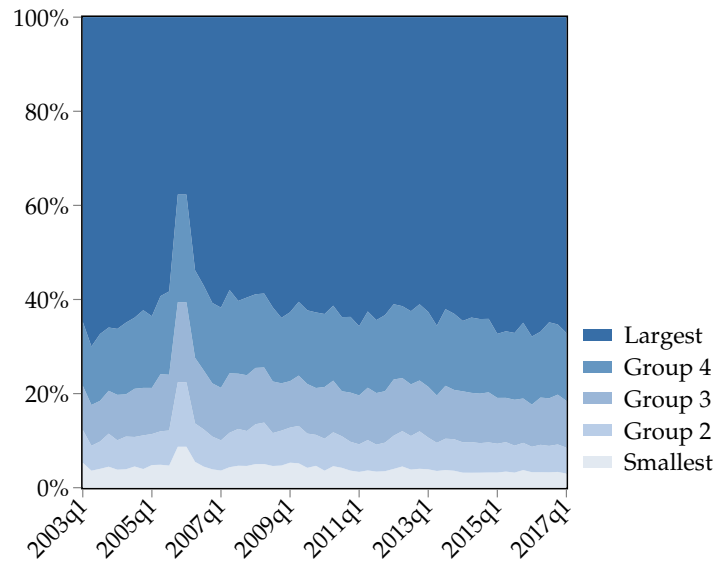
(a) Price Informativeness



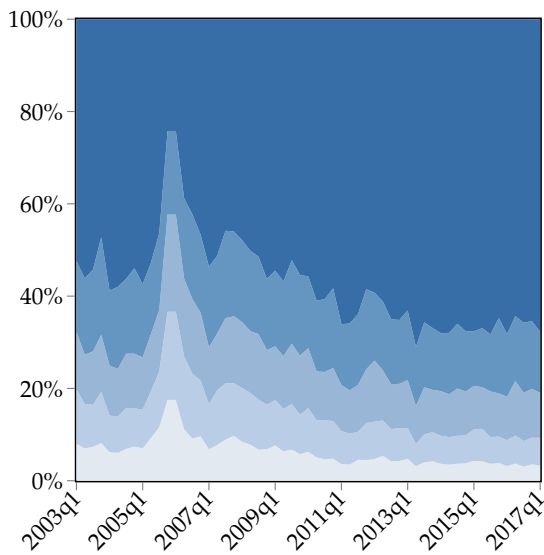
(b) Investment-to-Price Sensitivity

This figure plots the estimated coefficients on triple interactions of the market price variable ($\log(M/A)$) with treatment indicator variable ($Treat$) with a set of year dummy variables. The estimation window spans $(-3, +3)$ years, with year-0 denoting the merger completion year. Panel (a) measures price informativeness based on the earnings variable $EBITDA/A$ at the 1-year prediction horizon, while Panel (b) measures investment-to-price sensitivity based on the investment variable $Invest/K$ at the 1-year prediction horizon. We drop the interaction for the merger completion year (year-0) to avoid multicollinearity, and thus the effect is normalized to zero for that year. Standards errors are clustered at the year and firm levels.

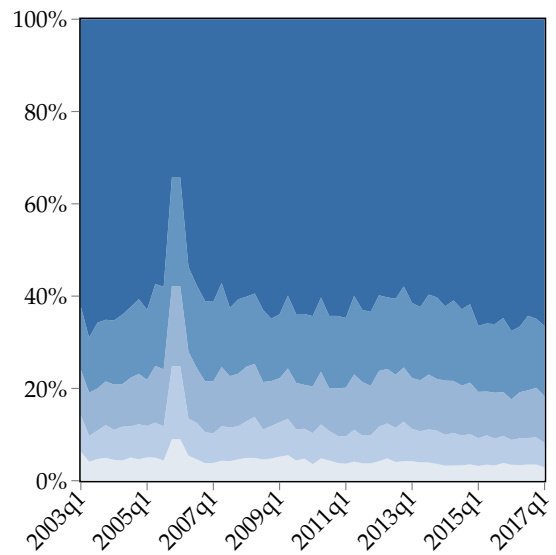
Figure 12: Event-Study Estimates



(a) All Active Investors



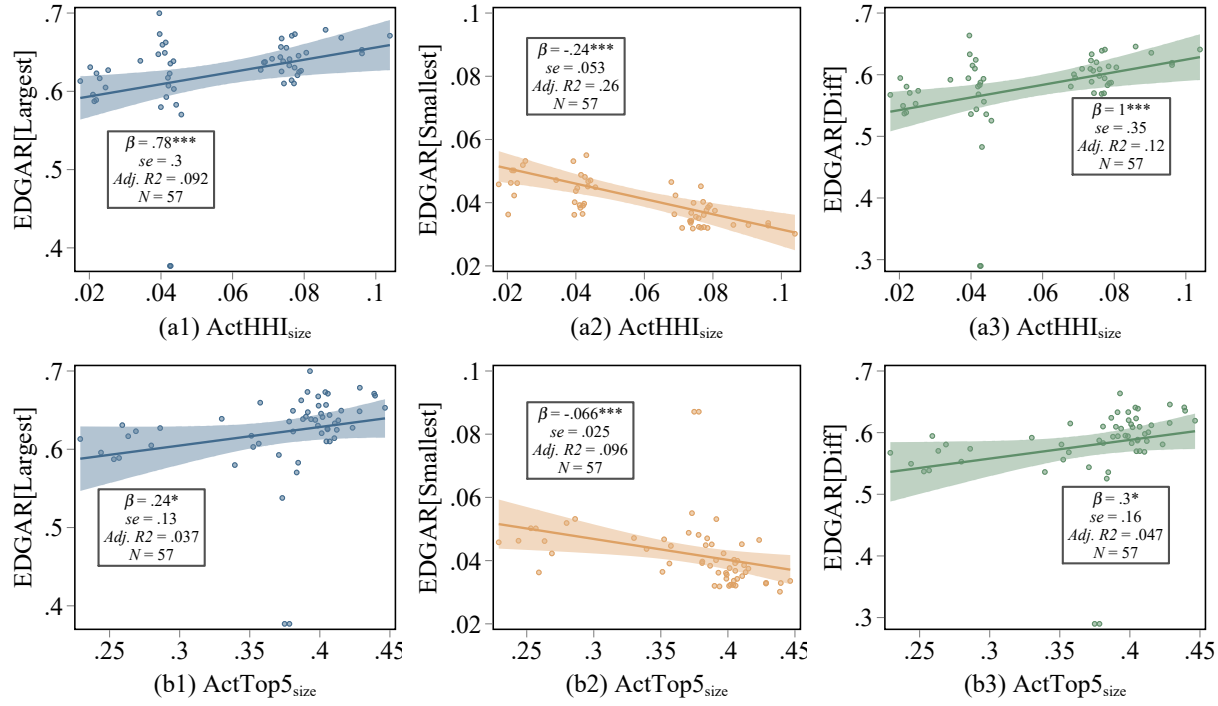
(b) Large Active Investors



(c) Small Active Investors

This figure depicts the time-series Edgar downloads for each stock size group. The downloads within each stock size group are normalized by the total number of downloads, such that their sum equals one. The largest group comprises sample firms with the highest market capitalization at each quarter's end, while the smallest group includes those with the lowest market capitalization. Panel (a) considers Edgar downloads from all active investors, while Panels (b) and (c) further separate downloads by large and small active investors.

Figure 13: Edgar Downloads for Each Group



This figure presents scatter plots illustrating the relation between EDGAR downloads (in percentage) by size group and size-based ownership concentration, as measured by $ActHHI_{size}$ in Panels (a1)-(a3) and $ActTop5_{size}$ in Panels (b1)-(b3). Each plot includes fitted lines and 95% confidence intervals. Panels (a1) and (b1) focus on the weighted average EDGAR downloads in the group with the largest market capitalization, while Panels (a2) and (b2) focus on the weighted average EDGAR downloads in the group with the smallest market capitalization. Panels (a3) and (b3) examine the learning imbalance, defined as the difference in the weighted average EDGAR downloads between the largest and smallest groups. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure 14: Size-based Ownership Concentration and EDGAR Downloads

Table 1: Parameter Values in Numerical Analysis

Parameter	Symbol	Value
Mean payoff	$\bar{z}_i$	10
Supply	$\bar{x}_i$	$\in [3, 6]$, linear distribution across i
Number of assets, oligopolists	n, l	5, 20
Gross risk-free rate	r	1.025
Vol. of asset supply	$\sigma_{x,i}$	Coefficient of variation of 0.2 for all i
Vol. of asset payoffs	σ_i	1 for all i
Risk aversion	ρ	2.32
Information capacities	K_j	12.5 for $j \in LA$ and 1.25 for $j \in SA$
Retail investors	λ_0	0.4
Passive investors	$\frac{\sum_{j \in LP \cup SP} \lambda_j}{\sum_{j=1}^l \lambda_j}$	0.5
Small active investors	$\frac{\sum_{j \in SA} \lambda_j}{\sum_{j \in SA \cup LA} \lambda_j}$	Varying linearly from 0.10 to 0.03
Small passive investors	$\frac{\sum_{j \in SP} \lambda_j}{\sum_{j \in SP \cup LP} \lambda_j}$	Varying linearly from 0.10 to 0.03
Relative size within large investors	$\frac{\lambda_1}{\lambda_2}, \frac{\lambda_3}{\lambda_4}$	Varying linearly from 1.1 to 10
Relative size within small investors	$\frac{\lambda_5}{\lambda_{12}}, \frac{\lambda_{13}}{\lambda_{20}}$	5

Table 2: Summary Statistics

This table presents the summary statistics for the variables used in our main analysis. The sample has an annual frequency and spans from 1980 to 2022. All continuous variables are winsorized at the top and bottom 1% to mitigate the influence of outliers. Variable definitions are provided in Table B1 in the online appendix.

Variable	N	Mean	SD	p10	p25	p50	p75	p90
Panel A: Ownership Concentration Variables								
<i>ActHHI_{size}</i>	42	0.048	0.034	0.019	0.021	0.036	0.076	0.102
<i>ActTop5_{size}</i>	42	0.333	0.102	0.211	0.224	0.357	0.411	0.455
<i>ActHHI</i>	89218	0.239	0.163	0.080	0.120	0.196	0.309	0.457
<i>ActTop5</i>	89218	0.768	0.171	0.524	0.637	0.781	0.924	0.992
Panel B: Earning Variables								
<i>EBIT/A</i>	88269	0.048	0.178	-0.110	0.027	0.079	0.130	0.189
<i>EBITDA/A</i>	89114	0.092	0.177	-0.060	0.067	0.121	0.175	0.237
<i>NI/A</i>	89218	0.001	0.189	-0.157	-0.004	0.042	0.081	0.126
Panel C: Investment Rate Variables								
<i>Intangible/K</i>	88833	0.106	0.095	0.004	0.032	0.087	0.150	0.234
<i>Physical/K</i>	88286	0.063	0.066	0.011	0.022	0.043	0.078	0.137
<i>Invest/K</i>	88797	0.170	0.111	0.058	0.091	0.143	0.215	0.319
Panel D: Control Variables								
<i>log(M/A)</i>	89218	0.020	0.979	-1.192	-0.616	0.020	0.660	1.268
<i>PasHHI</i>	89218	0.586	0.190	0.360	0.439	0.556	0.721	0.875
<i>PasTop5</i>	89218	0.123	0.109	0.041	0.057	0.087	0.147	0.245
<i>IO</i>	89218	0.567	0.271	0.197	0.348	0.568	0.790	0.928
<i>Leverage</i>	89218	0.217	0.184	0.000	0.037	0.199	0.346	0.471
<i>Sale</i>	89218	1.058	0.749	0.281	0.526	0.917	1.387	1.979
<i>Cash</i>	89218	0.188	0.222	0.008	0.026	0.095	0.268	0.536

Table 3: Price Informativeness and Trading-based Ownership Concentration

This table reports OLS estimates on the relation between price informativeness, which measures the predictability of future cash flows from current market prices, and trading-based ownership concentration. The dependent variable is future earnings, calculated as one of the three cash flow variables (EBIT, EBITDA, and NI) in year $t + h$ divided by total assets in year t . Here, h denotes the prediction horizons, set at 1 in Columns (1)-(3) and 3 in Columns (4)-(6). Concentration is measured by *ActHHI* in Panel A, representing the Herfindahl-Hirschman index of active institutional ownership, and by *ActTop5* in Panel B, denoting the proportion of shares held by the top five active institutional investors relative to the total shares held by all active institutional investors. $\log(M/A)$ is the log-ratio of a firm's market capitalization to its total assets. See Table B1 in the online appendix for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: <i>ActHHI</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)$	0.030*** (0.011)	0.041*** (0.007)	0.041*** (0.013)	0.013 (0.011)	0.048*** (0.010)	-0.028 (0.018)
E/A	0.539*** (0.024)	0.559*** (0.020)	0.288*** (0.031)	0.314*** (0.036)	0.322*** (0.032)	0.159*** (0.036)
$\log(M/A) * ActHHI$	-0.026*** (0.005)	-0.030*** (0.004)	-0.027*** (0.004)	-0.052*** (0.010)	-0.059*** (0.009)	-0.035*** (0.011)
$\log(M/A) * PasHHI$	-0.036*** (0.008)	-0.034*** (0.008)	-0.036*** (0.010)	-0.035** (0.013)	-0.028** (0.013)	-0.029* (0.015)
$\log(M/A) * IO$	0.025*** (0.008)	0.019*** (0.007)	0.028*** (0.008)	0.027*** (0.008)	0.015* (0.008)	0.041*** (0.009)
$\log(M/A) * Leverage$	-0.037*** (0.005)	-0.037*** (0.004)	-0.047*** (0.009)	-0.004 (0.013)	-0.013 (0.011)	-0.003 (0.019)
$\log(M/A) * Sale$	0.021*** (0.003)	0.019*** (0.002)	0.019*** (0.004)	0.026*** (0.003)	0.023*** (0.003)	0.029*** (0.004)
$\log(M/A) * Cash$	-0.069*** (0.012)	-0.060*** (0.008)	-0.083*** (0.011)	-0.097*** (0.012)	-0.085*** (0.009)	-0.107*** (0.014)
<i>ActHHI</i>	-0.012*** (0.003)	-0.010*** (0.004)	-0.022*** (0.004)	-0.013 (0.009)	-0.004 (0.008)	-0.023** (0.011)
<i>PasHHI</i>	0.030*** (0.009)	0.034*** (0.009)	0.015 (0.011)	0.076*** (0.019)	0.108*** (0.018)	0.010 (0.021)
<i>IO</i>	-0.005 (0.004)	-0.007* (0.004)	0.002 (0.006)	-0.028** (0.011)	-0.041*** (0.011)	-0.012 (0.009)
<i>Leverage</i>	0.054*** (0.005)	0.052*** (0.005)	0.064*** (0.010)	0.035** (0.014)	0.025* (0.013)	0.041** (0.017)
<i>Sale</i>	0.026*** (0.003)	0.024*** (0.002)	0.049*** (0.005)	0.049*** (0.005)	0.057*** (0.005)	0.046*** (0.005)
<i>Cash</i>	0.011 (0.010)	-0.010 (0.009)	0.068*** (0.012)	0.061*** (0.015)	0.058*** (0.015)	0.067*** (0.022)
Observations	83,054	83,794	83,952	69,612	70,250	70,402
R^2	0.823	0.837	0.714	0.677	0.697	0.579
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Table 3 – Continued

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: <i>ActTop5</i>						
$\log(M/A)$	0.056*** (0.012)	0.070*** (0.007)	0.059*** (0.014)	0.048*** (0.016)	0.084*** (0.013)	-0.004 (0.023)
E/A	0.540*** (0.024)	0.560*** (0.020)	0.288*** (0.031)	0.322*** (0.036)	0.334*** (0.032)	0.162*** (0.037)
$\log(M/A)*ActTop5$	-0.033*** (0.006)	-0.040*** (0.005)	-0.029*** (0.005)	-0.045*** (0.010)	-0.063*** (0.009)	-0.022* (0.012)
$\log(M/A)*PasTop5$	-0.016** (0.006)	-0.013* (0.006)	-0.013* (0.007)	-0.025** (0.012)	-0.005 (0.011)	-0.028** (0.013)
$\log(M/A)*IO$	0.021** (0.008)	0.016** (0.007)	0.027*** (0.008)	0.023*** (0.008)	0.014* (0.008)	0.037*** (0.009)
$\log(M/A)*Leverage$	-0.035*** (0.005)	-0.035*** (0.004)	-0.046*** (0.009)	-0.001 (0.013)	-0.010 (0.011)	-0.001 (0.019)
$\log(M/A)*Sale$	0.022*** (0.003)	0.019*** (0.002)	0.019*** (0.004)	0.027*** (0.003)	0.024*** (0.003)	0.029*** (0.004)
$\log(M/A)*Cash$	-0.070*** (0.012)	-0.062*** (0.008)	-0.084*** (0.011)	-0.097*** (0.011)	-0.087*** (0.010)	-0.105*** (0.014)
<i>ActTop5</i>	-0.026*** (0.004)	-0.023*** (0.004)	-0.036*** (0.005)	-0.004 (0.007)	0.006 (0.007)	-0.023** (0.009)
<i>PasTop5</i>	0.045*** (0.006)	0.050*** (0.006)	0.026*** (0.006)	0.103*** (0.013)	0.138*** (0.015)	0.048*** (0.012)
<i>IO</i>	-0.000 (0.004)	-0.001 (0.004)	0.003 (0.006)	-0.005 (0.010)	-0.011 (0.010)	0.000 (0.009)
<i>Leverage</i>	0.052*** (0.005)	0.050*** (0.005)	0.062*** (0.010)	0.031** (0.015)	0.019 (0.013)	0.039** (0.017)
<i>Sale</i>	0.025*** (0.003)	0.022*** (0.002)	0.049*** (0.005)	0.046*** (0.005)	0.053*** (0.005)	0.045*** (0.005)
<i>Cash</i>	0.010 (0.010)	-0.011 (0.009)	0.067*** (0.012)	0.058*** (0.014)	0.054*** (0.015)	0.064*** (0.022)
Observations	83,054	83,794	83,952	69,612	70,250	70,402
R^2	0.824	0.838	0.714	0.678	0.699	0.579
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Table 4: Investment-to-Price Sensitivity and Trading-based Ownership Concentration

