Institutional Ownership Concentration and Informational Efficiency

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Abstract

We study how the concentration of ownership among institutional investors influences the informational efficiency in financial markets, in terms of forecasting price efficiency (FPE) and revelatory price efficiency (RPE). We find that an increase in active ownership concentration, whether at the market level or the firm level, has a negative impact on both FPE and RPE. When ownership becomes more concentrated, active investors reallocate their attention across different assets and trade more cautiously, resulting in a reduced injection of information into asset prices and a subsequent decrease in the investment efficiency. 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, informational efficiency

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 size distribution of institutional investors and its implications for financial markets. Specifically, we focus on how this distribution affects price informativeness, a widely recognized measure of market efficiency (e.g., Bond et al., 2012).

To guide the empirical analysis, we first present a theoretical model that formalizes the relationship between institutional ownership concentration and informational efficiency. The framework is built on Kacperczyk et al. (2025), but focuses on how the concentration of institutional ownership shares impacts price informativeness.

Our model features both 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 with the goal of maximizing their expected utility.

Given that passive investors lack the capacity to gather information and do not engage in informed trading, their presence does not directly affect price informativeness. We thus focus our examination on the concentration of institutional ownership among active investors. Consistent with Kacperczyk et al. (2025), we discover that in the overall market, as active institutional ownership becomes more concentrated, on average, less information is reflected in asset prices. In other words, the average price informativeness declines.

The negative effect of active ownership concentration operates through two channels: the information pass-through channel, which reflects active investors' trading sensitivity to private information, and the learning channel, which isolates these investors' information choices. First, as large investors increase in size, they tend to trade more conservatively due to their significant price impact, thereby injecting less information into asset prices. Conversely, while small active investors may trade more aggressively, their diminishing economic significance reduces their overall influence. Thus, the information pass-through channel suggests that price informativeness decreases as active ownership concentration rises.

Second, as small active investors decrease in size, they often shift their learning toward larger assets. This shift can reduce the price informativeness of small assets while enhancing that of larger ones. Although large active investors diversify their learning across assets as they grow, this effect is somewhat limited due to their existing diversification. Collectively, the learning channel suggests a negative impact of active ownership concentration.

In addition to analyzing the overall market-level concentration of active ownership, we also explore the asset-level ownership concentration. This innovation in our framework allows us to leverage the rich available data and enhance the robustness of our empirical tests. Our findings indicate that an individual asset's price informativeness decreases as *its* active ownership concentration increases. In our model, asset-level ownership concentration is measured based on investors' trading volume, which is endogenously determined. We show that the rise in asset-level ownership concentration is driven by increasing market-level ownership concentration. Specifically, large active investors trade more across all risky assets as they grow, while small active investors trade less as they diminish, resulting in greater asset-level ownership concentration. Thus, the positive relationship between market- and asset-level ownership concentration, combined with the negative effect of market-level concentration on price informativeness, implies a negative impact of asset-level ownership concentration.

In summary, the theoretical model predicts that an increase in active ownership concentration, whether at the market level or the individual asset level, leads to a reduction in price informativeness. Assuming that more informative prices are associated with higher investment efficiency, we can extrapolate that greater active institutional ownership concentration would be linked to lower real investment efficiency.

We then begin the empirical analysis by examining the effect of active institutional ownership concentration at the market level. To measure this market-level concentration, we utilize two metrics: the Herfindahl-Hirschman Index (HHI) of assets under management (AUM) among active institutional investors, and the share of AUM held by the top five active institutional investors. Across multiple model specifications, we observe a statistically significant and economically meaningful negative correlation between market-level active ownership concentration and price informativeness. 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 find that real investment efficiency also declines with increasing active ownership concentration.

Despite their significance and robustness, the market-level results can be limited due to the small sample size. We thus move on and emphasize the firm-level evidence. The active ownership concentration at the firm level is defined in a similar way to that at the market level but is based on investors' holdings in each stock. We relate active ownership concentration to price informativeness at the stock level. We find that price informativeness of stocks with the highest active ownership concentration is significantly lower than that of stocks with the lowest concentration. The effect is statistically and economically significant for both short and long horizons. In addition, we find that the impact extends to real investment efficiency as well.

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 and investment efficiency 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. Moreover, our results also hold in an international context, extending beyond the U.S. market.

Finally, we explore how ownership concentration can undermine price informativeness by examining the learning and information pass-through channels, as outlined by Kacperczyk et al. (2025). First, the learning channel suggests 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 concentration rises. Second, the information pass-through channel indicates that as active institutional ownership becomes more concentrated, large investors adopt a conservative trading strategy to minimize price impact. This channel is corroborated by empirical evidence showing lower portfolio turnover among large shareholders and reduced information content in earnings announcements for stocks with concentrated active institutional ownership.

Our paper contributes to the literature on ownership structure. The study most closely related to ours is Kacperczyk et al. (2025), which analyze the joint impact of the size, concentration, and active/passive ownership share of large investors on price informativeness using a general equilibrium model. We build upon their framework to study the effect of ownership concentration. Our research not only provides empirical support for their theoretical predictions regarding market-level ownership concentration's impact on price informativeness but also examines its effects on real investment efficiency. Additionally, we expand their model to explore the impact of firm-level ownership concentration, presenting compelling empirical evidence that supports this new prediction. More recently, Glebkin et al. (2025) develop a non-CARA-normal model to examine how asset concentration among a few large investors affects asset prices and liquidity and find that higher concentration can enhance liquidity.

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). Porras 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. 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 such ownership concentration, by correlating the capital flows and trading strategies of the largest institutions, can induce higher volatility and introduce more noise into stock prices. Huang et al. (2024) demonstrate that in the corporate bond market, higher mutual fund ownership concentration leads to increased bond volatility. This correlation is particularly strong for more illiquid bonds, during times of increased bond market illiquidity, and for funds with more illiquid holdings. 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 efficiency and further real investment efficiency. Importantly, we document a distinct mechanism through the learning and trading decisions of large investors. This is distinct from other drivers such as the systematic risk embedded in large institutions (Greenwood and Thesmar, 2011; Ben-David et al., 2021; Friberg et al., 2024), the role of short selling (Porras Prado et al., 2016), investors' responses to anticipated changes in ownership concentration (Massa et al., 2021), or illiquidity exposure (Huang et al., 2024).

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 efficiency 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 predictions to guide the ensuing empirical investigation. Section 3 describes the data. Sections 4 and 5 present the main empirical findings at the market and firm levels, respectively. Section 6 delves into an analysis of the underlying mechanism. Section 7 concludes.

2 A Model of Ownership Concentration and Informational Efficiency

We present a theoretical framework that formalizes the relationship between institutional ownership concentration and informational efficiency. This model is built on Kacperczyk, Nosal, and Sundaresan (2025), but it focuses on the impact of institutional ownership concentration. In addition to the market-level implications discussed in Kacperczyk et al. (2025), our framework further investigates the effects of institutional ownership concentration at the asset level, as well as the distinct roles of passive versus active institutional investors.

2.1 Model 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, the asset markets open and investors trade. At date 2, the assets pay off and all investors consume.

2.1.1 Assets

There are one risk-free asset and $n > 1$ 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.

2.1.2 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.