This table reports OLS estimates on the relation between investment-to-price sensitivity, which measures the predictability of future investments from current market prices, and trading-based ownership concentration. The dependent variable is future investment rate, calculated as investment volume in year $t + h$ divided by total capital in year t . Here, h denotes the prediction horizons, set at 1 in Columns (1)-(3) and 3 in Columns (4)-(6). Investment volume is measured across one of the following three dimensions: (1) Intangible investment (*Intangible*) computed as R&D expense plus 30% SG&A expense; (2) Physical investment (*Physical*) captured by capital expenditure; (3) Total investment (*Invest*) representing the sum of *Physical* and *Intangible*. Trading-based ownership concentration is measured by *ActHHI* in Panel A, representing the Herfindahl-Hirschman index of active institutional ownership, and by *ActTop5* in Panel B, denoting the proportion of shares held by the top five active institutional investors relative to the total shares held by all active institutional investors. $\log(M/A)$ is the log-ratio of a firm's market capitalization to its total assets. See Table B1 in the online appendix for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: <i>ActHHI</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)$	0.033*** (0.006)	0.054*** (0.004)	0.085*** (0.008)	0.074*** (0.007)	0.070*** (0.007)	0.139*** (0.011)
I/K	1.091*** (0.049)	0.653*** (0.025)	0.927*** (0.039)	1.245*** (0.084)	0.378*** (0.041)	0.917*** (0.062)
$\log(M/A) * ActHHI$	-0.022*** (0.007)	-0.023*** (0.003)	-0.044*** (0.007)	-0.042*** (0.009)	-0.025*** (0.004)	-0.070*** (0.010)
$\log(M/A) * PasHHI$	0.013*** (0.005)	-0.001 (0.004)	0.016* (0.009)	0.030** (0.012)	-0.004 (0.010)	0.027 (0.021)
$\log(M/A) * IO$	-0.022*** (0.004)	-0.028*** (0.003)	-0.050*** (0.006)	-0.054*** (0.006)	-0.038*** (0.007)	-0.094*** (0.012)
$\log(M/A) * Leverage$	-0.016*** (0.003)	-0.006** (0.003)	-0.024*** (0.004)	-0.043*** (0.008)	-0.005 (0.006)	-0.046*** (0.013)
$\log(M/A) * Sale$	-0.003 (0.002)	-0.004*** (0.001)	-0.007** (0.003)	0.003 (0.003)	-0.000 (0.002)	0.003 (0.004)
$\log(M/A) * Cash$	0.072*** (0.013)	0.005 (0.006)	0.084*** (0.020)	0.136*** (0.013)	0.001 (0.009)	0.158*** (0.022)
<i>ActHHI</i>	-0.014*** (0.003)	-0.015*** (0.003)	-0.025*** (0.005)	-0.001 (0.007)	0.006 (0.005)	0.014 (0.010)
<i>PasHHI</i>	0.031*** (0.006)	0.030*** (0.005)	0.064*** (0.010)	0.142*** (0.020)	0.100*** (0.018)	0.256*** (0.038)
<i>IO</i>	-0.010*** (0.003)	-0.013*** (0.003)	-0.025*** (0.005)	-0.063*** (0.008)	-0.059*** (0.008)	-0.137*** (0.015)
<i>Leverage</i>	-0.008** (0.003)	-0.015*** (0.004)	-0.026*** (0.006)	-0.031*** (0.009)	-0.036*** (0.009)	-0.071*** (0.016)
<i>Sale</i>	-0.020*** (0.003)	-0.007*** (0.001)	-0.021*** (0.004)	-0.025*** (0.005)	0.004 (0.003)	-0.009 (0.006)
<i>Cash</i>	0.018** (0.008)	0.064*** (0.007)	0.100*** (0.013)	0.077*** (0.017)	0.100*** (0.013)	0.209*** (0.029)
Observations	83,616	82,913	83,549	70,174	69,462	70,098
R^2	0.863	0.692	0.771	0.765	0.613	0.681
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Table 4 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel B: <i>ActTop5</i>						
$\log(M/A)$	0.040*** (0.010)	0.060*** (0.006)	0.096*** (0.014)	0.074*** (0.011)	0.067*** (0.008)	0.136*** (0.015)
I/K	1.091*** (0.049)	0.655*** (0.025)	0.929*** (0.038)	1.242*** (0.083)	0.384*** (0.040)	0.921*** (0.061)
$\log(M/A)*ActTop5$	-0.027*** (0.009)	-0.024*** (0.005)	-0.050*** (0.012)	-0.049*** (0.011)	-0.028*** (0.004)	-0.082*** (0.013)
$\log(M/A)*PasTop5$	0.016*** (0.004)	0.011** (0.004)	0.030*** (0.007)	0.050*** (0.011)	0.025*** (0.009)	0.081*** (0.021)
$\log(M/A)*IO$	-0.022*** (0.005)	-0.027*** (0.003)	-0.048*** (0.007)	-0.045*** (0.006)	-0.028*** (0.005)	-0.074*** (0.010)
$\log(M/A)*Leverage$	-0.017*** (0.003)	-0.007** (0.003)	-0.025*** (0.004)	-0.045*** (0.008)	-0.006 (0.006)	-0.049*** (0.012)
$\log(M/A)*Sale$	-0.003 (0.002)	-0.004*** (0.001)	-0.007** (0.003)	0.002 (0.003)	-0.000 (0.002)	0.002 (0.004)
$\log(M/A)*Cash$	0.071*** (0.013)	0.003 (0.006)	0.080*** (0.020)	0.130*** (0.013)	-0.004 (0.008)	0.147*** (0.021)
<i>ActTop5</i>	-0.014*** (0.003)	-0.017*** (0.003)	-0.027*** (0.005)	-0.003 (0.007)	0.006 (0.005)	0.012 (0.011)
<i>PasTop5</i>	0.029*** (0.004)	0.034*** (0.005)	0.067*** (0.008)	0.130*** (0.014)	0.114*** (0.015)	0.262*** (0.030)
<i>IO</i>	-0.007** (0.003)	-0.008*** (0.003)	-0.016*** (0.005)	-0.042*** (0.007)	-0.036*** (0.006)	-0.087*** (0.012)
<i>Leverage</i>	-0.009*** (0.003)	-0.016*** (0.004)	-0.029*** (0.007)	-0.036*** (0.009)	-0.041*** (0.009)	-0.082*** (0.017)
<i>Sale</i>	-0.021*** (0.003)	-0.007*** (0.001)	-0.022*** (0.004)	-0.027*** (0.005)	0.002 (0.003)	-0.013** (0.006)
<i>Cash</i>	0.018** (0.008)	0.064*** (0.007)	0.099*** (0.013)	0.076*** (0.016)	0.098*** (0.013)	0.205*** (0.028)
Observations	83,616	82,913	83,549	70,174	69,462	70,098
R^2	0.863	0.693	0.771	0.766	0.616	0.684
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Table 5: Identification based on Active Institutional Mergers

This table reports our identification results based on a quasi-natural experiment of financial institution mergers. Panel A validates our DiD model by testing the impact of financial institution mergers among active institutional investors on two measures of trading-based ownership concentration: *ActHHI* in Columns (1) and (3), and *ActTop5* in Columns (2) and (4). *Treat* is a treatment dummy, equal to 1 for firms held by both acquirer and target for more than 0.01% of the stock's market capitalization before the merger events. Control firms are those held by either the acquirer or the target, amounting to at least 0.01% of the market capitalization before the merger events. Besides, control firms are restricted to those that had never been treated in any of the merger events. *Post* equals one for the post-merger period. The estimation is on a quarterly basis, with an estimation window of (-8, +8) quarters in Columns (1)-(2) and (-12, +12) quarters in Columns (3)-(4). Panel B (C) presents the relation between price informativeness (investment-to-price sensitivity) and trading-based ownership concentration using DiD models. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Trading-based Ownership Concentration and Active Institutional Mergers

Event window	(-8, +8) quarters		(-12, +12) quarters	
Dependent variable	<i>ActHHI</i> (1)	<i>ActTop5</i> (2)	<i>ActHHI</i> (3)	<i>ActTop5</i> (4)
<i>Treat*Post</i>	0.021*** (0.004)	0.034*** (0.005)	0.021*** (0.005)	0.034*** (0.006)
Observations	95,396	95,396	135,524	135,524
R^2	0.605	0.690	0.536	0.633
Merger-Firm	Y	Y	Y	Y
Merger-Quarter FE	Y	Y	Y	Y

Panel B: DiD Estimation of Price Informativeness within (-2, +2) years

where $E =$	$E_{h=1}/A$ <i>EBIT</i> (1)	$E_{h=1}/A$ <i>EBITDA</i> (2)	$E_{h=1}/A$ <i>NI</i> (3)	$E_{h=3}/A$ <i>EBIT</i> (4)	$E_{h=3}/A$ <i>EBITDA</i> (5)	$E_{h=3}/A$ <i>NI</i> (6)
$\log(M/A)*Treat*Post$	-0.014*** (0.003)	-0.013*** (0.004)	-0.012*** (0.004)	-0.029*** (0.010)	-0.034*** (0.011)	-0.011 (0.010)
Observations	23,504	23,661	23,737	21,563	21,660	21,738
R^2	0.839	0.846	0.737	0.741	0.757	0.624
Controls	Y	Y	Y	Y	Y	Y
Merger-Firm	Y	Y	Y	Y	Y	Y
Merger-Year FE	Y	Y	Y	Y	Y	Y

Panel C: DiD Estimation of Investment-to-Price Sensitivity within (-2, +2) years

where $I =$	$I_{h=1}/K$ <i>Intangible</i> (1)	$I_{h=1}/K$ <i>Physical</i> (2)	$I_{h=1}/K$ <i>Invest</i> (3)	$I_{h=3}/K$ <i>Intangible</i> (4)	$I_{h=3}/K$ <i>Physical</i> (5)	$I_{h=3}/K$ <i>Invest</i> (6)
$\log(M/A)*Treat*Post$	-0.001 (0.002)	-0.010*** (0.002)	-0.010** (0.004)	-0.023** (0.008)	-0.016*** (0.006)	-0.042*** (0.014)
Observations	23,619	23,360	23,607	21,638	21,317	21,623
R^2	0.897	0.748	0.812	0.847	0.725	0.770
Controls	Y	Y	Y	Y	Y	Y
Merger-Firm	Y	Y	Y	Y	Y	Y
Merger-Year FE	Y	Y	Y	Y	Y	Y

Table 6: International Evidence

This table utilizes the international sample to re-examine the relation between price informativeness and trading-based ownership concentration. The international sample is constructed by combining data on global institutional ownership from FactSet, accounting data from Worldscope, and stock market data from DataStream. Panels A and B focus on price informativeness, while Panels C and D focus on investment-to-price sensitivity. Trading-based ownership concentration is measured by *ActHHI* in Panels A and C, representing the Herfindahl-Hirschman index of active institutional ownership, and by *ActTop5* in Panels B and D, denoting the proportion of shares held by the top five active institutional investors relative to the total shares held by all active institutional investors. The sample possesses an annual frequency and spans from 2000 to 2022. The coefficients of the control variables are suppressed for brevity. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Informativeness and <i>ActHHI</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)^* ActHHI$	-0.021*** (0.003)	-0.021*** (0.003)	-0.018*** (0.003)	-0.025*** (0.005)	-0.026*** (0.006)	-0.022*** (0.005)
Observations	172,863	172,514	178,447	141,518	141,203	146,716
R^2	0.725	0.733	0.701	0.617	0.630	0.598
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Country-Year	Y	Y	Y	Y	Y	Y
Panel B: Price Informativeness and <i>ActTop5</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)^* ActTop5$	-0.029*** (0.003)	-0.029*** (0.003)	-0.024*** (0.003)	-0.037*** (0.006)	-0.041*** (0.006)	-0.031*** (0.005)
Observations	172,863	172,514	178,447	141,518	141,203	146,716
R^2	0.725	0.733	0.701	0.619	0.632	0.599
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Country-Year	Y	Y	Y	Y	Y	Y

Continued on next page

Table 6 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Investment-to-Price Sensitivity and <i>ActHHI</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)^* ActHHI$	-0.007*** (0.003)	-0.015*** (0.004)	-0.022*** (0.006)	-0.022** (0.008)	-0.023*** (0.006)	-0.049*** (0.013)
Observations	178,293	177,640	177,992	146,622	146,034	146,391
R^2	0.846	0.623	0.679	0.715	0.545	0.581
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Country-Year	Y	Y	Y	Y	Y	Y
Panel D: Investment-to-Price Sensitivity and <i>ActTop5</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)^* ActTop5$	-0.010*** (0.003)	-0.022*** (0.004)	-0.032*** (0.005)	-0.032*** (0.008)	-0.038*** (0.008)	-0.074*** (0.016)
Observations	178,293	177,640	178,293	146,622	146,034	146,622
R^2	0.846	0.623	0.676	0.715	0.545	0.580
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Country-Year	Y	Y	Y	Y	Y	Y

Table 7: Portfolio Turnover of Active Institutional Investors

This table compares the portfolio turnover (PTR) in the Top5 subgroup and the Non-Top5 subgroup. The Top5 subgroup comprises stocks where the investor ranks among the top five largest shareholders, while the Non-Top5 subgroup includes all other stocks. Panel A illustrates the distribution of PTR for both the Top5 and Non-Top5 subgroups. The final two rows of Panel A adjust the threshold to be the top 10 ranking. Panel B presents regression analyses. Column (1) shows the results of regressing PTR on the dummy variable $DumTop5$, which is set to one for investor's Top5 subgroup, and zero for her Non-Top5 subgroup. Column (2) substitutes the Top5 subgroup dummy variable with the Top10 subgroup dummy variable, which is set to one for investor's Top10 subgroup. PIO is the portfolio institution ownership calculated as the holding-weighted average of stock-level institution ownership; $PRet$ is the portfolio quarterly return; $PRetStd$ is the portfolio volatility, calculated as the standard deviation of the quarterly returns in the past two years; $PSize$ is the portfolio size, computed as the logarithm of holding amount in million dollars. Standard errors, clustered at the quarter and investor levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Distribution of Portfolio Turnover						
Subgroup	N	p10	p25	p50	p75	p90
Top5	69261	0.000	0.003	0.059	0.142	0.265
Non-Top5	69261	0.047	0.122	0.230	0.381	0.533
Top10	79249	0.000	0.020	0.095	0.190	0.326
Non-Top10	79249	0.039	0.116	0.231	0.396	0.560
Panel B: Regression of Portfolio Turnover						
	(1)	(2)				
	PTR	PTR				
$DumTop5$	-0.143*** (0.004)					
$DumTop10$		-0.125*** (0.003)				
PIO	0.046*** (0.010)	0.050*** (0.010)				
$PRet$	0.027*** (0.010)	0.037*** (0.011)				
$PRetStd$	-0.108*** (0.019)	-0.095*** (0.022)				
$PSize$	0.003** (0.001)	0.001 (0.001)				
Observations	114,396	130,924				
R^2	0.720	0.712				
Investor-Quarter	Y	Y				

Table 8: Information Content of Earnings Announcements

This table examines the relation between information content of earnings announcements and trading-based ownership concentration, as measured by *ActHHI* and *ActTop5*. Information content is measured by abnormal trading volume (*AVOL*) in Columns (1)-(2) and abnormal return volatility (*AVAR*) in Columns (3)-(4). Specifically, *AVOL* is calculated as the average trading volume in the event window $[0, 1]$, scaled by the counterparts in the non-event window $[-40, -6]$, where day 0 denotes the earnings announcement date; *AVAR* is calculated as the mean square of adjusted returns in the event window, scaled by the counterparts in the non-event window. Panel B mirrors Panel A, with the addition of several control variables as specified by [Pevzner, Xie, and Xin \(2015\)](#) (abbreviated PXX): *FirmSize* denotes the natural logarithm of the market capitalization at the fiscal quarter end; $|UE|$ is the absolute value of unexpected earnings, computed as actual annual earnings minus the most recent median analyst forecast scaled by the quarter-end stock price; *ReportLag* is the number of days from the fiscal quarter-end to the earnings announcement date; *ForeDisp* is the standard deviation of analysts' earnings forecasts scaled by the fiscal quarter-end stock price, and *ForeNum* is the number of annual earnings forecasts reported by IBES. The coefficients of the control variables are suppressed for brevity. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)
Panel A: Baseline Regression				
	<i>AVOL</i>	<i>AVOL</i>	<i>AVAR</i>	<i>AVAR</i>
<i>ActHHI</i>	-0.167*** (0.018)		-0.302*** (0.034)	
<i>ActTop5</i>		-0.169*** (0.018)		-0.301*** (0.037)
Observations	319,619	319,619	320,050	320,050
R^2	0.263	0.263	0.245	0.246
Controls	Y	Y	Y	Y
PXX's Controls	N	N	N	N
Firm	Y	Y	Y	Y
Industry-Quarter	Y	Y	Y	Y
Panel B: Including PXX's Control Variables				
	<i>AVOL</i>	<i>AVOL</i>	<i>AVAR</i>	<i>AVAR</i>
<i>ActHHI</i>	-0.141*** (0.024)		-0.207*** (0.057)	
<i>ActTop5</i>		-0.101*** (0.022)		-0.125** (0.048)
Observations	162,570	162,570	162,575	162,575
R^2	0.313	0.313	0.271	0.271
Controls	Y	Y	Y	Y
PXX's Controls	Y	Y	Y	Y
Firm	Y	Y	Y	Y
Industry-Quarter	Y	Y	Y	Y

Internet Appendix to “Institutional Ownership Concentration and Informational Efficiency”

A Details of Numerical Analysis

This section details the calibration process for determining the ownership sizes λ s of 21 investors across ten scenarios as mentioned at the end in Section 2.3.1. Investor 0 represents retail investors, while the remaining 20 investors are oligopolists. These oligopolists are further categorized into four distinct groups based on their size – large (L) or small (S) – and learning capacity – active (A) or passive (P). That is, $LA = \{1, 2\}$, $LP = \{3, 4\}$, $SA = \{5, \dots, 12\}$, and $SP = \{13, \dots, 20\}$.

We choose the mass of retail investors $\lambda_0 = 40\%$. The remaining 60% of ownership is allocated among the 20 oligopolists. Given that the sum of all ownership sizes must equal one, we have

$$\sum_{j \in LA} \lambda_j + \sum_{j \in SA} \lambda_j + \sum_{j \in LP} \lambda_j + \sum_{j \in SP} \lambda_j = 1 - \lambda_0 = 0.6. \quad (A1)$$

The relative size within each small group is set to be linearly distributed between 1 and 5. Specifically, $\frac{\lambda_5}{\lambda_{12}} = 5$ and $\frac{\lambda_{13}}{\lambda_{20}} = 5$. This allows us to express the total ownership of the small active and small passive investors as

$$\sum_{j \in SA} \lambda_j = 24\lambda_{12} \text{ and } \sum_{j \in SP} \lambda_j = 24\lambda_{20}, \quad (A2)$$

respectively. Furthermore, the passive sector is set at 50% of total institutional ownership:

$$\sum_{j \in LP} \lambda_j + \sum_{j \in SP} \lambda_j = 0.5(1 - \lambda_0) = 0.3. \quad (A3)$$

Next, we hold the total size of active section ($\sum_{j \in LA} \lambda_j + \sum_{j \in SA} \lambda_j$) and the total size of passive section ($\sum_{j \in LP} \lambda_j + \sum_{j \in SP} \lambda_j$) fixed, and reshuffle the ownership sizes λ s within each section create varying levels of ownership concentration. Specifically, we vary two sets of parameter values. First, we change the relative size of the two large active oligopolists and two large passive oligopolists by varying $a_{act} \equiv \lambda_1/\lambda_2$ and $a_{pas} \equiv \lambda_3/\lambda_4$ linearly from 1.1 to 10 in ten scenarios. That is, $a_{act}(k) = a_{pas}(k) = 1.1 + \frac{10-1.1}{9}(k-1)$, where k denotes the scenario. Consequently, we can express the total ownership of the large active and passive investors respectively

as

$$\sum_{j \in LA} \lambda_j = (1 + a_{act}(k))\lambda_2 \text{ and } \sum_{j \in LP} \lambda_j = (1 + a_{pas}(k))\lambda_4. \quad (\text{A4})$$

Second and at the same time, we vary the relative size of the small sector linearly from 10% to 3% in the ten scenarios. More formally:

$$\sum_{j \in SA} \lambda_j = (1 - 0.5)(1 - \lambda_0)b_{act}(k) = 0.3b_{act}(k), \quad (\text{A5})$$

$$\sum_{j \in SP} \lambda_j = 0.5(1 - \lambda_0)b_{pas}(k) = 0.3b_{pas}(k), \quad (\text{A6})$$

where $b_{act}(k) = b_{pas}(k) = 0.10 - \frac{0.10-0.03}{9}(k - 1)$.

Finally, with equations (A1)–(A6), we can solve for λ_j for each investor in each scenario k . Table A1 reports the ownership sizes λ_j along with the size-based ownership concentration values for the ten scenarios. Passive size-based ownership concentration is calculated as $PasHHI_{size} = \sum_{j \in SP \cup LP} \left(\frac{\lambda_j}{\sum_{k \in SP \cup LP} \lambda_k} \right)^2$.

While alternative methods exist to generate varying concentration levels, our simultaneous adjustment of parameters a and b is motivated by observed patterns in our empirical sample. Specifically, we categorize institutional investors in our sample into 20 groups, mirroring the 20 oligopolists in our calibration experiments. This allows us to examine the evolution of their size distribution over time.

Regarding the categorization, we use active investors as an example to illustrate. We begin by ranking active investors annually based on their AUM. The top 5% of active investors are classified as “Large.” Within this group, the top 1% are assigned to Group 1, while the remaining investors are placed in Group 2. The remaining 95% of active investors are considered “Small.” These small investors are further divided into 8 equally sized groups (Groups 5 through 12) based on their AUM. We then calculate the average AUM for each group, denoted as AUM_j for investor $j = \{1, 2, 5, \dots, 12\}$.¹ We repeat this procedure for passive investors, creating an analogous set

¹Instead of using AUM deciles, we define large investors as those in the top 5% by AUM. This better captures the role of the exceptionally large investors. Our results are robust to alternative thresholds, such as the top 3% and top 10%.

of groups.

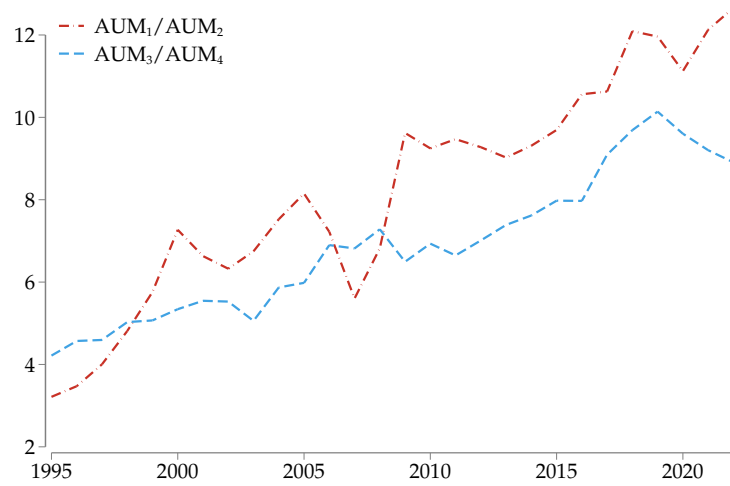
Figure A1 presents the time-series patterns of the relative sizes within the large sectors ($\frac{AUM_1}{AUM_2}$ and $\frac{AUM_3}{AUM_4}$) and the relative size of the small sectors ($\frac{AUM_{j \in SA}}{AUM_{j \in SA \cup LA}}$ and $\frac{AUM_{j \in SP}}{AUM_{j \in SP \cup LP}}$). We observe an overall increase in the relative size within the large sectors and a concurrent decrease in the relative size of the small sectors over time. These trends motivate our method of simultaneously varying a and b to generate increasing concentration in the calibration experiments.

We then compare the distribution of λ_j across the 10 calibration scenarios with the evolution of AUM_j in our empirical sample. Panels (a) and (c) of Figure A2 illustrate the evolution of AUM_j within the active and passive sectors, respectively.² Notably, these distributions closely resemble the distribution of λ_j across the 10 calibration scenarios, as shown in Panels (c) and (d). Therefore, the simultaneous adjustment of parameters a and b makes the size distribution in the calibration exercise match well with our empirical sample.

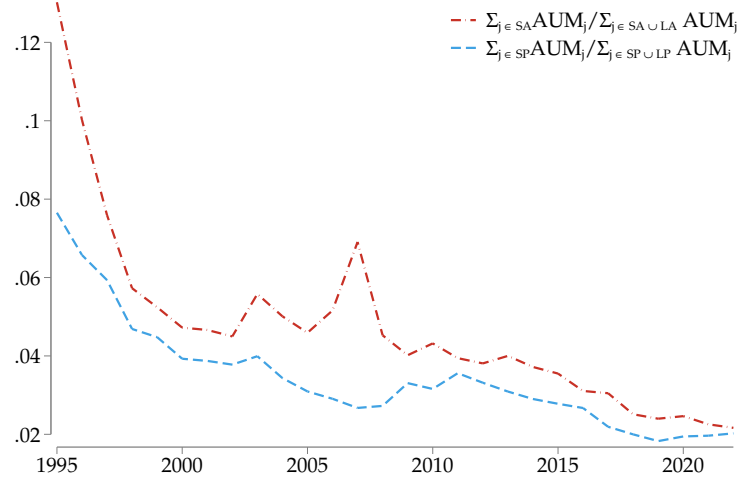
In the placebo tests mentioned in Section 2.3.4, we respectively fix the size distribution for active and passive investors throughout ten scenarios. For the first placebo test, the relative size of the two large active investors is fixed at 1.1, i.e., $a_{act}(k) = 1.1$ for $k = \{1, 2, \dots, 10\}$. Meanwhile, the relative size of the small active sector is fixed at 0.10, i.e., $b_{act}(k) = 0.10$ for $k = \{1, 2, \dots, 10\}$. We then resolve equations (A1)–(A6) to obtain λ_j in the first placebo test. Table A2 reports the results. While $PasHHI_{size}$ increases gradually from 0.4074 to 0.7855 across the ten scenarios, $ActHHI_{size}$ remains fixed at 0.4047.

For the second placebo test, the relative size of the two large passive investors is fixed at 1.1, i.e., $a_{pas}(k) = 1.1$ for $k = \{1, 2, \dots, 10\}$. Meanwhile, the relative size of the small passive sector is fixed at 0.10, i.e., $b_{pas}(k) = 0.10$ for $k = \{1, 2, \dots, 10\}$. We then resolve equations (A1)–(A6) again to obtain λ_j in the second placebo test. Table A3 reports the results. While $ActHHI_{size}$ increases gradually from 0.4074 to 0.7855 across the ten scenarios, $PasHHI_{size}$ remains fixed at 0.4047.

²The sample begins in 1995 due to the relatively small number of active investors prior to 1995 (less than 300), which would result in limited observations within each group.

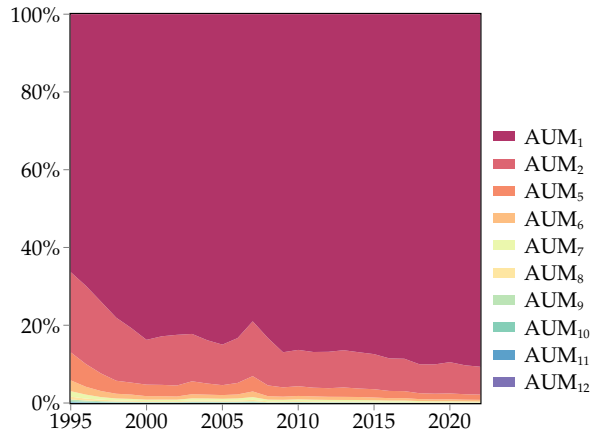


(a) Relative Size within the Large Sectors

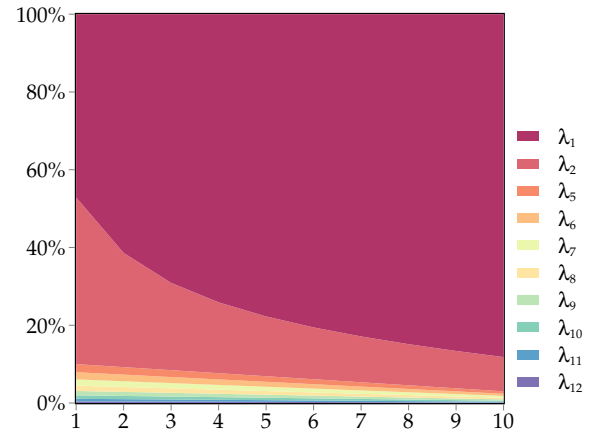


(b) Relative Size of the Small Sectors

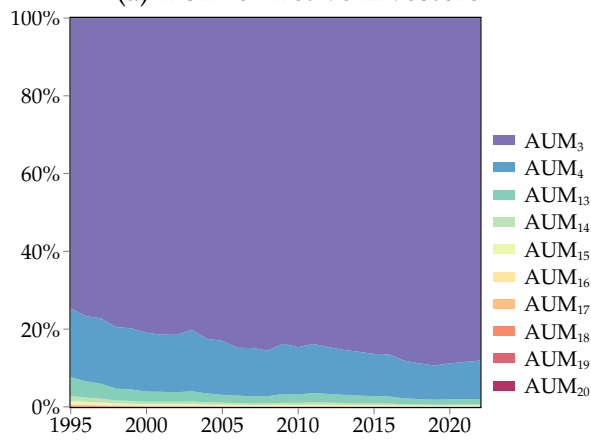
Figure A1: Relative Size Distribution



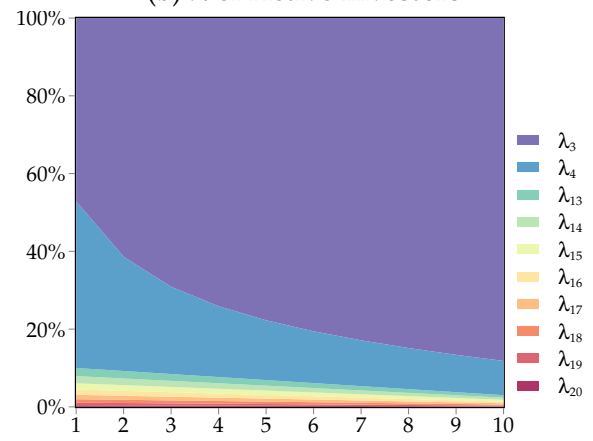
(a) AUM of Active Investors



(b) λ of Active Investors



(c) AUM of Passive Investors



(d) λ of Passive Investors

Figure A2: Size Distribution

Table A1: Ownership Sizes and Size-based Concentration in Ten Scenarios: Baseline

Investor Type		1	2	3	4	5	6	7	8	9	10
Panel A: λ_j											
Retail	λ_0	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000
Large Active	λ_1	0.1414	0.1842	0.2073	0.2223	0.2332	0.2417	0.2486	0.2546	0.2598	0.2645
	λ_2	0.1286	0.0882	0.0674	0.0547	0.0461	0.0400	0.0354	0.0317	0.0288	0.0265
Large Passive	λ_3	0.1414	0.1842	0.2073	0.2223	0.2332	0.2417	0.2486	0.2546	0.2598	0.2645
	λ_4	0.1286	0.0882	0.0674	0.0547	0.0461	0.0400	0.0354	0.0317	0.0288	0.0265
Small Active	λ_5	0.0063	0.0058	0.0053	0.0048	0.0043	0.0038	0.0033	0.0028	0.0024	0.0019
	λ_6	0.0055	0.0051	0.0047	0.0042	0.0038	0.0034	0.0030	0.0025	0.0021	0.0017
	λ_7	0.0048	0.0044	0.0041	0.0037	0.0033	0.0029	0.0026	0.0022	0.0018	0.0014
	λ_8	0.0041	0.0038	0.0035	0.0031	0.0028	0.0025	0.0022	0.0019	0.0016	0.0012
	λ_9	0.0034	0.0031	0.0029	0.0026	0.0023	0.0021	0.0018	0.0015	0.0013	0.0010
	λ_{10}	0.0027	0.0025	0.0023	0.0021	0.0018	0.0016	0.0014	0.0012	0.0010	0.0008
	λ_{11}	0.0020	0.0018	0.0017	0.0015	0.0014	0.0012	0.0010	0.0009	0.0007	0.0006
	λ_{12}	0.0013	0.0012	0.0011	0.0010	0.0009	0.0008	0.0007	0.0006	0.0005	0.0004
Small Passive	λ_{13}	0.0063	0.0058	0.0053	0.0048	0.0043	0.0038	0.0033	0.0028	0.0024	0.0019
	λ_{14}	0.0055	0.0051	0.0047	0.0042	0.0038	0.0034	0.0030	0.0025	0.0021	0.0017
	λ_{15}	0.0048	0.0044	0.0041	0.0037	0.0033	0.0029	0.0026	0.0022	0.0018	0.0014
	λ_{16}	0.0041	0.0038	0.0035	0.0031	0.0028	0.0025	0.0022	0.0019	0.0016	0.0012
	λ_{17}	0.0034	0.0031	0.0029	0.0026	0.0023	0.0021	0.0018	0.0015	0.0013	0.0010
	λ_{18}	0.0027	0.0025	0.0023	0.0021	0.0018	0.0016	0.0014	0.0012	0.0010	0.0008
	λ_{19}	0.0020	0.0018	0.0017	0.0015	0.0014	0.0012	0.0010	0.0009	0.0007	0.0006
	λ_{20}	0.0013	0.0012	0.0011	0.0010	0.0009	0.0008	0.0007	0.0006	0.0005	0.0004
Panel B: $ActHHI_{size}$ and $PasHHI_{size}$											
$ActHHI_{size}$		0.4074	0.4645	0.5290	0.5833	0.6286	0.6673	0.7013	0.7317	0.7596	0.7855
$PasHHI_{size}$		0.4074	0.4645	0.5290	0.5833	0.6286	0.6673	0.7013	0.7317	0.7596	0.7855

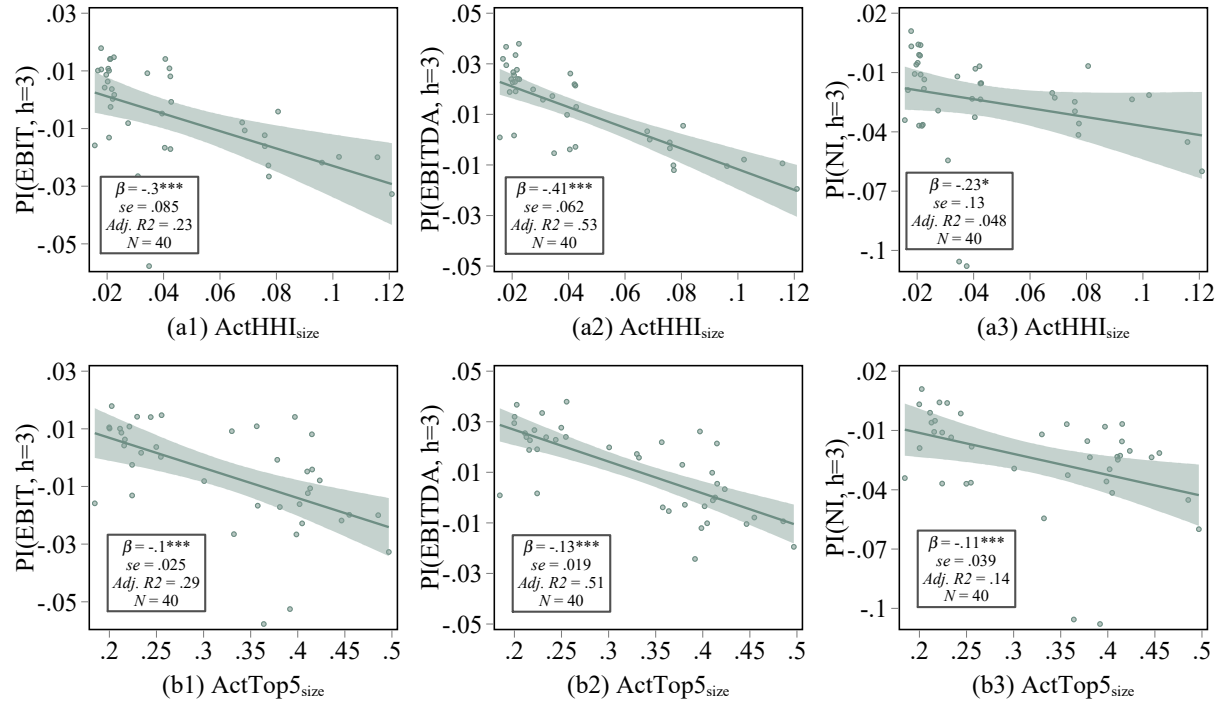
Table A2: Ownership Sizes and Size-based Concentration: Fixed $ActHHI_{size}$