We theoretically differentiate between retail and institutional investors. Specifically, a mass $\lambda_0 < 1$ of investors is competitive atomistic uninformed investors (i.e., retail investors), indexed by $j = 0$. The others are oligopolists (i.e., institutional investors). There is a number l of oligopolistic investors; each, indexed by $j \in \{1, ..., l\}$, has information-gathering capacity K_j and size λ_j such that $\sum_{j=0}^{l} \lambda_j = 1$. The sizes of the oligopolistic investors, parameterized by λs, 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 four distinct types based on their mass and information-gathering capacity to align our model with the ownership structure data. (i) Large active investors (LA) who have large mass and large capacity; (ii) large passive investors (LP) who have large mass but zero capacity; (iii) small active investors (SA) who have small mass and lower capacity than large active investors; and (iv) small passive investors (SP) who have small mass 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 following form:

$$\tilde{s}_{ji} = \tilde{z}_i - \tilde{\delta}_{ji},$$

where $\tilde{\delta}_{ji}$ represents information loss due to the learning capacity constraint and is independent of the signal $\tilde{s}_{ji}$. For fringe and passive investors, $\tilde{s}_{ji} = \bar{z}$.

Denote the vector of asset fundamental $\tilde{z} = (\tilde{z}_1, ..., \tilde{z}_n)$, the vector of asset prices $\tilde{p} = (\tilde{p}_1, ..., \tilde{p}_n)$, and investor j's private signal about the assets $\tilde{s}_j = (\tilde{s}_{j1}, ..., \tilde{s}_{jn})$. Investor j's information set is $\mathcal{F}_j$. Following Kacperczyk et al. (2025), active investors and the competitive fringe learn from prices, whereas passive investors do not learn from prices. 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 $j \in LP \cup SP$. 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:

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

2.1.3 Learning Capacity

At date 0, active investors can acquire private signals about the fundamental of 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 $\alpha_{ji} \equiv \frac{Var[\tilde{z}_i]}{Var[\tilde{z}_i|\tilde{s}_{ji}]}$ 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:

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

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 the competitive fringe and passive investors who do not have 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 $E[U_j]$, where U_j is given by equation (1).

2.2 Equilibrium Definition and Characterization

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

(i) Active investors' information allocation strategies $\{\alpha^*_{ji}\}_{j=1,\ldots,l;i=1,\ldots,n}$ form a Nash equilibrium:

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

(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 $i \in \{1, ..., n\}$:

$$\sum_{j=0}^{l} \lambda_j q_{ji} = \tilde{x}_i. \tag{3}$$

We next follow Kacperczyk et al. (2025) to characterize the equilibrium. As is standard in the literature (e.g., Kyle, 1989), we consider the following linear demand schedule of investor j for asset i:

$$q_{ji} = \beta_{0ji} + \beta_{1ji}\, \tilde{s}_{ji} - \beta_{2ji}\, r\, \tilde{p}_i, \tag{4}$$

where the β-coefficients are endogenously determined in equilibrium. For passive investors and the uninformed fringe, the signal, $\tilde{s}_{ji}$, is set to the prior $\bar{z}$.

At date 1, investors choose their demand $\{q_{ji}\}$ to maximize the utility (1). The solution to the problem depends on whether the investor is an oligopolistic or a member of the competitive fringe. Specifically, the demand of an oligopolist j for asset i is

$$q_{ji} = \frac{\mu_{ji} - r\tilde{p}_i}{\rho\hat{\sigma}_{ji}^2 + r\frac{d\tilde{p}_i}{dq_{ji}}}, \tag{5}$$

where we apply Bayes' rule to compute the conditional moments:

$$\mu_{ji} \equiv E[\tilde{z}_i \mid \mathcal{F}_j] = E_j[\tilde{z}_i] + \frac{Cov_j(\tilde{z}_i, \tilde{p}_i)}{Var_j(\tilde{p}_i)}(\tilde{p}_i - E_j[\tilde{p}_i]), \tag{6}$$

$$\hat{\sigma}^2_{ji} \equiv Var[\tilde{z}_i \mid \mathcal{F}_j] = Var_j(\tilde{z}_i) - \frac{Cov^2_j(\tilde{z}_i, \tilde{p}_i)}{Var_j(\tilde{p}_i)}. \tag{7}$$

Here, oligopolists internalize their price impact when making their trading decisions. Given the linear demand (5) and the market clearing condition (3), the price impact of investor j on asset i is $\frac{d\tilde{p}_i}{dq_{ji}} = \frac{\lambda_j}{r\sum_{k=-j}\lambda_k\beta_{2ki}}$. In addition, the demand by the competitive fringe investors does not move the price and is thus given by

$$q_{0i} = \frac{\mu_{0i} - r\tilde{p}_i}{\rho\hat{\sigma}^2_{0i}}. \tag{8}$$

Given equations (3), (5), and (8), investors' demand schedules, conditional on active investors' information choices at date 0, can be summarized by a fixed point of the system:

$$\beta_{0ji} = \frac{-\frac{\gamma_{ji}}{\Delta_i}\left(-\bar{x}_i + \sum_{k=0}^{l}\lambda_k\beta_{0ki} + \sum_{k\neq j}\lambda_k\beta_{1ki}\frac{1}{\alpha_{ki}}\bar{z}\right)}{\rho\hat{\sigma}^2_{ji} + r\frac{d\tilde{p}_i}{dq_{ji}}}, \tag{9}$$

$$\beta_{1ji} = \frac{1 - \frac{\gamma_{ji}}{\Delta_i}\left(\lambda_j\beta_{1ji} + \sum_{k\neq j}\lambda_k\beta_{1ki}\left(1 - \frac{1}{\alpha_{ki}}\right)\right)}{\rho\hat{\sigma}^2_{ji} + r\frac{d\tilde{p}_i}{dq_{ji}}}, \tag{10}$$

$$\beta_{2ji} = \frac{1 - \frac{\gamma_{ji}}{r}}{\rho\hat{\sigma}^2_{ji} + r\frac{d\tilde{p}_i}{dq_{ji}}}, \tag{11}$$

where $\gamma_{ji} \equiv \frac{Cov_j(\tilde{z}_i,\tilde{p}_i)}{Var_j(\tilde{p}_i)}$ 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 the fringe investors, there is no price impact, i.e., $\frac{d\tilde{p}_i}{dq_{0i}} = 0$. For passive investors, without private information, $\gamma_{ji} = 0$ and the system simplifies to:

$$\beta_{0ji} = 0 \text{ and } \beta_{1ji} = \beta_{2ji} = \frac{1}{\rho\hat{\sigma}^2_{ji} + r\frac{d\tilde{p}_i}{dq_{ji}}}. \tag{12}$$

We finally 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 as given follows, subject to the constraint (2),

$$E_0[U_j] = \sum_{i=1}^{n} E_0\left[(\mu_{ji} - r\tilde{p}_i)^2\right] \cdot \frac{\frac{\rho}{2}\hat{\sigma}_{ji}^2 + r\frac{d\tilde{p}_i}{dq_{ji}}}{\left(\rho\,\hat{\sigma}_{ji}^2 + r\frac{d\tilde{p}_i}{dq_{ji}}\right)^2}. \tag{13}$$

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.

2.3 Numerical Analysis

This section provides a numerical characterization of the relationship between price informativeness and ownership concentration at both the market and the asset levels. In Section 2.3.1, we introduce the measure of price informativeness, as well as that of the market- and asset-level ownership concentration. In Section 2.3.2, we discuss the selection of parameters, which generally follows Kacperczyk et al. (2025), but with some modifications to better capture empirical characteristics in our data. Section 2.3.3 presents the numerical results and discusses the underlying implications.