Investor Type		1	2	3	4	5	6	7	8	9	10
Panel A: λ_j											
Retail	λ_0	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000
Large Active	λ_1	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414
	λ_2	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286
Large Passive	λ_3	0.1414	0.1842	0.2073	0.2223	0.2332	0.2417	0.2486	0.2546	0.2598	0.2645
	λ_4	0.1286	0.0882	0.0674	0.0547	0.0461	0.0400	0.0354	0.0317	0.0288	0.0265
Small Active	λ_5	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063
	λ_6	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055
	λ_7	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048
	λ_8	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041
	λ_9	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034
	λ_{10}	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027
	λ_{11}	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020
	λ_{12}	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013
Small Passive	λ_{13}	0.0063	0.0058	0.0053	0.0048	0.0043	0.0038	0.0033	0.0028	0.0024	0.0019
	λ_{14}	0.0055	0.0051	0.0047	0.0042	0.0038	0.0034	0.0030	0.0025	0.0021	0.0017
	λ_{15}	0.0048	0.0044	0.0041	0.0037	0.0033	0.0029	0.0026	0.0022	0.0018	0.0014
	λ_{16}	0.0041	0.0038	0.0035	0.0031	0.0028	0.0025	0.0022	0.0019	0.0016	0.0012
	λ_{17}	0.0034	0.0031	0.0029	0.0026	0.0023	0.0021	0.0018	0.0015	0.0013	0.0010
	λ_{18}	0.0027	0.0025	0.0023	0.0021	0.0018	0.0016	0.0014	0.0012	0.0010	0.0008
	λ_{19}	0.0020	0.0018	0.0017	0.0015	0.0014	0.0012	0.0010	0.0009	0.0007	0.0006
	λ_{20}	0.0013	0.0012	0.0011	0.0010	0.0009	0.0008	0.0007	0.0006	0.0005	0.0004
Panel B: $ActHHI_{size}$ and $PasHHI_{size}$											
$ActHHI_{size}$		0.4074	0.4074	0.4074	0.4074	0.4074	0.4074	0.4074	0.4074	0.4074	0.4074
$PasHHI_{size}$		0.4074	0.4645	0.5290	0.5833	0.6286	0.6673	0.7013	0.7317	0.7596	0.7855

Table A3: Ownership Sizes and Size-based Concentration in Ten Scenarios: Fixed $PasHHI_{size}$

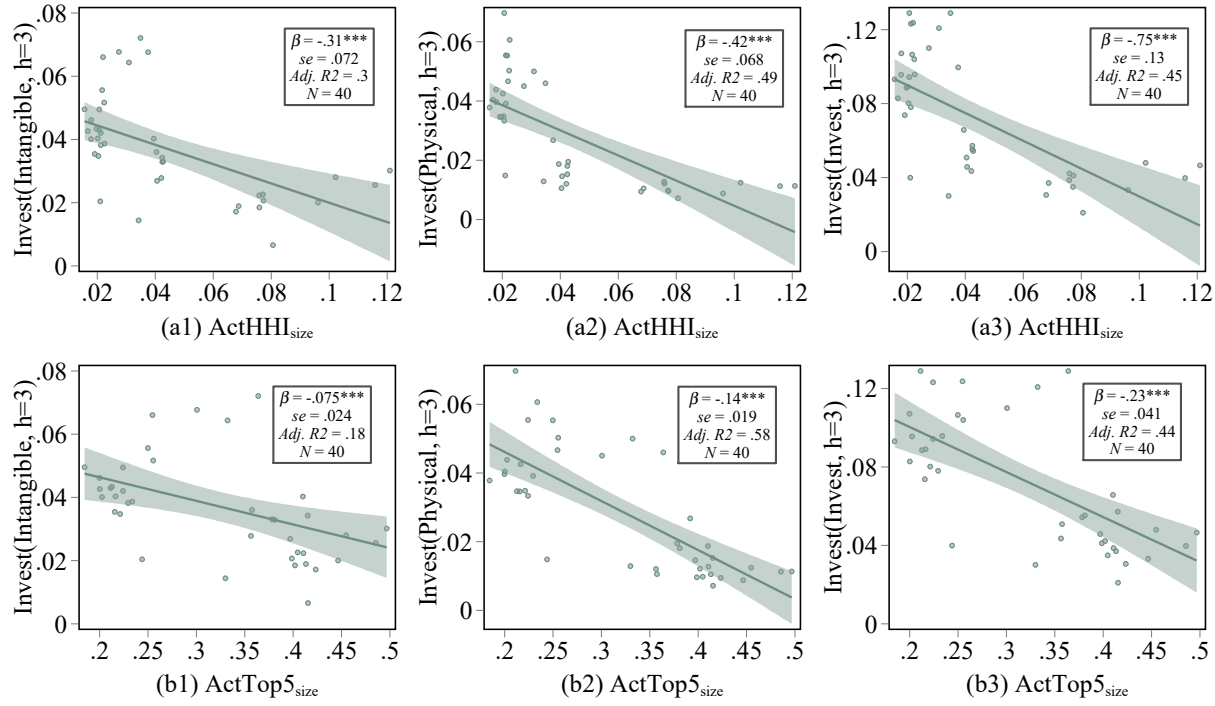
Investor Type		1	2	3	4	5	6	7	8	9	10
Panel A: λ_j											
Retail	λ_0	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000	0.4000
Large Active	λ_1	0.1414	0.1842	0.2073	0.2223	0.2332	0.2417	0.2486	0.2546	0.2598	0.2645
	λ_2	0.1286	0.0882	0.0674	0.0547	0.0461	0.0400	0.0354	0.0317	0.0288	0.0265
Large Passive	λ_3	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414	0.1414
	λ_4	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286	0.1286
Small Active	λ_5	0.0063	0.0058	0.0053	0.0048	0.0043	0.0038	0.0033	0.0028	0.0024	0.0019
	λ_6	0.0055	0.0051	0.0047	0.0042	0.0038	0.0034	0.0030	0.0025	0.0021	0.0017
	λ_7	0.0048	0.0044	0.0041	0.0037	0.0033	0.0029	0.0026	0.0022	0.0018	0.0014
	λ_8	0.0041	0.0038	0.0035	0.0031	0.0028	0.0025	0.0022	0.0019	0.0016	0.0012
	λ_9	0.0034	0.0031	0.0029	0.0026	0.0023	0.0021	0.0018	0.0015	0.0013	0.0010
	λ_{10}	0.0027	0.0025	0.0023	0.0021	0.0018	0.0016	0.0014	0.0012	0.0010	0.0008
	λ_{11}	0.0020	0.0018	0.0017	0.0015	0.0014	0.0012	0.0010	0.0009	0.0007	0.0006
	λ_{12}	0.0013	0.0012	0.0011	0.0010	0.0009	0.0008	0.0007	0.0006	0.0005	0.0004
Small Passive	λ_{13}	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063	0.0063
	λ_{14}	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055	0.0055
	λ_{15}	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048	0.0048
	λ_{16}	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041	0.0041
	λ_{17}	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034	0.0034
	λ_{18}	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027	0.0027
	λ_{19}	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020	0.0020
	λ_{20}	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013	0.0013
Panel B: $ActHHI_{size}$ and $PasHHI_{size}$											
$ActHHI_{size}$		0.4074	0.4645	0.5290	0.5833	0.6286	0.6673	0.7013	0.7317	0.7596	0.7855
$PasHHI_{size}$		0.4074	0.4074	0.4074	0.4074	0.4074	0.4074	0.4074	0.4074	0.4074	0.4074

B Additional Figures and Tables in Main Text



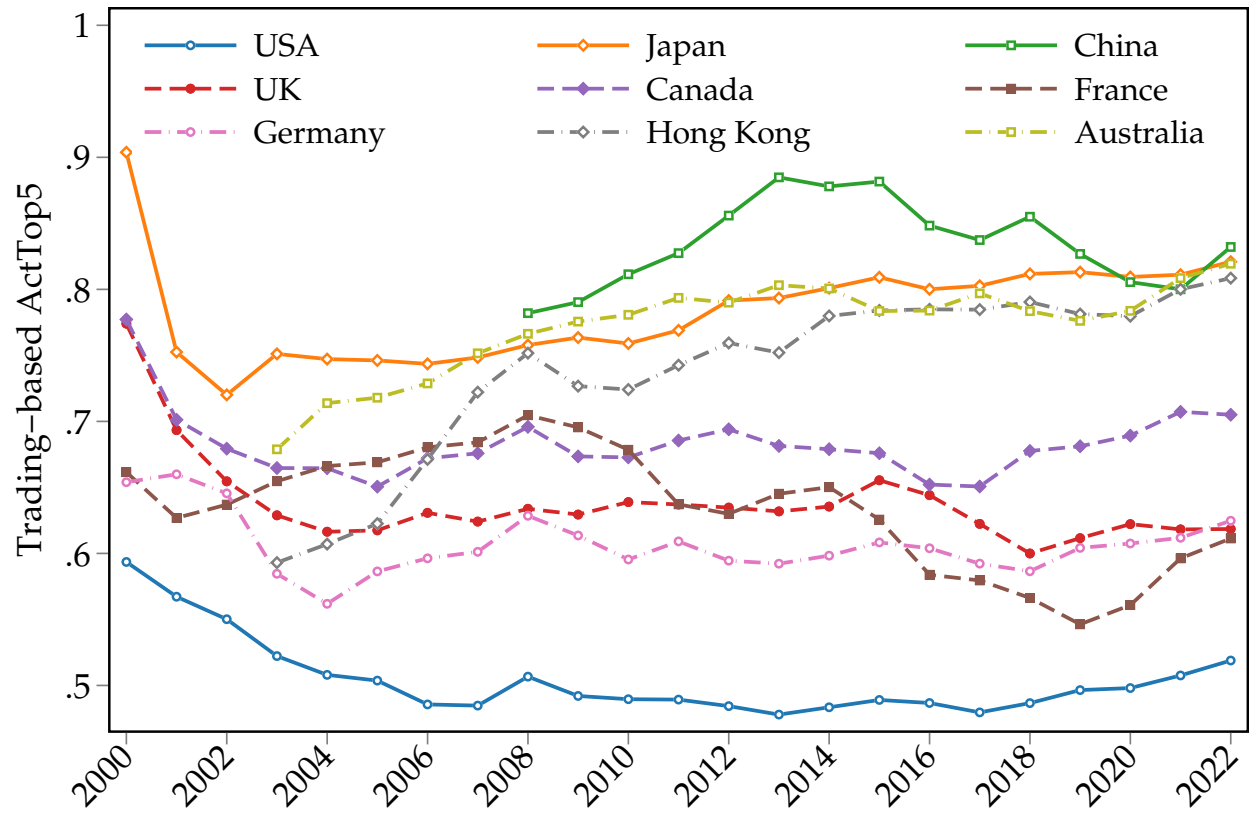
This figure presents scatter plots illustrating the relation between price informativeness and size-based ownership concentration. The plots include fit lines and 95% confidence intervals. Size-based ownership concentration is quantified using $ActHHI_{size}$ in Panels (a1)-(a3), and $ActTop5_{size}$ in Panels (b1)-(b3). PI is derived from equations (12) and (13) and measures the predictability of future cash flows based on current market prices, with future cash flows represented by one of three variables ($EBIT$, $EBITDA$, or NI) calculated as of year $t + h$ and divided by total assets in year t . The prediction horizon, denoted by h , is set at 3 years. The sample has an annual frequency and spans from 1980 to 2022. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure B1: Price Informativeness and Size-based Ownership Concentration: 3-year Prediction Horizon



This figure presents scatter plots illustrating the relation between investment-to-price sensitivity and size-based ownership concentration. The plots include fit lines and 95% confidence intervals. Size-based ownership concentration is quantified using $ActHHI_{size}$ in Panels (a1)-(a3), and $ActTop5_{size}$ in Panels (b1)-(b3). Investment-to-price sensitivity is derived from equation (14) and measures the extent to which current market prices reveal the information necessary for future investment decisions, with future investments represented by one of three variables (*Intangible*, *Physical*, or *Invest*) calculated as of year $t + h$ and divided by total capital in year t . The prediction horizon, denoted by h , is set at 3 years. The sample has an annual frequency and spans from 1980 to 2022. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure B2: Investment-to-Price Sensitivity and Size-based Ownership Concentration: 3-year Prediction Horizon



This figure displays the time-series average trading-based ownership concentration ($ActTop5$) for the largest equity markets worldwide, including the United States, the United Kingdom, Germany, Japan, Canada, Hong Kong, China, France, and Australia.

Figure B3: The Time Trend of Trading-based Ownership Concentration Worldwide

Table B1: Variable Definitions

Variable	Description
$ActHHI_{size}$	Herfindahl-Hirschman index of Assets Under Management (AUM) among active institutional investors: $ActHHI_{size,q} = \frac{\sum_{j=1}^{N_{mkt}} (AUM_{j,q}^2)}{\left(\sum_{j=1}^N AUM_{j,q}\right)^2},$ where N is the total number of institutional investors; $AUM_{j,q}$ is the AUM of institution j in quarter q. The definition of active and passive institutional investors is based on the classification scheme of Bushee (1998).
$ActTop5_{size}$	The proportion of AUM held by the top five active institutional investors relative to the total AUM of all active institutional investors: $ActTop5_{size,q} = \frac{\sum_{j=1}^{Top\ 5} AUM_{j,q}}{\sum_{j=1}^{N_{mkt}} AUM_{j,q}},$ where N is the total number of institutional investors; $AUM_{j,q}$ is the AUM of institution j in quarter q.
$ActHHI$	Herfindahl-Hirschman index of active institutional ownership: $ActHHI_{i,q} = \frac{\sum_{j=1}^{N_i} (S_{i,j,q}^2)}{\left(\sum_{j=1}^{N_i} S_{i,j,q}\right)^2},$ where $S_{i,j,q}$ denotes the equity shares of stock i owned by active institution j in quarter q; N_i is the number of active institutions holding stock i.
$ActTop5$	The proportion of shares held by the top five active institutional investors relative to the total shares held by all active institutional investors.: $ActTop5_{i,q} = \frac{\sum_{j=1}^{Top\ 5} S_{i,j,q}}{\sum_{j=1}^{N_i} S_{i,j,q}},$ where $S_{i,j,q}$ denotes the equity shares of stock i owned by active institution j in quarter q; N_i is the number of active institutions holding stock i.
$EBIT/A$	Earnings before interest and taxes scaled by total assets.
$EBITDA/A$	Earnings before interest, taxes, depreciation and amortization scaled by total assets.
NI/A	Net income scaled by total assets.

Continued on next page

Table B1 – *Continued*

Variable	Description
<i>Intangible/K</i>	Intangible investment rate, calculated as $R\&D + 0.3 \times SG\&A$ expenses, scaled by total capital. R&D is set to zero for missing values. The total capital is the sum of net property, plant and equipment (item PPENT from Compustat) and intangible capital (item K_INT from Peters and Taylor (2017)).
<i>Physical/K</i>	Physical investment rate, calculated as capital expenditure (CAPX) scaled by total capital. The total capital is the sum of net property, plant and equipment (item PPENT from Compustat) and intangible capital (item K_INT from Peters and Taylor (2017)).
<i>Invest/K</i>	Total investment rate, defined as the sum of <i>Physical</i> and <i>Intangible</i> .
$\log(M/A)$	The log-ratio of market capitalization at the end of March to the total asset value in the previous fiscal year.
<i>PasHHI</i>	Herfindahl-Hirschman index of passive institutional ownership. The calculation method closely resembles that of <i>ActHHI</i> , with the key distinction being the transition from active to passive investors within the cohort considered.
<i>PasTop5</i>	Holding percentage of the largest five passive shareholders. The calculation method closely resembles that of <i>ActTop5</i> , with the key distinction being the transition from active to passive investors within the cohort considered.
<i>IO</i>	Institutional ownership, calculated as the total institution holding divided by the market capitalization.
<i>Leverage</i>	Ratio of book debt to total assets.
<i>Sale</i>	Total sales scaled by total assets.
<i>Cash</i>	Cash holdings scaled by total assets.
$BHAR[\tau, T]$	Buy-and-hold abnormal returns from day τ to day T ($\tau < T$), where day 0 denotes the earnings announcement day.
<i>Rank</i>	A decile rank of the analyst earnings surprises, with analyst earnings surprises calculated as the difference between the quarter's actual earnings per share and the median of the latest analyst forecasts, divided by the firm's stock price five trading days prior to the announcement date.
<i>CPIE</i>	A microstructure-based measure developed by Duarte et al. (2020) , capturing the probability of private information arrival on a given day. The measure is derived from one of the four microstructure models of private information arrival: the PIN model (PIN) of Easley et al. (1996) , the adjusted PIN model (APIN) of Duarte and Young (2009) , the generalized PIN model (GPIN) of Duarte et al. (2020) , and the Odders-White and Ready (2008) model (OWR).