2.3.1 Variable Construction

The first key variable is price informativeness, also known as forecasting price efficiency (FPE), which measures the amount of information incorporated into asset prices. Following Bai et al. (2016), we measure it as the covariance of the price with the asset fundamental, normalized by the variance of the price:

$$PI_i \equiv \frac{Cov(p_i, z_i)}{\sqrt{Var(p_i)}} = \frac{\sigma_i \sum_{j=0}^{l} \omega_{ji}(1 - \frac{1}{\alpha_{ji}})}{\sqrt{\frac{\sigma_{x_i}^2}{\sigma_i^2} + \left(\sum_{j=0}^{l} \omega_{ji}(1 - \frac{1}{\alpha_{ji}})\right)^2 + \sum_{j=0}^{l} \omega_{ji}^2 \frac{\alpha_{ji}-1}{\alpha_{ji}^2}}}, \tag{14}$$

where $\omega_{ji} \equiv \frac{\partial \lambda_j q_{ji}}{\partial s_{ji}} = \lambda_j \beta_{1ji}$. 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 (14), 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*.

The second key variable is institutional ownership concentration. Given that passive investors do not acquire private information or engage in informed trading, we construct ownership concentration based on the ownership of active investors. Specifically, we consider two layers of ownership concentration. First, we follow Kacperczyk et al. (2025) to measure the concentration among active investors at the market level:

$$ActHHI_{mkt} = \sum_{j \in SA \cup LA} \left(\frac{\lambda_j}{\sum_{k \in SA \cup LA} \lambda_k} \right)^2. \tag{15}$$

Second, we introduce a novel asset-level ownership concentration measure, which is constructed based on active investors' endogenous trading volume:

$$ActHHI_{asset} = \sum_{j \in SA \cup LA} \left(\frac{\lambda_j E[|q_{ji}|]}{\sum_{k \in SA \cup LA} \lambda_k E[|q_{ki}|]} \right)^2, \tag{16}$$

where investor j's demand q_{ji} for asset i is given by equation (4). The availability of rich data and the resulting variation allows us to primarily focus on investor concentration at this granular asset level.

2.3.2 Parameter Assignment

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 effectively learned.

In addition, our investor mass $\{\lambda_j\}_{j=0}^{l}$ is set to match the empirical ownership distribution. Specifically, we choose the fringe 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 and passive group, 2 oligopolists are assumed to be large, and the other 8 oligopolists are assumed to be small. That is, $LA = \{1, 2\}$, $LP = \{3, 4\}$, $SA = \{5, \ldots, 12\}$, and $SP = \{13, \ldots, 20\}$. 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 US stock market in the past decade. Thus, in our model, with 40% fringe ownership, the passive sector is around 50% of total institutional ownership, that is, $\sum_{j\in SP\cup LP} \lambda_j / \sum_{j=1}^{l} \lambda_j = 50\%$ (note that our results remain robust if we vary the value between 20% and 60%).

Finally, to study the effect of ownership concentration on price informativeness, we follow Kacperczyk et al. (2025) and generate different concentration levels by varying two values. First, we change the relative size of the two large active oligopolists and two large passive oligopolists by varying λ_1/λ_2 and λ_3/λ_4 linearly from 1.1 to 10 in ten scenarios. Second and at the same time, we vary the relative size of the small sector, $\sum_{j\in SA} \lambda_j / \sum_{j\in SA\cup LA} \lambda_j$ and $\sum_{j\in SP} \lambda_j / \sum_{j\in SP\cup LP} \lambda_j$, linearly from 10% to 3% in the ten scenarios. This experiment generates an increasing HHI index for active oligopolistic ownership.

We summarize the parameter values in Table 1.

2.3.3 Model Predictions

In this section, we explore the implications of institutional ownership concentration for both price efficiency and real efficiency within our model economy. We will test these predictions in the subsequent sections.

Ownership Concentration at the Market Level Figure 2 presents the effect of market-level concentration among active oligopolists, as defined in equation (15), 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 the price informativeness of all assets decreases with higher market-level concentration among active investors, which leads to the following prediction:

Prediction 1 (Market-level concentration)**.** *Price informativeness is lower when market-level ownership concentration among active institutional investors is higher.*

To understand the mechanism, we follow Kacperczyk et al. (2025) and decompose the overall effect by fixing the degree of learning (α_{ji}) at the level in the first scenario of the concentration experiment and by holding the information pass-through (ω_{ji}) fixed at values from the same first scenario. Panels (b) and (c) of Figure 2 present the results. As in Figure 9 of Kacperczyk et al. (2025), the average price informativeness decreases with concentration in both cases.

Firstly, as shown in Panel (b) of Figure 2, 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 oligopolistic 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 average price informativeness down. These results are summarized as follows:

Prediction 2 (Information pass-through effect)**.** *Higher ownership concentration leads to lower average trading intensity, especially among large investors.*

Secondly, when information pass through (ω_{ji}) is fixed, large active investors diversify their learning as they grow, increasing average price informativeness. In contrast, small active investors, as they decrease in size, tend to specialize their learning in large assets, which reduces average price informativeness. The decreasing pattern in Panel (c) of Figure 2 suggests that the specialized learning by small active investors dominate.

To further clarify the learning effect, we compare the learning choices of the largest active investors with those of other active investors in Figure 3. 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). However, since she has already diversified her learning in the beginning, further diversification has a marginal impact on price informativeness.

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, the specialized learning by smaller active investors prevails, leading to the decreasing average price informativeness pattern observed in Panel (c) of Figure 2.

These results are summarized as follows:

Prediction 3 (Learning effect)**.** *Higher ownership concentration leads to increased learning in large assets and diminished learning in small assets, on average.*

Ownership Concentration at the Asset Level We then explore the effect of asset-level ownership concentration, as defined in equation (16), in Figure 4. This is the new part of our theory. Analyzing all panels of Figure 4 for assets of varying sizes, we observe that higher ownership concentration at the asset level is associated with a decline in individual price informativeness. Given the endogenous nature of our asset-level ownership concentration measure, the primary driver of ownership concentration at the asset level, calculated based on trading volume as shown in equation (16), and their implications for price efficiency is the market-level ownership structure.

Specifically, as the size of large active investors increases, they trade risky assets more, as shown in Panel (a) of Figure 5. As noted, these large active investors diversify their learning, leading to varying increases in trading volume across different assets. Conversely, as their size decreases, small active investors' trading volume across all assets declines, illustrated in Panel (b) of Figure 5. This results in increased asset-level concentration, directly linked to the rise in market-level concentration. Combined with the negative impact of market-level ownership concentration, asset-level ownership concentration is also negatively related to individual price informativeness.