Continued on next page

Table B1 – *Continued*

Variable	Description
<i>ITI</i>	A machine learning-based measure of informed trading intensity by Bogousslavsky et al. (2024) . The measure is trained from one of the three samples: Schedule 13D trading, opportunistic insider trades, and short sales.
<i>VR(q)</i>	A q -period bias-corrected variance ratio by Lo and MacKinlay (1988) : $VR(q) = \left \frac{\sigma^2(q)}{q \times \sigma^2} - 1 \right ,$ where $\sigma^2(q)$ denotes the variance of returns over a q-day horizon; σ^2 denotes the variance of daily returns.
$\tau_{\pi}^{R,j}$	A measure of relative price informativeness by Dávila and Parlato (2025) , which corresponds to the Kalman gain of a Bayesian external observer who only learns from the price under a Gaussian environment.
<i>PTR</i>	Portfolio turnover, calculated as $PTR_{k,g,q} = \frac{\min(AgBuy_{k,g,q}, AgSell_{k,g,q})}{\sum_{i \in N_{k,g}} (S_{k,g,i,q} P_{i,q} + S_{k,g,i,q-1} P_{i,q-1}) / 2},$ where $AgBuy_{k,g,q}$ and $AgSell_{k,g,q}$ are the aggregate purchase and sale of portfolio g held by active institutional investor k in quarter q, respectively; S is the number of holding shares; P is the share price.
<i>AVAR</i>	Abnormal return volatility, calculated as the mean of the squared market-model-adjusted returns in the event window (earnings announcement event), scaled by the counterparts in the non-event window.
<i>AVOL</i>	Abnormal trading volume, calculated as the mean of share turnover in the event window (earnings announcement event), scaled by the counterparts in the non-event window.

Table B2: Active Financial Institution Mergers

This table lists the sample of 11 active financial institution mergers that are used for identification, including the announcement date, completion date, acquirer name and target name of the merger.

Announce- ment Date	Completion Date	Acquirer Name	Target Name
1986/7/15	1986/8/28	Travelers Corp	Dillon Read & Co Inc
1995/5/8	1995/12/27	U.S. Bancorp	West One Bank, Idaho NA
1996/4/15	1996/4/30	Equitable Life Assurance	Natl Mutual Funds Mgmt
1996/6/24	1996/10/31	Morgan Stanley Group Inc	Van Kampen Amer Capital
1997/11/5	1997/12/1	PIMCO Advisors LP	Oppenheimer Group Inc
2003/7/22	2003/10/31	Lehman Brothers Hldgs	Neuberger Berman, LLC (Sloate)
2003/10/14	2004/2/27	Hennessy Advr Inc	Lindner Asset Management, Inc
2004/8/26	2005/1/31	Blackrock Inc	State Str Research & Mgmt Co
2010/2/16	2010/4/19	Fortress Invt Grp, LLC	Guggenheim Capital, LLC
2017/5/9	2017/10/2	Two Sigma Secs, LLC	Timber Hill LLC
2018/4/10	2018/4/10	Schonfeld Strategic Advr LLC	Folger Hill Asset Mgmt LLC

Table B3: DiD Estimation Using Active Institutional Mergers: Alternative Control Group

This table replicates our DiD results from Table 5, with an alternative strategy for selecting control firms: Control firms are re-defined as those held by the acquirer but not the target, with a 0.01% or greater ownership prior to the merger announcement. Panel A focuses on price informativeness, while Panel B focuses on investment-to-price sensitivity. *Treat* is a treatment dummy, equal to 1 for firms held by both acquirer and target for more than 0.01% of the stock's market capitalization before the merger events. *Post* equals one for the post-merger period. The estimation is conducted on an annual basis, with an estimation window from 2 years before to 2 years after mergers. The coefficients of the control variables are suppressed for brevity. See Table B1 for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Informativeness within $(-2, +2)$ years						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)*Treat*Post$	-0.016*** (0.003)	-0.015*** (0.004)	-0.013*** (0.004)	-0.031*** (0.010)	-0.035*** (0.011)	-0.014 (0.010)
Observations	20,740	20,897	20,967	19,021	19,118	19,190
R^2	0.840	0.848	0.739	0.750	0.765	0.633
Controls	Y	Y	Y	Y	Y	Y
Merger-Firm	Y	Y	Y	Y	Y	Y
Merger-Year FE	Y	Y	Y	Y	Y	Y
Panel B: Investment-to-Price Sensitivity within $(-2, +2)$ years						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)*Treat*Post$	-0.000 (0.002)	-0.010*** (0.002)	-0.009** (0.004)	-0.020** (0.009)	-0.017*** (0.006)	-0.039*** (0.014)
Observations	20,849	20,600	20,840	19,090	18,784	19,078
R^2	0.897	0.746	0.810	0.845	0.723	0.770
Controls	Y	Y	Y	Y	Y	Y
Merger-Firm	Y	Y	Y	Y	Y	Y
Merger-Year FE	Y	Y	Y	Y	Y	Y

Table B4: DiD Estimation Using Active Institutional Mergers: Alternative Event Window

This table replicates our DiD results from Table 5, with the key distinction that the estimation window is extended to (-3, +3) years, with year-0 denoting the merger completion year. Panel A focuses on price informativeness, while Panel B focuses on investment-to-price sensitivity. *Treat* is a treatment dummy, equal to 1 for firms held by both acquirer and target for more than 0.01% of the stock's market capitalization before the merger events. Control firms are those held by either the acquirer or the target, amounting to at least 0.01% of the market capitalization before the merger events. Besides, control firms are restricted to those that had never been treated in any of the merger events. *Post* equals one for the post-merger period. The estimation is conducted on an annual basis, with an estimation window from 3 years before to 3 years after mergers. The coefficients of the control variables are suppressed for brevity. See Table B1 for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Informativeness within (-3, +3) years						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)*Treat*Post$	-0.012** (0.005)	-0.012*** (0.004)	-0.009** (0.004)	-0.038*** (0.010)	-0.042*** (0.011)	-0.019* (0.010)
Observations	32,001	32,210	32,310	29,416	29,557	29,658
R^2	0.810	0.820	0.688	0.700	0.713	0.585
Controls	Y	Y	Y	Y	Y	Y
Merger-Firm	Y	Y	Y	Y	Y	Y
Merger-Year	Y	Y	Y	Y	Y	Y
Panel B: Investment-to-Price Sensitivity within (-3, +3) years						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)*Treat*Post$	0.000 (0.002)	-0.008** (0.004)	-0.007 (0.005)	-0.025** (0.010)	-0.022*** (0.007)	-0.046*** (0.017)
Observations	32,156	31,776	32,139	29,527	29,097	29,505
R^2	0.876	0.712	0.789	0.803	0.658	0.716
Controls	Y	Y	Y	Y	Y	Y
Merger-Firm	Y	Y	Y	Y	Y	Y
Merger-Year FE	Y	Y	Y	Y	Y	Y

Table B5: Summary Statistics for the International Sample

This table presents the summary statistics for the variables in the international sample. The international sample is constructed by combining data on global institutional ownership from FactSet, accounting data from Worldscope, and stock market data from DataStream. The sample has an annual frequency and spans from 2000 to 2022. All continuous variables are winsorized at the top and bottom 1% to mitigate the influence of outliers. Variable definitions are provided in Table B1.

Variable	N	Mean	SD	p10	p25	p50	p75	p90
Panel A: Ownership Concentration Variables								
<i>ActHHI</i>	196120	0.202	0.189	0.036	0.063	0.137	0.277	0.468
<i>ActTop5</i>	196120	0.675	0.241	0.333	0.462	0.691	0.908	0.988
Panel B: Earning Variables								
<i>EBIT/A</i>	191854	0.050	0.158	-0.060	0.027	0.067	0.114	0.176
<i>EBITDA/A</i>	191574	0.091	0.156	-0.014	0.060	0.105	0.158	0.224
<i>NI/A</i>	196112	0.019	0.155	-0.078	0.009	0.040	0.078	0.128
Panel C: Investment Rate Variables								
<i>Intangible/K</i>	195916	0.143	0.132	0.007	0.046	0.119	0.195	0.293
<i>Physical/K</i>	195533	0.100	0.106	0.014	0.033	0.068	0.128	0.221
<i>Invest/K</i>	195755	0.245	0.154	0.097	0.151	0.212	0.294	0.420
Panel D: Control Variables								
$\log(M/A)$	196120	-0.101	0.996	-1.342	-0.751	-0.110	0.555	1.186
<i>PasHHI</i>	196120	0.833	0.165	0.589	0.705	0.868	1.000	1.000
<i>PasTop5</i>	196120	0.366	0.293	0.098	0.147	0.243	0.508	0.966
<i>IO</i>	196120	0.319	0.322	0.028	0.069	0.177	0.485	0.928
<i>Leverage</i>	196120	0.218	0.188	0.000	0.047	0.193	0.339	0.475
<i>Sale</i>	196120	0.939	0.654	0.264	0.491	0.806	1.213	1.763
<i>Cash</i>	196120	0.189	0.186	0.021	0.056	0.129	0.256	0.452

Table B6: International Evidence: Exclude U.S. Firms

This table utilizes the international sample excluding firms in the United States to re-examine the relation between price informativeness and trading-based ownership concentration. The international sample is constructed by combining data on global institutional ownership from FactSet, accounting data from Worldscope, and stock market data from DataStream. Panels A and B focus on price informativeness, while Panels C and D focus on investment-to-price sensitivity. Trading-based ownership concentration is measured by *ActHHI* in Panels A and C, representing the Herfindahl-Hirschman index of active institutional ownership, and by *ActTop5* in Panels B and D, denoting the proportion of shares held by the top five active institutional investors relative to the total shares held by all active institutional investors. The sample possesses an annual frequency and spans from 2000 to 2022. The coefficients of the control variables are suppressed for brevity. See Table B1 for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Informativeness and <i>ActHHI</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)^* ActHHI$	-0.020*** (0.003)	-0.020*** (0.003)	-0.014*** (0.002)	-0.020*** (0.005)	-0.021*** (0.006)	-0.015*** (0.005)
Observations	120,376	120,170	123,243	99,368	99,160	102,132
R^2	0.694	0.708	0.666	0.599	0.625	0.572
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Panel B: Price Informativeness and <i>ActTop5</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)^* ActTop5$	-0.030*** (0.004)	-0.030*** (0.004)	-0.022*** (0.003)	-0.042*** (0.006)	-0.046*** (0.007)	-0.034*** (0.005)
Observations	120,376	120,170	123,243	99,368	99,160	102,132
R^2	0.695	0.709	0.666	0.602	0.628	0.574
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y

Continued on next page

Table B6 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Investment-to-Price Sensitivity and <i>ActHHI</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)^* ActHHI$	-0.005*** (0.002)	-0.011** (0.004)	-0.017*** (0.005)	-0.015** (0.007)	-0.015* (0.008)	-0.031** (0.014)
Observations	123,162	122,660	122,906	102,078	101,598	101,867
R^2	0.822	0.627	0.652	0.686	0.553	0.568
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y
Panel D: Investment-to-Price Sensitivity and <i>ActTop5</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)^* ActTop5$	-0.008*** (0.002)	-0.019*** (0.005)	-0.027*** (0.005)	-0.023*** (0.007)	-0.033*** (0.009)	-0.055*** (0.015)
Observations	123,162	122,660	122,906	102,078	101,598	101,867
R^2	0.822	0.626	0.652	0.686	0.553	0.568
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Country-Year FE	Y	Y	Y	Y	Y	Y

C Robustness Checks

In this section, we conduct several tests to demonstrate the robustness of the negative effect of trading-based ownership concentration on price informativeness.

C.1 Alternative Measures of Price Informativeness

Our baseline analysis follows [Bai et al. \(2016\)](#) to measure price informativeness. Although this particular measure is closely related to our theoretical analysis and has a strong economic appeal as a welfare measure under Q-theory, there is no general consensus on how to measure price informativeness. Therefore, we explore several alternative measures of price informativeness and demonstrate the robustness of the negative impact of trading-based ownership concentration.

C.1.1 Post-Earnings-Announcement Drift (PEAD)

To attenuate the concern of model misspecification, we consider post-earnings-announcement drift (PEAD), a model-free measure of price informativeness. Our sample of earnings announcement starts in 1984 due to the data availability of analyst forecast in I/B/E/S, and ends in 2022. We construct scaled earnings surprises following [Akey et al. \(2022\)](#):

$$SUE_{i,t} = \frac{EPS_{i,t} - E_{t-1}[EPS_{i,t}]}{P_{i,t-5}}, \quad (C1)$$

where $EPS_{i,t}$ is the earnings per share for firm i announced on day t , and $E_{t-1}[EPS_{i,t}]$ is the expectation of earnings per share, measured by the median of all analyst forecasts issued over the 90 days before the earnings announcement date.³ If analysts revise their forecasts during this interval, only their most recent forecasts are included. We scale the surprise by the firm's stock price five trading days before the announcement.

³We collect earnings announcement dates from Compustat and I/B/E/S and go through the following steps to determine the effective date on which earnings announcements are made. First, we compare the announcement dates in the two databases and pick up the earlier one. Second, we eliminate cases where the earning announcement dates in the two databases are more than two trading days apart. Third, if the earnings are released prior to 4:00 PM Eastern Time from Monday through Friday according to the time stamp in I/B/E/S, the corresponding date is designated as the effective announcement date. Conversely, if the earnings are released at or after 4:00 PM Eastern Time from Monday through Friday, over the weekend, or on a trading holiday, the next trading date in CRSP is designated as the effective announcement date.

To quantify the efficiency of stock prices in incorporating earnings surprises on the announcement date, we first construct buy-and-hold abnormal returns for firm i 's earnings announcement from day τ to day T ($\tau < T$) as $BHAR[\tau, T] = \prod_{k=\tau}^T (1 + R_{i,k}) - \prod_{k=\tau}^T (1 + R_{p,k})$, where the daily stock return $R_{i,k}$ is adjusted by the return on the size and book-to-market matching Fama-French portfolio $R_{p,k}$. Specifically, stocks are matched to one of 25 portfolios every year based on their market capitalization and book-to-market ratio. Market capitalization is calculated at the end of June, whereas the book-to-market ratio is calculated as the book equity of the last fiscal year end in the prior calendar year divided by the market value of equity at the end of December of the previous year.

Martineau (2022) shows that stock prices have become more efficient in incorporating earnings surprises in the last decade, especially for large stocks, as $BHAR$ jumped on the announcement date and has remained essentially flat for the following sixty trading days. We take a further step to study the interaction effect of ownership concentration on price efficiency by estimating the following regression models:

$$BHAR[0, 2]_{i,t} = \beta_1 Rank_{i,t} + \beta_2 Rank_{i,t} \times Concentration_{i,t} + \beta_3 Concentration_{i,t} + \rho X_{i,t} + FE_{i,t} + \varepsilon_{i,t}, \quad (C2)$$

$$BHAR[3, 24]_{i,t} = \gamma_1 Rank_{i,t} + \gamma_2 Rank_{i,t} \times Concentration_{i,t} + \gamma_3 Concentration_{i,t} + \rho X_{i,t} + FE_{i,t} + \varepsilon_{i,t}, \quad (C3)$$

where $BHAR[0, 2]_{i,t}$ and $BHAR[3, 24]_{i,t}$ correspond to firm i 's announcement date and post-announcement BHAR, respectively. $Rank_{i,t}$ is a decile rank of the analyst earnings surprises defined in equation (C1). Decile ranks are established for each year-quarter by utilizing observations from the preceding quarter to define the decile breakpoints, thereby mitigating any potential look-ahead bias. As claimed by Martineau (2022), the decile rank is preferred compared to the original earnings surprise, because the distribution of earnings surprises has high kurtosis relative to a normal- or t -distribution.

Our coefficients of interest are β_2 in equation (C2) and γ_2 in equation (C3). If ownership

concentration impedes the efficiency of stock prices in incorporating earnings surprises around the announcement date, β_2 is expected to be negative. At the same time, we would expect a more persistent price drift as indicated by a positive γ_2 . Panel A of Table C1 presents the results. Consistent with our hypothesis, stocks with higher concentration of active institutional ownership exhibit a smaller response of BHAR to earnings surprises around the announcement, along with larger price drifts. The result holds for two different measures of ownership concentration, namely, *ActHHI* and *ActTop5*.

C.1.2 Conditional Probability of An Information Event (CPIE)

We consider a microstructure-based price informativeness measure developed by Duarte et al. (2020), *CPIE*, which captures the probability of private information arrival on a given day, conditional on the estimated structural model parameters and the observed daily stock characteristics. Specifically, the authors consider four microstructure models of private information arrival: the PIN model (PIN) of Easley et al. (1996), the adjusted PIN model (APIN) of Duarte and Young (2009), the generalized PIN model (GPIN) of Duarte et al. (2020), and the Odders-White and Ready (2008) model (OWR).⁴ The authors estimate each of these models for each stock per year to obtain the structural parameters, and then calculate the daily *CPIE* as the probability of an information event given the estimated structural parameters, as well as the observed daily order flows and stock returns for each stock.

We aggregate *CPIE* to the stock-quarter level by taking the average, and regress it on the ownership concentration at the end of each quarter. Owing to the data availability of *CPIE*, our sample commences on January 4, 1993, and concludes on December 31, 2012. Panel B of Table C1 reports the results. From Columns (1) to (4), *CPIE* is calculated based on the PIN, APIN, GPIN, and OWR models, respectively. Consistent with our hypothesis, the coefficients on *ActHHI* are negative and statistically significant at the 1% level except for Column (4), suggesting that active

⁴The PIN model identifies private information based on order flow imbalance. The APIN model is a mixture of two independent PIN models, which allows the intensity of noise-trade arrivals to vary. In contrast to the APIN model, the GPIN model allows the noise trade intensity to vary continuously. While the PIN, APIN, and GPIN model only rely on order flow to infer whether private information has arrived, the OWR model takes into account the intra-day and overnight returns as well. See Duarte et al. (2020) for a more detailed discussion.

institutional ownership concentration lowers the probability of informed trading. The results are robust if we use *ActTop5* as an alternative measure of the active institutional ownership concentration, as shown in Columns (5)-(8) in Panel B of Table C1.

C.1.3 Informed Trading Intensity

We also consider a machine learning-based measure of informed trading intensity (ITI) developed by Bogousslavsky et al. (2024). The authors define informed trading days as those that involve Schedule 13D trading, significant opportunistic insider trading, and significant short selling. They use a Gradient Boosted Trees (GBT) algorithm incorporating 41 concurrent daily variables (related to liquidity, return, volatility, and volume) to detect informed trading days. The developed ITI measure increases before earnings, M&A, and news announcements, indicating its effectiveness in detecting informed trading.

We collect firm-level daily ITI indexes from the authors' website and aggregate them to the firm-quarterly level by simply taking the average. Due to the data availability of ITI indexes, our sample period is from January 5, 1993 to July 31, 2019. We regress ITI indexes on the active institutional ownership concentration at the end of each quarter. Panel C of Table C1 reports the results. From Columns (1) to (3), the ITI measure is trained on informed trading samples of Schedule 13D trades, opportunistic insiders, and short sellers, respectively. The coefficients on *ActHHI* remain significantly negative across all specifications, suggesting that stocks with more concentrated active institutional ownership are associated with less informed trading activities. The result remains robust if we use *ActTop5* as the alternative measure of ownership concentration.

C.1.4 Variance Ratio

We next consider a weak-form price efficiency measure. Under perfect weak-form efficiency, stock prices evolve according to a random walk. A testable prediction of the random walk hypothesis is that returns over a q -day horizon should have a variance ($\sigma^2(q)$) that is q times the variance of daily returns (σ^2). Formally, we use the q -period bias-corrected variance ratio of Lo

and MacKinlay (1988):

$$VR(q) = \left| \frac{\sigma^2(q)}{q \times \sigma^2} - 1 \right|, \quad (C4)$$

where $\sigma^2 = \frac{1}{nq-1} \sum_{k=1}^{nq} (X_k - X_{k-1} - \hat{\mu})^2$, $\sigma^2(q) = \frac{1}{m} \sum_{k=q}^{nq} (X_k - X_{k-q} - q\hat{\mu})^2$, $\hat{\mu} = \frac{1}{nq} \sum_{k=1}^{nq} (X_k - X_{k-1})$, and $m = q(nq - q + 1)(1 - \frac{q}{nq})$. X denotes the log price, n denotes the number of nonoverlapping q -period returns in the measurement interval, and nq denotes the number of daily returns in the measurement interval. When prices follow a random walk, $VR(q)$ equals 0. The higher the value of $VR(q)$, the further the stock price process deviates from a random walk. If ownership concentration undermines weak-form price efficiency, we should obtain a positive relation between $VR(q)$ in equation (C4) and ownership concentration.

We conduct our tests using stock-quarter-level observations. More specifically, we first compute variance ratios over horizons of $q = 5, 10, 15$, and 20 trading days using overlapping observations during a quarter. We then regress them on the active institutional ownership concentration controlling for the firm fixed effect and industry-quarter fixed effects. Panel D of Table C1 shows that the variance ratio increases with active institutional ownership concentration, consistent with a lower price efficiency for stocks with more concentrated active institutional ownership. The results hold for different estimation horizons and are statistically significant at the 1% level.

C.1.5 Relative Price Informativeness

Dávila and Parlato (2025) identify a measure of relative price informativeness, which corresponds to the Kalman gain of a Bayesian external observer who only learns from the price under a Gaussian environment. Formally, the authors employ the following panel regression models:

$$\begin{aligned} \Delta p_t^j &= \bar{\beta} (Y_t^j) + \beta_0 (Y_t^j) \Delta x_t^j + \beta_1 (Y_t^j) \Delta x_{t+4}^j + \varepsilon_t^j, \\ \Delta p_t^j &= \bar{\zeta} (Y_t^j) + \zeta_0 (Y_t^j) \Delta x_t^j + \varepsilon_t^j, \end{aligned}$$

where Δp_t^j is the year-on-year changes in log-price of stock j in quarter t ; Δx_t^j and its one-year ahead counterpart Δx_{t+4}^j are measures of earnings growth, calculated as the log of one plus

the year-on-year changes in EBIT divided by book equity; The coefficients are modeled as affine functions of firm-specific characteristics Y_t^j . The error variances specific to each firm $\text{Var}[\varepsilon_t^j]$ and $\text{Var}[\hat{\varepsilon}_t^j]$ are estimated respectively using $\widehat{\text{Var}}[\varepsilon_t^j] = \exp\{\lambda_0 + \lambda_1 Y_t^j + Y_t^{j'} \lambda_2 Y_t^j + \frac{1}{2} \text{Var}[v_t^j]\}$ and $\widehat{\text{Var}}[\hat{\varepsilon}_t^j] = \exp\{\hat{\lambda}_0 + \hat{\lambda}_1 Y_t^j + Y_t^{j'} \hat{\lambda}_2 Y_t^j + \frac{1}{2} \text{Var}[\hat{v}_t^j]\}$. Finally, the relative price informativeness for stock j in quarter t is quantified by $\hat{\tau}_{\pi,t}^{R,j} = \frac{\widehat{\text{Var}}[\hat{\varepsilon}_t^j] - \widehat{\text{Var}}[\varepsilon_t^j]}{\widehat{\text{Var}}[\varepsilon_t^j]}$.

The sample selection procedure is similar to that in our baseline analysis, except for the additional requirement that stocks' relative price informativeness should be positive. Following [Dávila and Parlatore \(2025\)](#), we conduct our tests at the portfolio level. Specifically, we divide the sample into twenty bins each quarter based on the ownership concentration of each firm, and then aggregate the quarterly measures of relative price informativeness within each bin-quarter. We conduct panel regressions of relative price informativeness on the ownership concentration variables at the bin-quarter level, controlling for the quarter fixed effect. The results in Panel E of Table [C1](#) echo those in Table 2 in [Dávila and Parlatore \(2025\)](#). The coefficients on *ActHHI* and *ActTop5* are significantly negative, indicating that portfolios with more concentrated ownership have lower relative price informativeness. To control for the size effect, we take the residual from the regression of relative price informativeness on size with quarter fixed effect before running the panel regressions. As shown in the last two rows in Panel E of Table [C1](#), the results remain significantly negative. Figures [C1](#) and [C2](#) provide alternative graphical illustrations of our results, indicating that the cross-sectional relations identified in Panel E of Table [C1](#) are stable over time.

C.2 Alternative Sample: Mutual Fund Holdings

Form 13F filings are filed at the management company level rather than at the portfolio or individual fund level ([Agarwal et al., 2013](#)). This poses a challenge as a fund management company may oversee both passive and active mutual funds, potentially leading to measurement errors in the classification method proposed by [Bushee \(1998\)](#). To address this issue, we utilize fund-level holdings data from Thomson Reuters S12 as an alternative source to distinguish between active and passive mutual funds. While the S12 data provide a more precise measure of active/passive

ownership, it does not encompass other institutional investors beyond mutual fund management companies, such as banks, insurance companies, pension funds, and independent investment advisors. Thus, we rely on 13F holdings data for our primary analysis, using S12 data as a supplementary check for robustness.

Following previous studies (e.g., [Appel et al., 2016](#)), we flag a fund as passively managed if its fund name includes a string that identifies it as an index fund or if the CRSP Mutual Fund Database classifies the fund as an index fund.⁵ Table C2 replicates the baseline results by using S12 holdings data. The coefficients on the interaction term are negative and statistically significant throughout, suggesting that our result is robust to the alternative definition of institutional investor at the disaggregated level.

C.3 Other Robustness Tests

Table C3 replicates our baseline results in Tables 3-4, with the distinction that we use Bushee’s time-varying classification scheme to distinguish active/passive institutional investors, which updates the classification for every year in our sample period. The results are virtually unchanged.

While we compute trading-based ownership concentration based on the detailed holding data of each institution in our baseline analysis, Table C4 shows that our results remain robust if we calculate it based on each institution’s trading volume in each firm’s stock, as shown equation (8) defined in our model.

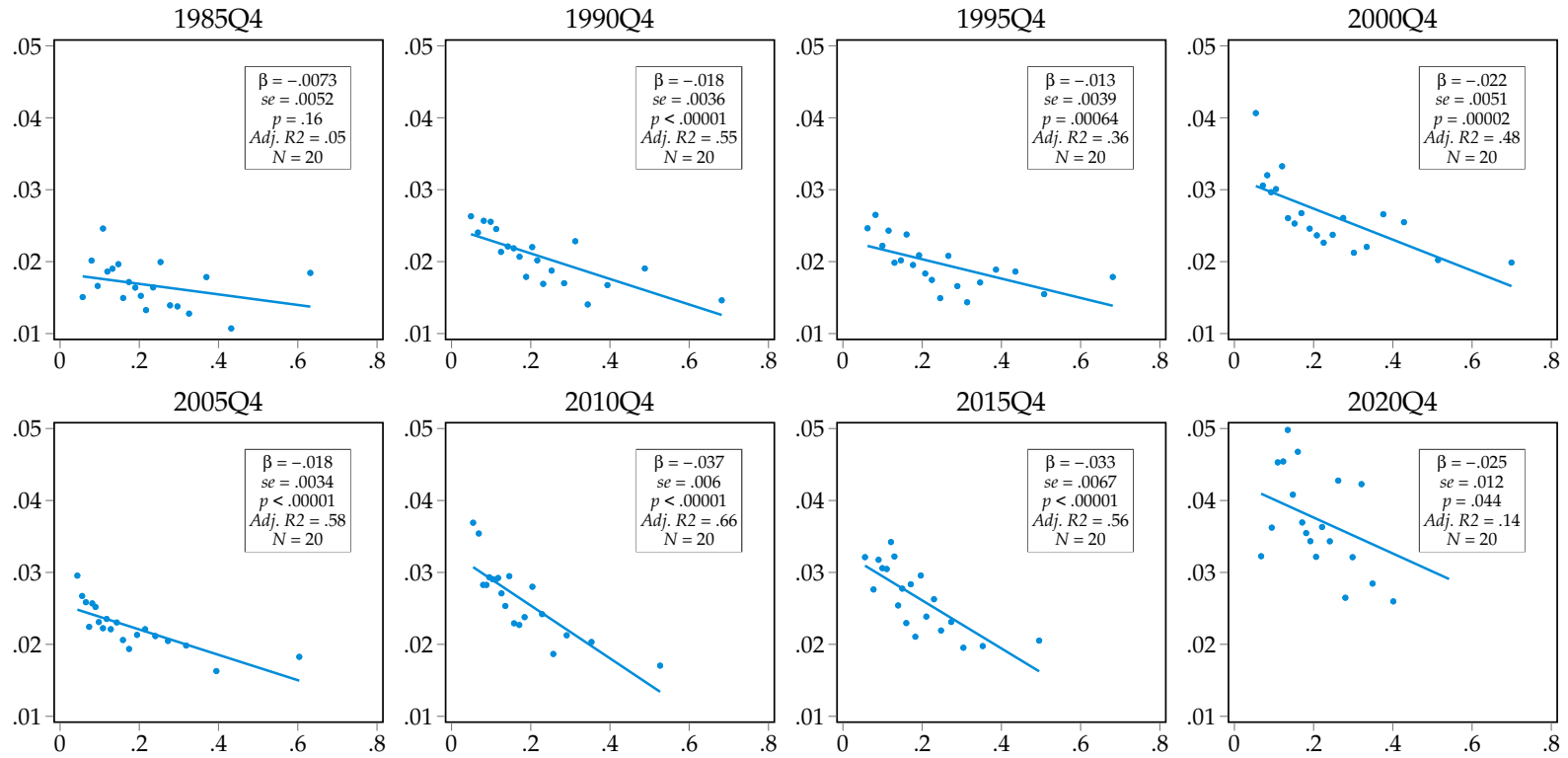
Although passive institutional investors do not directly affect the information level of stock prices as indicated in equation (6), they may indirectly affect price informativeness through the trading activities of active investors as discussed in Section 2.3. Our baseline analysis accounts for this potential effect by controlling for the passive institutional ownership ($PasHHI$ or $PasTop5$). Alternatively, Table C5 reconstructs our concentration measures without distin-

⁵The strings we use to identify index funds include: Index, Idx, Indx, Ind_ (where _ indicates a space), Russell, S & P, S and P, S&P, SandP, SP, DOW, Dow, DJ, MSCI, Bloomberg, KBW, NASDAQ, NYSE, STOXX, FTSE, Wilshire, Morningstar, 100, 400, 500, 600, 900, 1000, 1500, 2000, and 5000. In addition, in CRSP, a fund with flag D is a “pure index fund” whose “objective is to match the total investment performance of a publicly recognized securities market index.”

guishing between active and passive investors. Specially, $TotHHI_{i,q} = \frac{\sum_{j=1}^{N_{tot}} (S_{i,j,q}^2)}{(\sum_{j=1}^{N_{tot}} S_{i,j,q})^2}$ captures HHI of institutional shares, where N_{tot} denotes the number of institutions holding stock i . Similarly, $TotTop5_{i,q} = \frac{\sum_{j=1}^{Top\ 5} S_{i,j,q}}{\sum_{j=1}^{N_{tot}} S_{i,j,q}}$ measures the proportion of shares held by the top five largest institutional investors relative to the total shares held by all institutional investors. We continue to observe a significant negative effect of trading-based ownership concentration on both price informativeness and investment-to-price sensitivity.

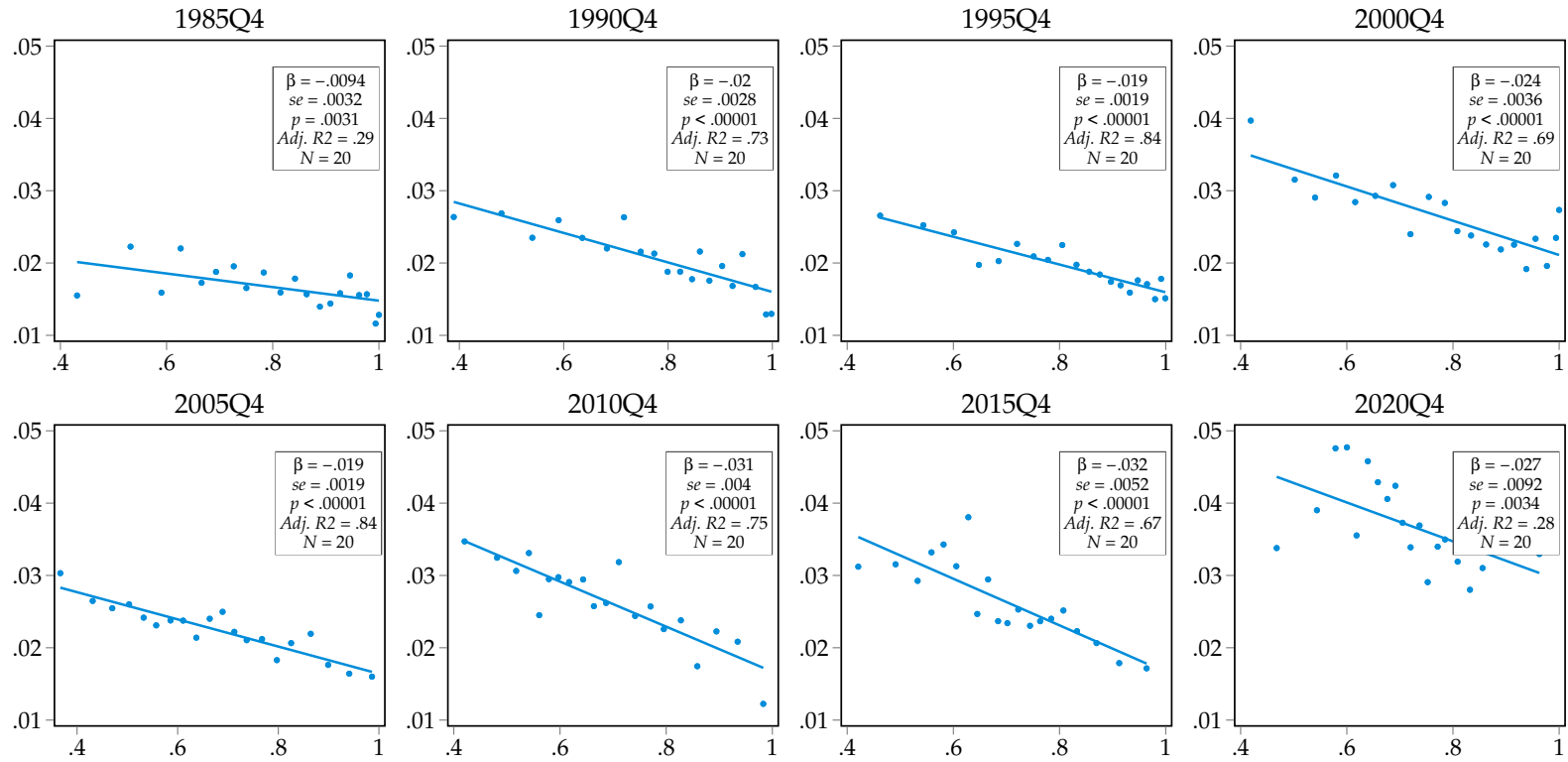
In our baseline analysis, we regress future investment rates on normalized market price (M/A), where market price is measured at the end of March and scaled by book assets. For robustness, Table C6 employs the Tobin's Q measure from Peters and Taylor (2017), which uses fiscal year-end market prices normalized by total capital. Results remain consistent.

In unreported robustness tests, we also augment the regressions of future investment on current prices with two additional controls and their interactions with normalized market price. First, following Edmans et al. (2017), we include operating cash flow (scaled by total assets) as a non-price measure of investment opportunities. Second, per Kacperczyk et al. (2021), we control for price nonsynchronicity, calculated from the R-squared of a regression of individual stock returns on the market factor. Results remain unchanged.



This figure shows quarter-by-quarter cross-sectional regressions of relative price informativeness (in twentiles) on trading-based ownership concentration, as measured by $ActHHI$. The estimate result reported in the first row in Panel E of Table C1 can be interpreted as a weighted average of the quarter-by-quarter slope coefficients illustrated here.

Figure C1: Relative Price Informativeness and Trading-based Ownership Concentration: HHI Index



This figure shows quarter-by-quarter cross-sectional regressions of relative price informativeness (in twentiles) on trading-based ownership concentration, as measured by *ActTop5*. The estimate result reported in the second row in Panel E of Table C1 can be interpreted as a weighted average of the quarter-by-quarter slope coefficients illustrated here.