Prediction 4 (Asset-level concentration)**.** *Price informativeness is lower when asset-level active ownership concentration is higher.*

Real Price Efficiency As will be shown later, our empirical research will also examine the implications of active ownership concentration on real price efficiency (RPE), which pertains to how the information contained in prices guides real investment decisions (Bond et al., 2012). Due to the complexity of the framework, we do not explicitly model how asset prices affect managers' investment decisions. Instead, we adopt the approach of Subrahmanyam and Titman (2001) and assume that more informative prices tend to result in higher investment efficiency. Based on this assumption and Predictions 1 and 4, we anticipate that higher ownership concentration, whether at the market level or the asset level, is likely associated with lower real price efficiency, as summarized in the following prediction:

Prediction 5 (Revelatory price efficiency)**.** *Revelatory price efficiency is lower when ownership concentration among active institutional investors is higher, whether at the market level or the asset level.*

Comparison Between Active and Passive Ownership Concentration Our experiment generates increasing ownership concentration for both active and passive investors, which maps well to the patterns observed in Figure 1. However, one potential concern is that the decreasing price informativeness might be caused by the increasing ownership concentration among passive investors, rather than active ones. 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 (12), 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 this possibility, we conduct a placebo test by fixing the size distribution for active investors throughout the experiment. Specifically, 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. The latter is defined similarly to equations (15) and (16), but with active investors replaced by passive investors. If the decreasing price informativeness is primarily driven by active investors, then the pattern should collapse in the placebo test. Panels (a) and (b) of Figure 6 illustrate the results at the market and asset levels, respectively. We find that as $PasHHI$ increases, price informativeness remains relatively unchanged.[1]

3 Data

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 market-level empirical tests, we construct ownership-related variables in the fourth quarter and merge them with price informativeness measures, which will be introduced shortly. For firm-level empirical tests, 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 market-level and firm-level 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

[1] For comparison, we conduct an additional experiment where the size distribution of passive investors is held constant while varying that of active investors. The results are shown in Figures A1 and A2 in the online appendix and are quantitatively similar to those in Figures 2 and 4.

and observations with a market capitalization below 500 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 firm-level 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 A1. 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.[2] 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 ownership concentration measure at the market level. In each quarter, we calculate 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:

$$ActHHI_{mkt,q} = \frac{\sum_{j=1}^{N_{mkt}} \left(AUM_{j,q}^2\right)}{\left(\sum_{j=1}^{N_{mkt}} AUM_{j,q}\right)^2}, \tag{17}$$

[2]Bushee'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. Moreover, institution here represents the level at which institutional holdings are recorded in 13F holdings data.

where $AUM_{j,q}$ is the AUM of active institutional investor j in quarter q and N_{mkt} 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:

$$ActTop5_{mkt,q} = \frac{\sum_{j=1}^{\text{Top 5}} AUM_{j,q}}{\sum_{j=1}^{N_{mkt}} AUM_{j,q}}. \tag{18}$$

At the firm level, we construct the ownership concentration measure in a similar way as that at the market level:

$$ActHHI_{i,q} = \frac{\sum_{j=1}^{N_i} \left(S_{i,j,q}^2\right)}{(\sum_{j=1}^{N_i} S_{i,j,q})^2}, \text{ and } ActTop5_{i,q} = \frac{\sum_{j=1}^{\text{Top 5}} S_{i,j,q}}{\sum_{j=1}^{N_i} S_{i,j,q}}, \tag{19}$$

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 $ActTop5$, at either the market or firm level, 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. To estimate FPE, we first run cross-sectional regressions of future earnings on current market prices for each year:

$$\frac{E_{i,t+h}}{A_{i,t}} = a_{t,h} + b_{t,h} \log\left(\frac{M_{i,t}}{A_{i,t}}\right) + c_{t,h}\left(\frac{E_{i,t}}{A_{i,t}}\right) + d_{t,h}^s \mathbf{1}_{i,t}^s + \epsilon_{i,t,h}, \tag{20}$$

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 market-level FPE in year t at prediction horizon h is then calculated as the forecasting coefficient $b_{t,h}$ in equation (20) multiplied by $\sigma_t(\log(M/A))$, the cross-sectional standard deviation of the scaled market price $\log(M/A)$ in year t:

$$FPE_{t,h} = b_{t,h} \times \sigma_t(\log(M/A)). \tag{21}$$

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

$$\frac{I_{i,t+h}}{K_{i,t}} = a_{t,h} + b_{t,h} \log\left(\frac{M_{i,t}}{A_{i,t}}\right) + c_{t,h}\left(\frac{E_{i,t}}{A_{i,t}}\right) + d_{t,h}\left(\frac{I_{i,t}}{K_{i,t}}\right) + e^s_{t,h}\mathbf{1}^s_{i,t} + \epsilon_{i,t,h}, \tag{22}$$

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 × SG&A expenses,[3] 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 market-level RPE in year t at prediction horizon h is then calculated as the forecasting coefficient $b_{t,h}$ in equation (22) multiplied by $\sigma_t(\log(M/A))$.

By conducting the cross-sectional regressions for each year, we are able to estimate a time-

[3]Only 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).

series set of FPE and RPE measures, and examine their relation with the market-level active institutional ownership concentration.

However, the cross-sectional nature of this estimation makes it unsuitable for studying the relationship between firm-level active institutional ownership concentration and price informativeness, since the firm-level ownership concentration is panel data while price informativeness is time-series data. Kacperczyk, Sundaresan, and Wang (2021) address this issue by modifying the cross-sectional regression into a pooled regression. Therefore, we use the cross-sectional regression model to estimate price informativeness when studying the effect of *market-level* concentration on price informativeness, and use the modified pooled regression model as detailed in Section 5.1 when studying the effect of *firm-level* concentration on price informativeness.

4 Implications of Market-level Ownership Concentration

This section investigates the effect of market-level active institutional ownership concentration on FPE and RPE. These analyses empirically test Predictions 1 and 5 in Section 2.3.3.

Firstly, we visually inspect the relationship between market-level active institutional ownership concentration and FPE estimated from equation (21), using a one-year prediction horizon.[4] Figure 7 presents scatter plots along with the fitted lines and the 95% confidence intervals. Panels (a)-(c) use $ActHHI_{mkt}$ in equation (17) to measure concentration, while Panels (d)-(f) use $ActTop5_{mkt}$ in equation (18) as an alternative measure. We observe a significantly negative correlation between market-level active institutional ownership concentration and FPE across different specifications, consistent with Prediction 1 and its numerical analysis in Panel (a) of Figure 2. Moreover, the effect is economically meaningful. For example, the correlation coefficient is -0.18 in Panel (b) of Figure 7, suggesting that a one percentage point increase in $ActHHI_{mkt}$ is associated with a 25.7% decrease in FPE relative to its mean level of 0.007.

Secondly, we divide the sample firms into five groups based on their market capitalization,

[4]This negative relation remains robust when we change the prediction horizon from one year to three years, as shown in Figures A3 and A4 in the online appendix.

and estimate the FPE for each group. Figure 8 presents the scatter plots along with the fitted lines. Two observations are worth noting. First, larger firms enjoy higher FPE on average, consistent with our numerical results in Panel (a) of 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 market-level ownership concentration and FPE holds for all size groups, suggesting that our results are not driven by any specific group of firms.

Finally, we examine the relation between market-level active institutional ownership concentration and RPE. We observe a negative correlation in all specifications, which is generally statistically significant except for Panel (d). This implies that ownership concentration also inhibits price efficiency in guiding real investment decisions, as predicted by Prediction 5.

Despite the significance and robustness of the market-level results, we are also aware of its limitations. For instance, some FPE estimates in Figures 7 and 8 are negative, which is also observed in previous studies using the similar estimation process (e.g. Farboodi et al., 2022; Dávila and Parlatore, 2025). In addition, the sample size is relatively 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. These limitations thereby motivate and justify our further intensive exploration at the firm level, as will be presented in the next section.

5 Implications of Firm-level Ownership Concentration

This section investigates the impact of firm-level active institutional ownership concentration on FPE and RPE. Section 5.1 conducts baseline regressions. Section 5.2 conducts additional analyses to ensure the robustness of our results. Section 5.3 addresses the endogeneity issue by examining the context of mergers among active financial institutions. Section 5.4 expands the sample to an international setting.

5.1 Baseline Regression Models

To examine the effect of firm-level active ownership concentration on FPE as stated in Prediction 4, we follow Kacperczyk et al. (2021) and estimate the following pooled regression model using firm-level data at the annual frequency:

$$
\begin{aligned}
\frac{E_{i,t+h}}{A_{i,t}} = a_h + b_h \log\left(\frac{M_{i,t}}{A_{i,t}}\right) + c_h \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times Concentration_{i,t} + d_h Concentration_{i,t} \\
+ e_h \frac{E_{i,t}}{A_{i,t}} + f_h \chi_{i,t} + g_h \log\left(\frac{M_{i,t}}{A_{i,t}}\right) \times \chi_{i,t} + FE_{i,t} + \varepsilon_{i,t+h},
\end{aligned}
\tag{23}
$$

where h denotes the prediction horizons, equaling 1 or 3 in this paper. $Concentration_{i,t}$ denotes the firm-level ownership concentration among active institutional investors, measured by $ActHHI$ or $ActTop5$ as defined in equation (19). $E_{i,t}/A_{i,t}$ 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 FPE, 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, FPE decreases by 24.2%. In Columns (4)-(6), we perform the same estimation regression for FPE 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, FPE 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 firm-level active institutional ownership concentration on FPE. 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 variables held constant at their mean levels, corresponds to a decrease of 27.8% and 45.2% in FPE at the 1-year and 3-year prediction horizons, respectively. These results are consistent with Prediction 4 in Section 2.3.3.

We then estimate the effect of active institutional ownership concentration on RPE in a similar fashion to the regression (23), 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, RPE 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 Prediction 5 in Section 2.3.3.

5.2 Robustness Checks

5.2.1 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 active institutional ownership concentration.

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):

$$SUE_{i,t} = \frac{EPS_{i,t} - E_{t-1}\left[EPS_{i,t}\right]}{P_{i,t-5}}, \tag{24}$$

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.[5] 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.

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

[5] We 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.

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:

$$\begin{aligned} BHAR[0,2]_{i,t} =& \beta_1 Rank_{i,t} + \beta_2 Rank_{i,t} \times Concentration_{i,t} + \beta_3 Concentration_{i,t} + \\ & \rho\chi_{i,t} + FE_{i,t} + \varepsilon_{i,t}, \qquad (25) \\ BHAR[3,24]_{i,t} =& \gamma_1 Rank_{i,t} + \gamma_2 Rank_{i,t} \times Concentration_{i,t} + \gamma_3 Concentration_{i,t} + \\ & \rho\chi_{i,t} + FE_{i,t} + \varepsilon_{i,t}, \qquad (26) \end{aligned}$$

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 (24). 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 (25) and γ_2 in equation (26). 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 5 presents the results. Consistent with our hypothesis, stocks with higher concentrations 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 $ActTop5$.

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).[6] 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 5 reports the results. From Columns (1) to (4), $CPIE$ is calculated based on the PIN, APIN, GPIN, and OWR model, 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 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

[6]The 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.

concentration, as shown in Columns (5)-(8) in Panel B of Table 5.

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 5 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.

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):

$$VR(q) = \left| \frac{\sigma^2(q)}{q \times \sigma^2} - 1 \right|, \tag{27}$$

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 (27) 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 5 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.

Relative Price Informativeness Dávila and Parlatore (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:

$$\Delta p_t^j = \bar{\beta}\left(Y_t^j\right) + \beta_0\left(Y_t^j\right)\Delta x_t^j + \beta_1\left(Y_t^j\right)\Delta x_{t+4}^j + \varepsilon_t^j,$$
$$\Delta p_t^j = \bar{\zeta}\left(Y_t^j\right) + \zeta_0\left(Y_t^j\right)\Delta x_t^j + \hat{\varepsilon}_t^j,$$

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 $\mathbb{V}\mathrm{ar}[\varepsilon_t^j]$ and $\mathbb{V}\mathrm{ar}[\hat{\varepsilon}_t^j]$ are estimated respectively using $\widehat{\mathbb{V}\mathrm{ar}}\left[\varepsilon_t^j\right] = \exp\left\{\lambda_0 + \lambda_1 Y_t^j + Y_t^{j\prime}\lambda_2 Y_t^j + \frac{1}{2}\mathbb{V}\mathrm{ar}[v_t^j]\right\}$

and $\widehat{\mathbb{V}\text{ar}}\left[\hat{\varepsilon}_t^j\right] = \exp\left\{\hat{\lambda}_0 + \hat{\lambda}_1 Y_t^j + Y_t^{j\prime}\hat{\lambda}_2 Y_t^j + \frac{1}{2}\,\mathbb{V}\text{ar}[\hat{v}_t^j]\right\}$. Finally, the relative price informativeness for stock j in quarter t is quantified by $\hat{\tau}_{\pi,t}^{R,j} = \frac{\widehat{\mathbb{V}\text{ar}}\left[\hat{\varepsilon}_t^j\right] - \widehat{\mathbb{V}\text{ar}}\left[\varepsilon_t^j\right]}{\widehat{\mathbb{V}\text{ar}}\left[\hat{\varepsilon}_t^j\right]}$.

The sample selection procedure is similar to that in our baseline analysis, expect for the additional requirement that stocks' relative price informativeness should be positive. This resulting smaller sample size leads to a shorter sample period, spanning from 1985 to 2021. 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-quater. 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 5 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 5, the results remain statistically significantly negative. Figures A5 and A6 provide alternative graphical illustrations of our results, indicating that the cross-sectional relations identified in Panel E of Table 5 are stable over time.

5.2.2 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.[7] Table 6 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.

5.2.3 Other Robustness Tests

In the online appendix, we perform additional tests to further illustrate the robustness of the negative relationship between institutional ownership concentration and FPE/RPE. Table A2 in the online appendix 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 firm-level ownership concentration based on the detailed holding data of each institution in our baseline analysis, Table A3 in the online appendix shows that our results remain robust if we calculate it based on each institution's trading volume in each firm's stock, which is a closer empirical counterpart of equation (16) defined in our model.

Although passive institutional investors do not directly affect the information level of stock prices as indicated in equation (14), they may indirectly affect price informativeness through the trading activities of active investors as discussed in Section 2.3.3. Our baseline analysis ac-

[7]The 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."

counts for this potential effect by controlling for the passive institutional ownership ($PasHHi$ or $PasTop5$). Alternatively, Table A4 in the online appendix reconstructs our concentration measures without distinguishing between active and passive investors. Specially, $TotHHI_{i,q} = \frac{\sum_{j=1}^{N_{tot}} \left(S_{i,j,q}^2\right)}{(\sum_{j=1}^{N_{tot}} S_{i,j,q})^2}$ captures firm-level HHI of institutional shares, where N_{tot} denotes the number of institutions holding stock i. Similarly, $TotTop5_{i,q} = \frac{\sum_{j=1}^{\text{Top 5}} S_{i,j,q}}{\sum_{j=1}^{N_{tot}} S_{i,j,q}}$ 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 institutional ownership concentration on both FPE and RPE.