Figure C2: Relative Price Informativeness and Trading-based Ownership Concentration: Top-5 Holdings

Table C1: Alternative Measure of Price Informativeness

This table considers several alternative measures of price informativeness. Panel A estimates price informativeness from the Post-Earnings-Announcement Drift (PEAD) model. The dependent variable is buy-and-hold abnormal returns for firm i 's earnings announcement in the estimation window from day τ to day T . *Rank* is the decile rank of the analyst earnings surprises. Panel B considers a microstructure-based measure *CPIE* developed by Duarte et al. (2020). *CPIE* quantifies the probability of private information arrival on a given day, derived from one of four microstructure models of private information arrival: the PIN model (PIN) of Easley et al. (1996), the adjusted PIN model (APIN) of Duarte and Young (2009), the generalized PIN model (GPIN) of Duarte et al. (2020), and the Odders-White and Ready (2008) model (OWR). Panel C considers a machine learning-based measure of informed trading intensity (*ITI*) by Bogousslavsky et al. (2024). *ITI* is trained from one of the three samples: Schedule 13D trading, opportunistic insider trades, and short sales. Panel D focuses on the q -period bias-corrected variance ratio ($VR(q)$) by Lo and MacKinlay (1988). $VR(q)$ is defined as the absolute value of the variance of returns over a q -day horizon divided by q times the variance of daily returns, minus one. We compute $VR(q)$ over horizons of $q = 5, 10, 15$, and 20 trading days using overlapping observations within a quarter. Panel E considers a relative price informativeness measure ($\tau_{\pi}^{R,j}$) by Dávila and Parlatore (2025). We divide the sample into twenty bins each quarter based on the ownership concentration of each firm (*ActHHI* or *ActTop5*), and then aggregate the quarterly measures of relative price informativeness ($\tau_{\pi}^{R,j}$) within each bin-quarter. The first two rows reports the panel regression results of relative price informativeness in twentiles on the active ownership concentration variables, controlling for the quarter fixed effects. The last two rows mirror the first two rows, except that the dependent variables are the residualized form of relative price informativeness, estimated from the regression of relative price informativeness on size with quarter fixed effects. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Post-Earnings-Announcement Drift				
	<i>BHAR</i> [0, 2] (1)	<i>BHAR</i> [0, 2] (2)	<i>BHAR</i> [3, 24] (3)	<i>BHAR</i> [3, 24] (4)
<i>Rank</i>	0.0029*** (0.001)	0.0037*** (0.001)	0.0017*** (0.001)	0.0007 (0.001)
<i>Rank*ActHHI</i>	-0.0027*** (0.001)		0.0015* (0.001)	
<i>Rank*ActTop5</i>		-0.0049*** (0.001)		0.0016** (0.001)
<i>Rank*PasHHI</i>	0.0045*** (0.001)		0.0026 (0.002)	
<i>Rank*PasTop5</i>		0.0052*** (0.001)		0.0006 (0.001)
Observations	201,240	201,240	201,240	201,240
R^2	0.172	0.173	0.150	0.150
Controls	Y	Y	Y	Y
Firm	Y	Y	Y	Y
Industry-Qtr	Y	Y	Y	Y

Continued on next page

Table C1 – *Continued*

Panel B: Conditional Probability of An Information Event								
Model:	<i>CPIE</i> PIN (1)	<i>CPIE</i> APIN (2)	<i>CPIE</i> GPIN (3)	<i>CPIE</i> OWR (4)	<i>CPIE</i> PIN (5)	<i>CPIE</i> APIN (6)	<i>CPIE</i> GPIN (7)	<i>CPIE</i> OWR (8)
<i>ActHHI</i>	-0.088*** (0.012)	-0.054*** (0.008)	-0.036*** (0.012)	-0.007 (0.014)				
<i>ActTop5</i>					-0.123*** (0.013)	-0.064*** (0.008)	-0.064*** (0.012)	-0.001 (0.014)
<i>PasHHI</i>	-0.184*** (0.034)	-0.166*** (0.026)	0.055 (0.044)	0.168*** (0.055)				
<i>PasTop5</i>					-0.079*** (0.014)	-0.067*** (0.010)	0.020 (0.018)	0.090*** (0.021)
Observations	66,681	66,681	66,681	66,681	66,681	66,681	66,681	66,681
R^2	0.493	0.316	0.320	0.503	0.495	0.317	0.321	0.503
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y	Y	Y
Industry-Qtr	Y	Y	Y	Y	Y	Y	Y	Y
Panel C: Informed Trading Intensity								
Training	<i>ITI</i> 13D (1)	<i>ITI</i> Insider (2)	<i>ITI</i> Short Sale (3)		<i>ITI</i> 13D (4)	<i>ITI</i> Insider (5)	<i>ITI</i> Short Sale (6)	
<i>ActHHI</i>	-0.049*** (0.002)	-0.055*** (0.002)	-0.026*** (0.001)					
<i>ActTop5</i>					-0.057*** (0.003)	-0.075*** (0.002)	-0.035*** (0.001)	
<i>PasHHI</i>	-0.042*** (0.005)	-0.030*** (0.006)	-0.028*** (0.003)					
<i>PasTop5</i>					-0.028*** (0.003)	-0.007** (0.003)	-0.017*** (0.002)	
Observations	225,723	225,653	225,754		225,723	225,653	225,754	
R^2	0.329	0.291	0.471		0.333	0.303	0.482	
Controls	Y	Y	Y		Y	Y	Y	
Firm	Y	Y	Y		Y	Y	Y	
Industry-Qtr	Y	Y	Y		Y	Y	Y	

Continued on next page

Table C1 – *Continued*

Panel D: Variance Ratio								
	<i>VR</i> (5) (1)	<i>VR</i> (10) (2)	<i>VR</i> (15) (3)	<i>VR</i> (20) (4)	<i>VR</i> (5) (5)	<i>VR</i> (10) (6)	<i>VR</i> (15) (7)	<i>VR</i> (20) (8)
<i>ActHHI</i>	0.045*** (0.003)	0.049*** (0.005)	0.043*** (0.006)	0.036*** (0.007)				
<i>ActTop5</i>					0.045*** (0.004)	0.052*** (0.006)	0.042*** (0.007)	0.040*** (0.008)
<i>PasHHI</i>	0.054*** (0.006)	0.048*** (0.008)	0.047*** (0.010)	0.042*** (0.011)				
<i>PasTop5</i>					0.058*** (0.005)	0.058*** (0.006)	0.058*** (0.008)	0.050*** (0.009)
Observations	374,450	374,450	374,450	374,450	374,450	374,450	374,450	374,450
R^2	0.113	0.096	0.090	0.089	0.114	0.097	0.091	0.090
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y	Y	Y
Industry-Qtr	Y	Y	Y	Y	Y	Y	Y	Y
Panel E: Relative Price Informativeness								
	Estimate		Std		<i>t</i> -value		Obs.	
(1) <i>ActHHI</i>	-0.018620***		0.000412		-45.22		2960	
(2) <i>ActTop5</i>	-0.020837***		0.000319		-65.22		2960	
(3) <i>ActHHI</i> (<i>Residual</i>)	-0.003438***		0.000390		-8.82		2960	
(4) <i>ActTop5</i> (<i>Residual</i>)	-0.001325***		0.000326		-4.07		2960	

Table C2: Alternative Sample: Mutual Fund Holdings

This table replicates Tables 3-4, with the distinction that the institutional ownership data is sourced from Thomson Reuters S12 mutual fund holdings. The coefficients of the control variables are suppressed for brevity. See Table B1 for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Informativeness and <i>ActHHI</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)^*ActHHI$	-0.027*** (0.008)	-0.034*** (0.006)	-0.024** (0.010)	-0.049*** (0.011)	-0.054*** (0.010)	-0.028* (0.016)
$\log(M/A)^*PasHHI$	-0.001 (0.007)	0.004 (0.005)	-0.011 (0.008)	0.009 (0.010)	0.020** (0.009)	-0.008 (0.015)
Observations	69,996	70,284	70,414	58,626	58,823	58,961
R^2	0.808	0.827	0.686	0.668	0.693	0.553
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel B: Price Informativeness and <i>ActTop5</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A)^*ActTop5$	-0.030*** (0.008)	-0.041*** (0.004)	-0.017* (0.010)	-0.047*** (0.013)	-0.058*** (0.014)	-0.022 (0.022)
$\log(M/A)^*PasTop5$	0.006 (0.009)	0.020*** (0.007)	-0.011 (0.011)	0.011 (0.019)	0.041** (0.016)	-0.027 (0.028)
Observations	69,996	70,284	70,414	58,626	58,823	58,961
R^2	0.808	0.828	0.686	0.668	0.694	0.554
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Continued on next page

Table C2 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Investment-to-Price Sensitivity and <i>ActHHI</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)^*ActHHI$	-0.032*** (0.012)	-0.022*** (0.005)	-0.054*** (0.014)	-0.049*** (0.010)	-0.022*** (0.006)	-0.072*** (0.012)
$\log(M/A)^*PasHHI$	0.024*** (0.006)	0.020*** (0.002)	0.044*** (0.007)	0.047*** (0.006)	0.028*** (0.006)	0.080*** (0.010)
Observations	70,162	69,631	70,106	58,767	58,246	58,711
R^2	0.874	0.713	0.788	0.788	0.616	0.694
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel D: Investment-to-Price Sensitivity and <i>ActTop5</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)^*ActTop5$	-0.031** (0.012)	-0.023*** (0.006)	-0.053*** (0.017)	-0.047*** (0.012)	-0.017** (0.007)	-0.063*** (0.013)
$\log(M/A)^*PasTop5$	0.038*** (0.007)	0.040*** (0.006)	0.078*** (0.012)	0.088*** (0.010)	0.047*** (0.008)	0.136*** (0.017)
Observations	70,162	69,631	70,106	58,767	58,246	58,711
R^2	0.873	0.712	0.786	0.787	0.615	0.692
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Table C3: Distinguish Active/Passive Institutional Investors Using Bushee's Time-varying Classification

This table replicates Tables 3-4, with the distinction that we use Bushee's time-varying classification to distinguish active/passive institutional investors. Panels A and B focus on price informativeness, while Panels C and D focus on investment-to-price sensitivity. Trading-based ownership concentration is measured by *ActHHI* in Panels A and C, representing the Herfindahl-Hirschman index of active institutional ownership, and by *ActTop5* in Panels B and D, denoting the proportion of shares held by the top five active institutional investors relative to the total shares held by all active institutional investors. The sample has an annual frequency and spans from 1980 to 2022. The coefficients of the control variables are suppressed for brevity. See Table B1 for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Informativeness and <i>ActHHI</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A) * ActHHI$	-0.026*** (0.005)	-0.030*** (0.004)	-0.027*** (0.004)	-0.052*** (0.010)	-0.059*** (0.009)	-0.035*** (0.011)
Observations	83,054	83,794	83,952	69,612	70,250	70,402
R^2	0.823	0.837	0.714	0.677	0.697	0.579
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel B: Price Informativeness and <i>ActTop5</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A) * ActTop5$	-0.033*** (0.006)	-0.040*** (0.005)	-0.029*** (0.005)	-0.045*** (0.010)	-0.063*** (0.009)	-0.022* (0.012)
Obs	83,054	83,794	83,952	69,612	70,250	70,402
R^2	0.824	0.838	0.714	0.678	0.699	0.579
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Continued on next page

Table C3 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Investment-to-Price Sensitivity and <i>ActHHI</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A) * ActHHI$	-0.022*** (0.007)	-0.023*** (0.003)	-0.044*** (0.007)	-0.042*** (0.009)	-0.025*** (0.004)	-0.070*** (0.010)
Observations	83,616	82,913	83,549	70,174	69,462	70,098
R^2	0.863	0.692	0.771	0.765	0.613	0.681
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel D: Investment-to-Price Sensitivity and <i>ActTop5</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A) * ActTop5$	-0.027*** (0.009)	-0.024*** (0.005)	-0.050*** (0.012)	-0.049*** (0.011)	-0.028*** (0.004)	-0.082*** (0.013)
Observations	83,616	82,913	83,549	70,174	69,462	70,098
R^2	0.863	0.693	0.771	0.766	0.616	0.684
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Table C4: Concentration Measures Based on Trading Volume

This table replicates Tables 3-4, with the distinction that trading volume, rather than holdings, is utilized to construct measures of trading-based ownership concentration. Specifically, concentration is measured by *ActHHI* in Panels A and C, representing the Herfindahl-Hirschman index of trading volume of active institutional investors, and by *ActTop5* in Panels B and D, denoting the proportion of trading volume of the top five active institutional investors relative to the total trading volume of all active institutional investors. Panels A and B focus on price informativeness, while Panels C and D focus on investment-to-price sensitivity. The sample has an annual frequency and spans from 1980 to 2022. The coefficients of the control variables are suppressed for brevity. See Table B1 for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Informativeness and <i>ActHHI</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A) * ActHHI$	-0.013*** (0.005)	-0.016*** (0.004)	-0.015** (0.005)	-0.033*** (0.010)	-0.035*** (0.009)	-0.029*** (0.010)
Observations	84,042	84,783	84,944	70,442	71,084	71,236
R^2	0.821	0.835	0.712	0.673	0.693	0.576
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel B: Price Informativeness and <i>ActTop5</i>						
where $E =$	$E_{h=1}/A$ <i>EBIT</i>	$E_{h=1}/A$ <i>EBITDA</i>	$E_{h=1}/A$ <i>NI</i>	$E_{h=3}/A$ <i>EBIT</i>	$E_{h=3}/A$ <i>EBITDA</i>	$E_{h=3}/A$ <i>NI</i>
$\log(M/A) * ActTop5$	-0.024*** (0.005)	-0.027*** (0.004)	-0.027*** (0.007)	-0.035*** (0.008)	-0.041*** (0.008)	-0.028*** (0.009)
Observations	84,042	84,783	84,944	70,442	71,084	71,236
R^2	0.821	0.835	0.712	0.673	0.694	0.576
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Continued on next page

Table C4 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Investment-to-Price Sensitivity and <i>ActHHI</i>						
where $I=$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)^*ActHHI$	-0.017*** (0.006)	-0.014*** (0.003)	-0.031*** (0.009)	-0.025*** (0.007)	-0.011*** (0.004)	-0.037*** (0.008)
Observations	84,607	83,891	84,538	71,004	70,282	70,928
R^2	0.862	0.689	0.768	0.761	0.607	0.675
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel D: Investment-to-Price Sensitivity and <i>ActTop5</i>						
where $I=$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)^*ActTop5$	-0.012* (0.007)	-0.008* (0.004)	-0.021** (0.010)	-0.014* (0.008)	-0.003 (0.005)	-0.021* (0.010)
Observations	84,607	83,891	84,538	71,004	70,282	70,928
R^2	0.862	0.688	0.768	0.762	0.609	0.676
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Table C5: Concentration Measures Without Distinguishing Active/Passive Investors

This table replicates Tables 3-4, with the distinction that we reconstruct the trading-based concentration measures without distinguishing active/passive investors. Ownership concentration among all institutional investors is measured by $TotHHI$ in Panels A and C, and $TotTop5$ in Panels B and D. Specially, $TotHHI_{i,q} = \frac{\sum_{j=1}^{N_{tot}} (S_{i,j,q}^2)}{(\sum_{j=1}^{N_{tot}} S_{i,j,q})^2}$ captures HHI of institutional shares, where N_{tot} denotes the number of institutions holding stock i ; $TotTop5_{i,q} = \frac{\sum_{j=1}^{Top\ 5} S_{i,j,q}}{\sum_{j=1}^{N_{tot}} S_{i,j,q}}$ measures the proportion of shares held by the top five largest institutional investors relative to the total shares held by all institutional investors. Panels A and B focus on price informativeness, while Panels C and D focus on investment-to-price sensitivity. The sample has an annual frequency and spans from 1980 to 2022. The coefficients of the control variables are suppressed for brevity. See Table B1 for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Price Informativeness and $TotHHI$						
where $E =$	$E_{h=1}/A$ $EBIT$	$E_{h=1}/A$ $EBITDA$	$E_{h=1}/A$ NI	$E_{h=3}/A$ $EBIT$	$E_{h=3}/A$ $EBITDA$	$E_{h=3}/A$ NI
$\log(M/A)^*TotHHI$	-0.045*** (0.006)	-0.046*** (0.006)	-0.047*** (0.009)	-0.081*** (0.016)	-0.078*** (0.014)	-0.075*** (0.014)
Observations	108,681	109,667	109,876	91,018	91,869	92,074
R^2	0.805	0.816	0.694	0.659	0.675	0.569
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel B: Price Informativeness and $TotTop5$						
where $E =$	$E_{h=1}/A$ $EBIT$	$E_{h=1}/A$ $EBITDA$	$E_{h=1}/A$ NI	$E_{h=3}/A$ $EBIT$	$E_{h=3}/A$ $EBITDA$	$E_{h=3}/A$ NI
$\log(M/A)^*TotTop5$	-0.039*** (0.005)	-0.041*** (0.004)	-0.037*** (0.006)	-0.066*** (0.010)	-0.066*** (0.010)	-0.052*** (0.009)
Observations	108,681	109,667	109,876	91,018	91,869	92,074
R^2	0.805	0.816	0.694	0.660	0.676	0.569
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Continued on next page

Table C5 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Panel C: Investment-to-Price Sensitivity and <i>TotHHI</i>						
where $I=$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)*TotHHI$	-0.020*** (0.006)	-0.021*** (0.005)	-0.040*** (0.011)	-0.033*** (0.009)	-0.033*** (0.007)	-0.068*** (0.012)
Observations	109,450	108,359	109,304	91,771	90,687	91,613
R^2	0.847	0.643	0.730	0.738	0.570	0.641
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel D: Investment-to-Price Sensitivity and <i>TotTop5</i>						
where $I=$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$\log(M/A)*TotTop5$	-0.015*** (0.006)	-0.018*** (0.004)	-0.032*** (0.009)	-0.018** (0.007)	-0.021*** (0.006)	-0.041*** (0.011)
Observations	109,450	108,359	109,304	91,771	90,687	91,613
R^2	0.847	0.643	0.730	0.738	0.571	0.643
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Table C6: Alternative Measure of Investment-to-Price Sensitivity

This table replicates Table 4, but replaces the normalized market price ($\frac{M}{A}$) with the Tobin's Q measure from Peters and Taylor (2017). Q is calculated as fiscal year-end market prices normalized by total capital (taking the logarithm). Trading-based ownership concentration is measured by *ActHHI* in Panel A, representing the Herfindahl-Hirschman index of active institutional ownership, and by *ActTop5* in Panel B, denoting the proportion of shares held by the top five active institutional investors relative to the total shares held by all active institutional investors. The coefficients of the control variables are suppressed for brevity. See Table B1 for the complete list of variable definitions. Standard errors, clustered at the year and firm levels, are reported in parentheses. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: <i>ActHHI</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$Q^*ActHHI$	-0.025*** (0.007)	-0.029*** (0.003)	-0.051*** (0.008)	-0.051*** (0.009)	-0.027*** (0.005)	-0.076*** (0.011)
Observations	79,099	78,456	79,040	66,505	65,845	66,432
R^2	0.873	0.696	0.782	0.770	0.615	0.686
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel B: <i>ActTop5</i>						
where $I =$	$I_{h=1}/K$ <i>Intangible</i>	$I_{h=1}/K$ <i>Physical</i>	$I_{h=1}/K$ <i>Invest</i>	$I_{h=3}/K$ <i>Intangible</i>	$I_{h=3}/K$ <i>Physical</i>	$I_{h=3}/K$ <i>Invest</i>
$Q^*ActTop5$	-0.035*** (0.010)	-0.036*** (0.005)	-0.069*** (0.013)	-0.066*** (0.011)	-0.035*** (0.006)	-0.102*** (0.013)
Observations	79,099	78,456	79,040	66,505	65,845	66,432
R^2	0.874	0.696	0.783	0.772	0.619	0.690
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

D Alternative Explanations

In this section, we consider and rule out several alternative explanations for the negative association between active institutional ownership concentration and price informativeness. For brevity, we report only the results for the 1-year prediction horizon.