In our baseline analysis, we estimate RPE by regressing 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 A5 in the online appendix 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 augment the RPE regressions 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.

5.3 Identification

One potential concern is that the observed negative relationship might be attributable to unobservable economic forces correlated with both a firm's ownership concentration and its price efficiency. Another concern suggests that firms with lower price efficiency 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 (1) the target firm is incorporated in the U.S.; (2) both the acquirer and target are in the finance industry; (3) 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.[8] Upon merging the SDC and 13F data, we further mandate that either the target firm ceases filing 13F 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

[8] SDC 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.

in Table A6 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. 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).[9] 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.[10]

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

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

where $Concentration_{i,t}$ denotes the firm-level 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

[9]We consider an alternative strategy for selecting control firms in Table A7 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.

[10]Table A8 in the online appendix shows that our results are robust to an alternative estimation window from 3 years before to 3 years after mergers.

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 7 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 FPE by estimating the subsequent regression model based on annual accounting information:

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

$Post$ 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 RPE 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 the change in price efficiency around the treatment group's shock relative to the control group.

Panels B and C of Table 7 present the results of FPE and RPE, respectively. We find that both FPE and RPE of treatment firms diminish significantly following the shock, implying that more concentrated active institutional ownership leads to lower informational efficiency. Additionally, the effect is generally larger for the 3-year horizon compared to the 1-year short-run horizon.

Figure 10 plots the estimated effect on informational efficiency over time in an extended window of $(-3, +3)$ years, with year-0 denoting the merger completion year. Panel (a) measures FPE based on the earnings variable $EBITDA/A$ at the 1-year prediction horizon, while Panel (b) measures RPE based on $Invest/K$ at the same horizon. Notably, the negative effect of active financial institution mergers on FPE or RPE 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 on FPE and RPE is gradual, increasing in magnitude over time following the merger completion year without exhibiting any reversal. Overall, our DiD estimation results provide evidence that, on average, firms' active institutional ownership concentration has a negative causal effect on their informational efficiency.

5.4 International Evidence

In this section, 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 A9 in the online appendix. Figure A7 in the online appendix displays the time-series average firm-level $ActTop5$ 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 8 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 persists in the international setting. 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 A10.

6 Mechanisms

In Section 2.3.3, we discuss two underlying channels through which ownership concentration might undermine price informativeness, which we explore in this section. The first channel, the "learning channel" (Prediction 3), posits that increased ownership concentration leads larger investors to diversify their learning, while smaller investors specialize. The second channel, the "information pass-through channel" (Prediction 2), suggests that larger investors trade more conservatively on their private information due to the heightened price impact.

6.1 The Learning Channel

We first test the learning channel, as outlined in Prediction 3. 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 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).[11] 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.

[11] First, 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.

Panel (a) of Figure 11 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 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 12, we explore the impact of market-level ownership concentration among active institutional investors on their learning choices. In Panel (a), we identify a significantly positive correlation between market-level $ActHHI$ and EDGAR downloads in the largest group. This implies that more investor attention is allocated to large stocks as market-level concentration increases. The pattern reverses in the smallest group, as depicted in Panel (b). This indicates that small stocks are poorly learned when active institutional ownership is concentrated. In Panel (c), we measure the learning imbalance by calculating the difference in EDGAR downloads between the largest and smallest groups. Consistent with our prediction and numerical results in Figure 2, Panel (c), we observe a positive correlation between market-level concentration and learning imbalance. The results remain robust when using $ActTop5$ as an alternative measure of ownership concentration, as shown in Panels (d)-(f) of Figure 12.

6.2 The Information Pass-through Channel

In this section, we test the information-pass channel as outlined in Predictions 2 in the following two settings.

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 and sale for each subgroup g as follows:

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

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

$S_{k,g,i,q}$ 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 $PTR_{k,g,q} = \frac{\min\left(AgBuy_{k,g,q}, AgSell_{k,g,q}\right)}{\sum_{i \in N_{k,g}} (S_{k,g,i,q} P_{i,q} + S_{k,g,i,q-1} P_{i,q-1})/2}$.

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 9 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 9 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 5.2 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 10 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) [12] and demonstrate the robust negative relation

[12] We 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;

between the information content and active institutional ownership concentration.

6.3 Alternative Explanations

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

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 11 reports the results. The negative effect of active ownership con-

$ReportLag$ 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.

centration on informational efficiency remain 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.

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 ($\frac{F_{j,t}}{TA_{i,j,t-1}} < -5\%$) 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 11 replicates 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 in the RPE case, as the coefficients of $\log(M/A) * Pressure$ are negative and weakly significant in Panel D, it is overturned in the FPE case in Panel C. In contrast, the coefficients on the interaction 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.

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. $EPSGuideFreq$ and $EPSGuideDummy$ measure the frequency and propensity of earnings forecasts.

Panels E and F of Table 11 reports 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.

7 Conclusion

Over the past few decades, equity ownership has become increasingly concentrated in the hands of large investors. This skewed ownership structure has significant implications for the informational efficiency of stock prices, which is closely tied to the informed trading activities of active investors. Our paper provides a theoretical framework and compelling empirical evidence that a more concentrated ownership structure among active institutional investors, whether at the market or firm level, can ultimately erode the efficiency of stock prices in reflecting future firm fundamentals.

Further analysis reveals that the adverse effect can be divided into two channels: the learning channel and the information pass-through channel. First, as small active investors decrease in size, they redirect their learning efforts toward larger assets, reducing the price informativeness of smaller assets while enhancing that of larger ones. Although large active investors may diversify their learning, their impact is limited due to their existing diversification, leading to an overall decrease in average price informativeness through this learning channel.

Second, as large active investors grow, they trade more conservatively on their private signals due to heightened price impact concerns, diminishing price informativeness. While smaller active investors may trade more aggressively as their price impact concerns lessen, their decreasing size reduces their economic significance. Thus, the information pass-through channel also indicates a negative effect of ownership concentration. Together, these learning and trading behaviors shape the efficiency of stock prices.

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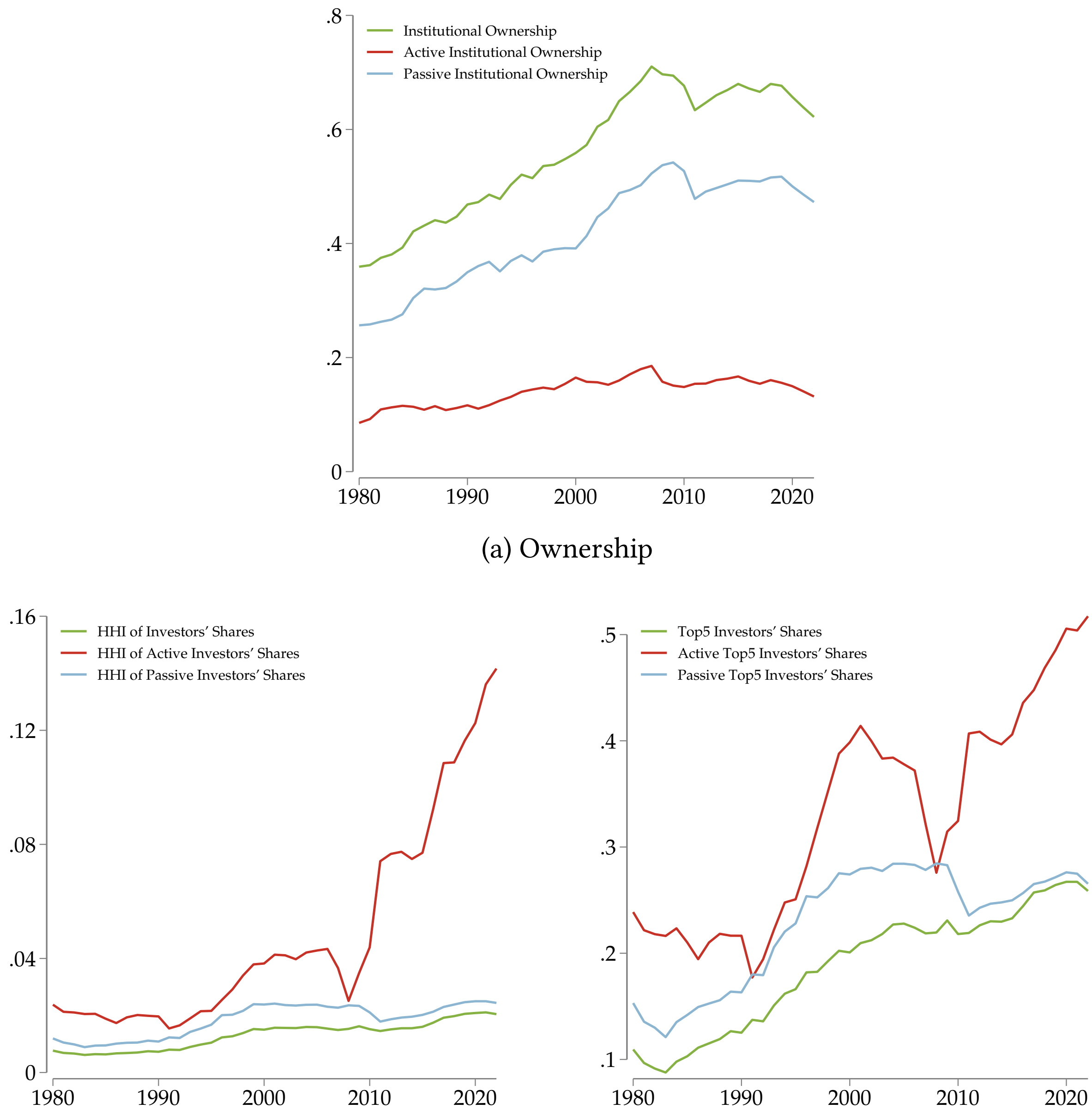


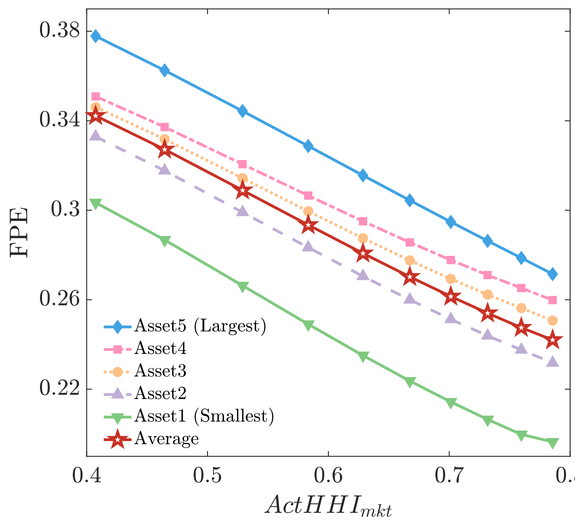
(a) Ownership

(b) Concentration: HHI

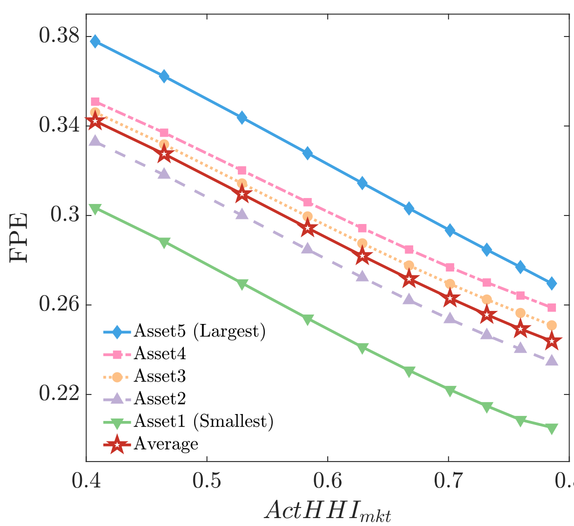
(c) Concentration: Top 5 Investor Shares

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.

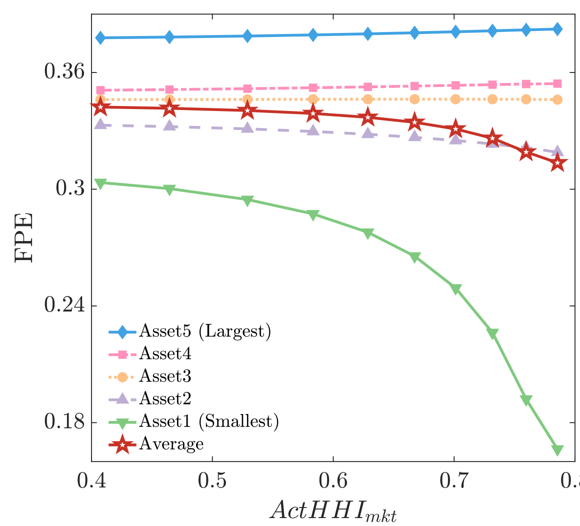
Figure 1: The Time Trend of Institutional Ownership and Its Concentration