D.1 Short-sale Constraints

One alternative interpretation is that stocks with more concentrated ownership coincide with higher short-sale constraints. In this case, arbitrageurs may refrain from correcting mispricing, leading to low informational efficiency. For instance, [Porras Prado et al. \(2016\)](#) claim that investors with larger holdings are reluctant to lend stocks due to concerns that short selling could decrease stock prices and weaken their monitoring control. The authors find that stocks with more concentrated ownership exhibit lower lending supply and higher shorting costs.

To evaluate this alternative explanation, we combine equity lending data sourced from Markit with our main sample. The combined sample shrinks in size because equity lending data is only available from 2002 onward. If the negative effect is mainly driven by short-sale constraints rather than investors' learning and trading decisions, it should diminish when stocks are easy to borrow. Following [Muravyev et al. \(2022\)](#), a stock is considered easy to borrow if the indicative borrowing fee is less than or equal to 1%. We exclude stocks with annual average indicative borrowing fee greater than 1% and re-conduct our baseline analysis in the remaining easy-to-borrow subsample. Simultaneously, we include lending supply (*Supply*) along with its interaction term with market price in the regression models. Lending supply is defined as the annual average dollar value of lendable shares relative to a firm's market capitalization.

Panels A and B of Table [D1](#) report the results. The negative effect of active ownership concentration on price informativeness remains significant in the easy-to-borrow subsample with the additional control for lending supply. Therefore, it is unlikely that the documented results are

attributed to the short-sale constraints.

D.2 Institutional Price Pressure

Another alternative interpretation is that stocks with more concentrated ownership face higher institutional price pressure (Greenwood and Thesmar, 2011). For example, forced fire sales by mutual funds experiencing large outflows can create large nonfundamental price declines in underlying stocks. Stocks with more concentrated ownership are likely more vulnerable to such nonfundamental price pressure, resulting in lower informational efficiency.

To examine this possibility, we construct a measure of mutual fund fire-sale pressure, *Pressure*, following Wardlaw (2020). Formally,

$$Pressure_{i,t} = \sum_j^m \frac{|F_{j,t}|}{TA_{j,t-1}} \times \frac{Shares_{i,j,t-1}}{Shrout_{i,t-1}},$$

where $F_{j,t}$ denotes the net dollar flow to mutual fund j in quarter t , $TA_{j,t-1}$ is the total asset value of mutual fund j in quarter $t - 1$, $Shares_{i,j,t-1}$ indicates the shares of firm i held by fund j in quarter $t - 1$, and $Shrout_{i,t-1}$ denotes the total shares outstanding of firm i in quarter $t - 1$. In the calculation, only funds with outflow greater than 5% of total assets ($\frac{F_{j,t}}{TA_{j,t-1}} < -5\%$) are included because they are most likely to be forced into a fire sale of their holdings. This measure captures the total share amount of each stock sold by funds with extreme outflows, if all of the funds were to sell their stocks in proportion to their initial holdings. We aggregate *Pressure* to the firm-year level by averaging its quarterly values, and assign a value of zero to firms with missing values.

Panels C and D of Table D1 replicate the baseline regressions, but explicitly control for *Pressure* and its interaction term with the market price. The effect of institutional price pressure on informational efficiency is not evident. While the effect is negative when examining real investment, as the coefficients of $\log(M/A) * Pressure$ are negative and weakly significant in Panel D, it is overturned in the price informativeness case in Panel C. In contrast, the coefficients on the inter-

action term between our concentration measures and market price remain significantly negative across all specifications. Therefore, our main results do not seem to be driven by institutional price pressure.

D.3 Voluntary Disclosure

Another possibility is that the negative impact on informational efficiency stems from companies' voluntary disclosure decisions. When active ownership concentration increases, large shareholders become more influential. They may gain easier access to managers and substitute private communication for public information acquisition. Consequently, managers have less incentive to provide voluntary disclosures, leading to higher information asymmetry and lower informational efficiency. To explore this possibility, we investigate whether firms with higher active ownership concentration issue fewer management forecasts, a proxy for voluntary disclosure.

We obtain management forecasts from the LSEG IBES guidance database, available since 1993. Following prior studies (e.g., [Boone and White, 2015](#)), we treat all management forecasts issued on the same day as a single observation, as they are usually released in one press release. We also exclude pre-earnings announcement forecasts made on or after the fiscal period end, as per previous research (e.g., [Rogers and Stocken, 2005](#)). Our first measure of voluntary disclosure is guidance frequency (*GuideFreq*), representing the number of management forecasts at the firm-year level. This includes all types of quarterly and annual forecasts, such as earnings, sales, and capital expenditure. Firms without forecasts in a given year receive a value of zero. The second measure is *GuideDummy*, which indicates the propensity of voluntary disclosure and equals one if any management forecasts are provided. We also focus on management earnings forecasts, which are the most common and notable guidance. *EPSSGuideFreq* and *EPSSGuideDummy* measure the frequency and propensity of earnings forecasts.

Panels E and F of Table [D1](#) report regressions of year $t + 1$ management forecasts on year t ownership concentration. Beyond baseline controls and fixed effects, we include book-to-market

ratio, ROA, and log book assets as per prior studies (e.g., [Chen et al., 2008](#)). If concentrated ownership hinders voluntary disclosure, we would expect negative coefficients for our concentration measures (*ActHHI* and *ActTop5*). This is not the case. Across all specifications, the coefficients are either insignificant or even significantly positive. Thus, reduced voluntary disclosure does not seem to explain our results.

Table D1: Alternative Explanations

This table considers and rules out several alternative explanations for the negative association between active institutional ownership concentration and informational efficiency. Panels A and B replicate Tables 3-4 in the easy-to-borrow subsample, with additional controls for lending supply along with its interaction term with market price. A stock is considered easy to borrow if its annual average indicative borrowing fee is less than or equal to 1%. Lending supply, *Supply*, is defined as the annual average dollar value of lendable shares relative to a firm's market capitalization. Panels C and D replicate Tables 3-4 while controlling for institutional price pressure along with its interaction term with market price. Panels E and F regress voluntary disclosure in year $t + 1$ on active ownership concentration in year t . We construct four proxies of voluntary disclosure: *GuideFreq* denotes the number of management forecasts at the firm-year level. This includes all types of quarterly and annual forecasts, such as earnings, sales, and capital expenditure. Firms without forecasts in a given year receive a value of zero. *GuideDummy* indicates the propensity of voluntary disclosure and equals one if any management forecasts are provided. *EPSGuideFreq* and *EPSGuideDummy* measure the frequency and propensity of earnings forecasts. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Short Sale Constraints and Price Informativeness						
where $E =$	$E_{h=1}/A$ <i>EBIT</i> (1)	$E_{h=1}/A$ <i>EBITDA</i> (2)	$E_{h=1}/A$ <i>NI</i> (3)	$E_{h=1}/A$ <i>EBIT</i> (4)	$E_{h=1}/A$ <i>EBITDA</i> (5)	$E_{h=1}/A$ <i>NI</i> (6)
$\log(M/A) * ActHHI$	-0.017** (0.006)	-0.019*** (0.006)	-0.017** (0.006)			
$\log(M/A) * ActTop5$				-0.031*** (0.005)	-0.033*** (0.005)	-0.027*** (0.007)
$\log(M/A) * Supply$	-0.001 (0.010)	-0.004 (0.010)	0.028*** (0.010)	0.003 (0.010)	-0.000 (0.010)	0.032*** (0.010)
Observations	34,962	34,954	34,965	34,962	34,954	34,965
R^2	0.821	0.829	0.699	0.821	0.829	0.699
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel B: Short Sale Constraints and Investment-to-Price Sensitivity						
where $I =$	$I_{h=1}/K$ <i>Intangible</i> (1)	$I_{h=1}/K$ <i>Physical</i> (2)	$I_{h=1}/K$ <i>Invest</i> (3)	$I_{h=1}/K$ <i>Intangible</i> (4)	$I_{h=1}/K$ <i>Physical</i> (5)	$I_{h=1}/K$ <i>Invest</i> (6)
$\log(M/A) * ActHHI$	-0.006** (0.003)	-0.007** (0.003)	-0.016*** (0.005)			
$\log(M/A) * ActTop5$				-0.010*** (0.003)	-0.010*** (0.003)	-0.022*** (0.005)
$\log(M/A) * Supply$	-0.018*** (0.005)	-0.004 (0.005)	-0.024*** (0.008)	-0.018*** (0.005)	-0.004 (0.004)	-0.023*** (0.008)
Observations	34,841	34,799	34,838	34,841	34,799	34,838
R^2	0.932	0.769	0.840	0.932	0.769	0.840
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Continued on next page

Table D1 – *Continued*

Panel C: Liquidity Shock and Price Informativeness						
where $E =$	$E_{h=1}/A$ <i>EBIT</i> (1)	$E_{h=1}/A$ <i>EBITDA</i> (2)	$E_{h=1}/A$ <i>NI</i> (3)	$E_{h=1}/A$ <i>EBIT</i> (4)	$E_{h=1}/A$ <i>EBITDA</i> (5)	$E_{h=1}/A$ <i>NI</i> (6)
$\log(M/A)^*ActHHI$	-0.026*** (0.005)	-0.030*** (0.004)	-0.027*** (0.004)			
$\log(M/A)^*ActTop5$				-0.033*** (0.006)	-0.040*** (0.005)	-0.028*** (0.005)
$\log(M/A)^*Pressure$	0.017* (0.010)	0.011 (0.009)	0.054*** (0.012)	0.019 (0.012)	0.012 (0.011)	0.056*** (0.014)
Observations	83,054	83,794	83,952	83,054	83,794	83,952
R^2	0.823	0.837	0.714	0.824	0.838	0.714
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel D: Liquidity Shock and Investment-to-Price Sensitivity						
where $I =$	$I_{h=1}/K$ <i>Intangible</i> (1)	$I_{h=1}/K$ <i>Physical</i> (2)	$I_{h=1}/K$ <i>Invest</i> (3)	$I_{h=1}/K$ <i>Intangible</i> (4)	$I_{h=1}/K$ <i>Physical</i> (5)	$I_{h=1}/K$ <i>Invest</i> (6)
$\log(M/A)^*ActHHI$	-0.022*** (0.007)	-0.023*** (0.003)	-0.044*** (0.007)			
$\log(M/A)^*ActTop5$				-0.027*** (0.009)	-0.024*** (0.005)	-0.050*** (0.012)
$\log(M/A)^*Pressure$	-0.013 (0.012)	-0.015* (0.009)	-0.024 (0.015)	-0.015 (0.012)	-0.016* (0.008)	-0.027* (0.014)
Observations	83,616	82,913	83,549	83,616	82,913	83,549
R^2	0.863	0.692	0.771	0.863	0.693	0.771
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

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Table D1 – *Continued*

Panel E: Concentration and Voluntary Disclosure (Management Forecast)				
	<i>GuideFreq</i>		<i>GuideDummy</i>	
	(1)	(2)	(3)	(4)
<i>ActHHI</i>	-0.259 (0.350)		0.005 (0.025)	
<i>ActTop5</i>		0.016 (0.427)		0.050* (0.026)
Observations	72,223	72,223	72,223	72,223
R^2	0.660	0.660	0.628	0.628
Controls	Y	Y	Y	Y
Firm	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y
Panel F: Concentration and Voluntary Disclosure (Management Earnings Forecast)				
	<i>EPSTGuideFreq</i>		<i>EPSTGuideDummy</i>	
	(1)	(2)	(3)	(4)
<i>ActHHI</i>	-0.107 (0.144)		0.011 (0.022)	
<i>ActTop5</i>		0.087 (0.180)		0.072*** (0.024)
Observations	72,223	72,223	72,223	72,223
R^2	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Firm	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y

E Competing Hypothesis: Corporate Governance

Our theoretical model and empirical findings indicate that active ownership concentration impairs informational efficiency. However, a competing hypothesis posits that concentration enhances shareholder engagement and corporate governance, potentially improving informational efficiency. For instance, [Hartzell and Starks \(2003\)](#) document a positive relationship between institutional ownership concentration and the pay-for-performance sensitivity of executive compensation. Furthermore, prior research ([Cai et al., 2006](#); [Lee et al., 2016](#)) demonstrates that informational efficiency increases with governance quality. Thus, concentrated ownership could theoretically enhance informational efficiency through better governance. The negative effects identified in our baseline analysis suggest that this potential governance channel, if present, is dominated by the learning and information pass-through mechanisms. In this section, we empirically assess the validity of this competing hypothesis by examining whether concentrated ownership is associated with improved corporate governance.

Following prior research (e.g., [Albuquerque et al., 2022](#); [Guo et al., 2021](#)), we measure shareholder activism using Schedule 13D filings.⁶ We obtain Schedule 13D filings from the Audit Analytics Shareholder Activism database, which has been available since 2000. Audit Analytics categorizes each filing into one of seven types: concern, dispute, control, discussion, support, agreement, and other. [Agrawal and Lim \(2022\)](#) classify filings in the categories of concern, dispute, and control as hard activism, characterized by confrontational and hostile tactics. Based on this classification, we create two dummy variables: *Activism*, which is set to one if a firm has a 13D filing in any category during a given year; and *HardActivism*, which is set to one if a firm has a 13D filing in the categories of concern, dispute, or control within a given year.

In addition, we use corporate fraud as a proxy for the quality of corporate governance. Fewer cases of corporate fraud indicate better corporate governance. Following [Liu \(2016\)](#), we create a fraud dummy variable (*Fraud*), which is equal to one if the firm experiences any of the fol-

⁶Gaining 5% or more ownership in a public company triggers an SEC filing obligation. The choice between filing the detailed Schedule 13D or the simpler Schedule 13G depends on the investor's intentions: those aiming to actively influence company management file a 13D, while passive investors opt for a 13G.

lowing three events in a given year. First, the firm is subject to class action lawsuits in a given year. Securities class action lawsuit filings are sourced from the Stanford Securities Class Action Clearinghouse (SCAC). Following previous studies (e.g., [Kempf and Spalt, 2023](#)), cases related to initial public offering underwriter allocation, analyst coverage, and mutual funds, rather than firm management, are excluded. Moreover, to ensure the materiality of the cases, we exclude those that are subsequently dismissed, as per [Dyck et al. \(2010\)](#). Second, earnings are misstated in that firm-year according to the SEC’s Accounting and Auditing Enforcement Releases (AAER), which are issued for violations of SEC Rule 10b-5. AAER data is sourced from [Dechow et al. \(2011\)](#). Third, the firm announced an earnings restatement in that year according to the Audit Analytics Database. We exclude restatements arising from clerical errors (identified by the Audit Analytics “RES_CLER_ERR” flag) to distinguish material financial restatements from unintentional errors ([Wang, 2022](#)). We further require the restatements disclosed via Form 8-K Item 4.02, as these are deemed more material due to SEC regulatory requirements ([Cahan et al., 2024](#)).

Table [E1](#) reports regression results of the aforementioned proxies on active ownership concentration. We retain the same control variables and fixed effects as in the baseline model. The coefficients on the concentration measures (*ActTop5* and *ActHHI*) are statistically insignificant and sensitive to different specifications. When we use *HardActivism* to measure shareholder activism, the coefficient of *ActTop5* is significantly positive. However, this result is not robust: the coefficient of the alternative concentration measure, *ActHHI*, is insignificant and economically close to zero. Therefore, we find no empirical support for the competing hypothesis that active ownership concentration enhances informational efficiency through improved corporate governance.

Table E1: Competing Hypothesis: Corporate Governance

This table reports regression results of shareholder activism and corporate fraud proxies on trading-based ownership concentration. *Activism* is set to one if a firm has a 13D filing during a given year; *HardActivism* is set to one if a firm has a 13D filing in the categories of concern, dispute, or control within a given year. *Fraud* is set to one if the firm experienced any of the following events in a given year: involvement in class action lawsuits, earnings misstated according to the SEC's AAER, or an earnings restatement per the Audit Analytics. Trading-based ownership concentration is measured by *ActHHI*, representing the Herfindahl-Hirschman index of active institutional ownership, and by *ActTop5*, denoting the proportion of shares held by the top five active institutional investors relative to the total shares held by all active institutional investors. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

	<i>Activism</i>		<i>HardActivism</i>		<i>Fraud</i>	
	(1)	(2)	(3)	(4)	(5)	(6)
<i>ActHHI</i>	-0.003 (0.020)		0.004 (0.009)		-0.011 (0.007)	
<i>ActTop5</i>		0.015 (0.019)		0.021** (0.009)		-0.000 (0.009)
Observations	52,368	52,368	52,368	52,368	88,256	88,256
R^2	0.408	0.409	0.210	0.210	0.353	0.353
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y