(a) Overall Effect



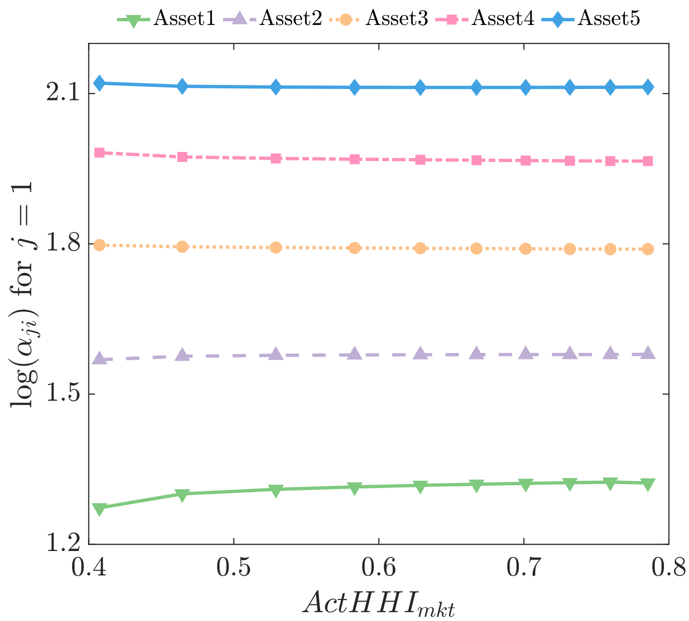
(b) Information Pass-through Effect



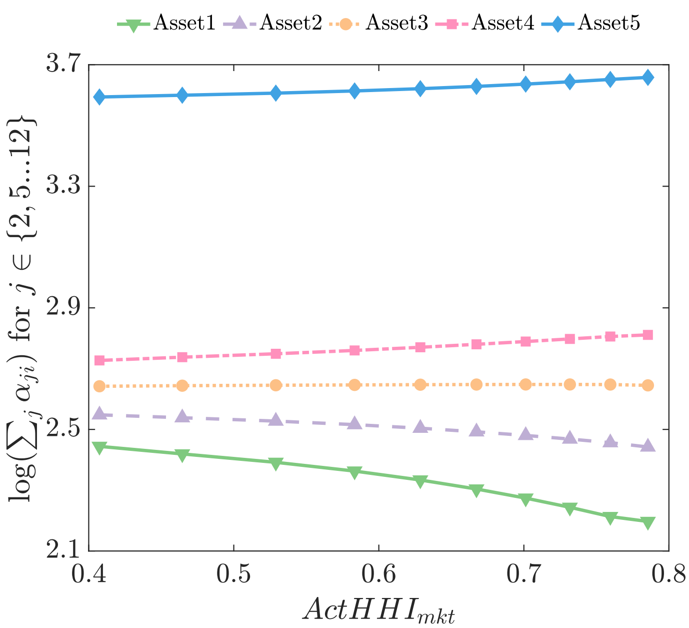
(c) Learning Effect

Panel (a) of this figure plots the average and individual price informativeness against different values of ownership concentration at the market level. Price informativeness and market-level concentrations are defined in equations (14) and (15) respectively. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5). Panels (b) and (c) decompose the overall effect of ownership concentration by respectively fixing the degree of learning (α_{ji}) and fixing the information pass-through (ω_{ji}).

Figure 2: The Effect of Market-level Ownership Concentration



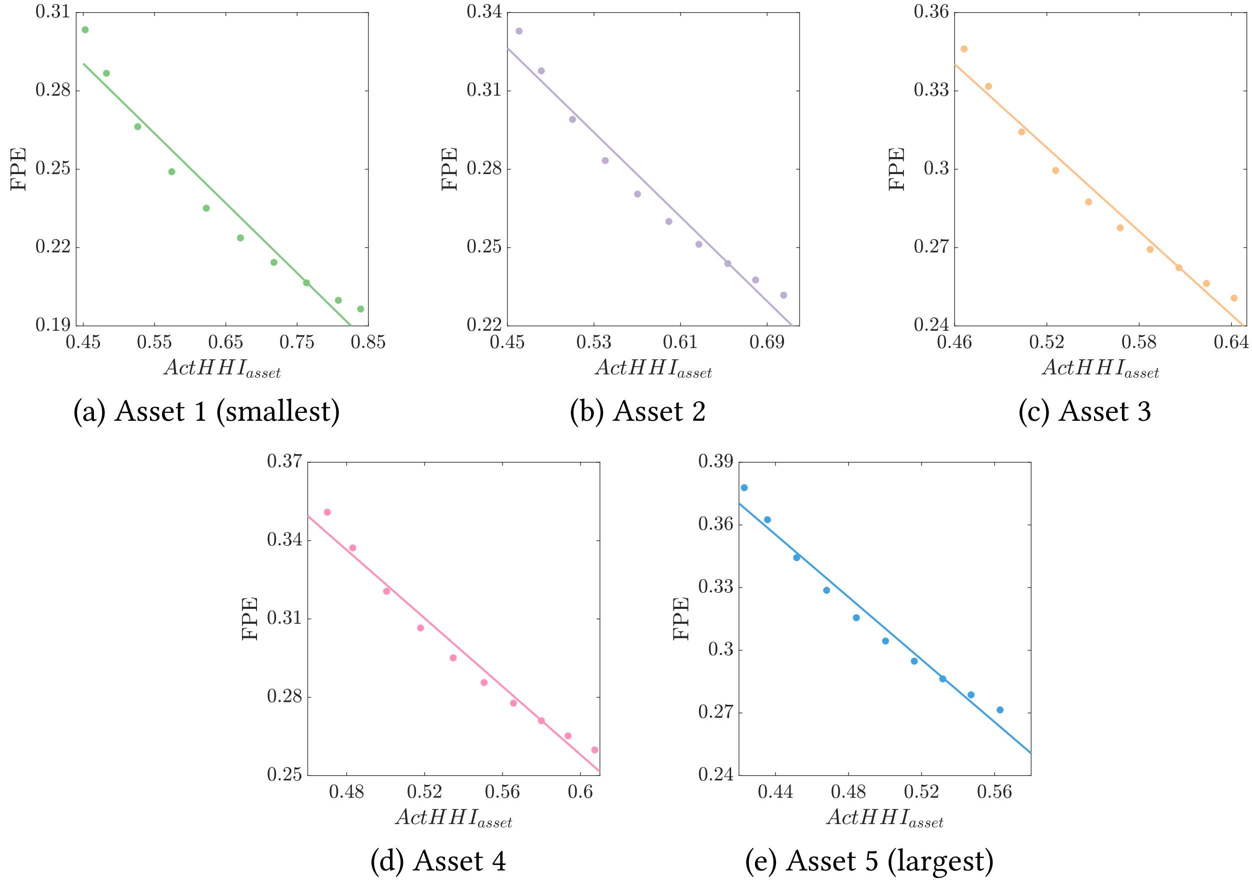
(a) Learning Choices by the Largest Active Investors



(b) Learning Choices by All Other Active Investors

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

Figure 3: Learning Choices by Active Investors



(a) Asset 1 (smallest)

(b) Asset 2

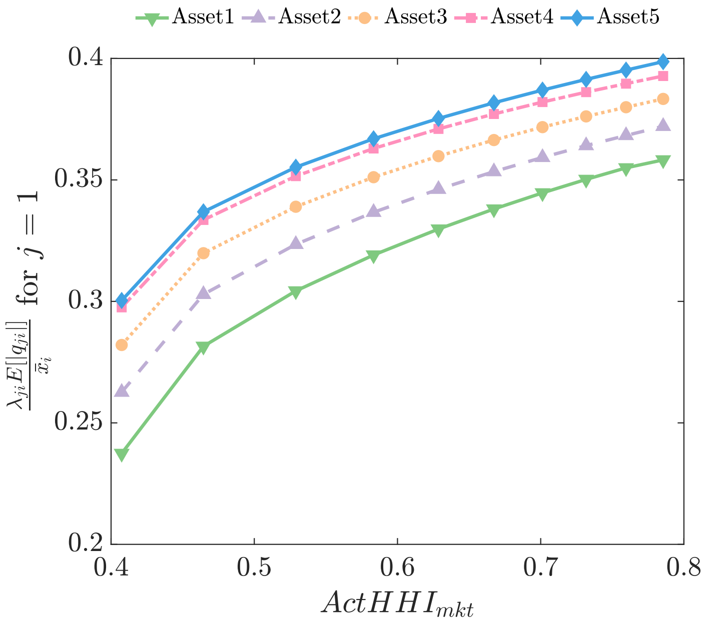
(c) Asset 3

(d) Asset 4

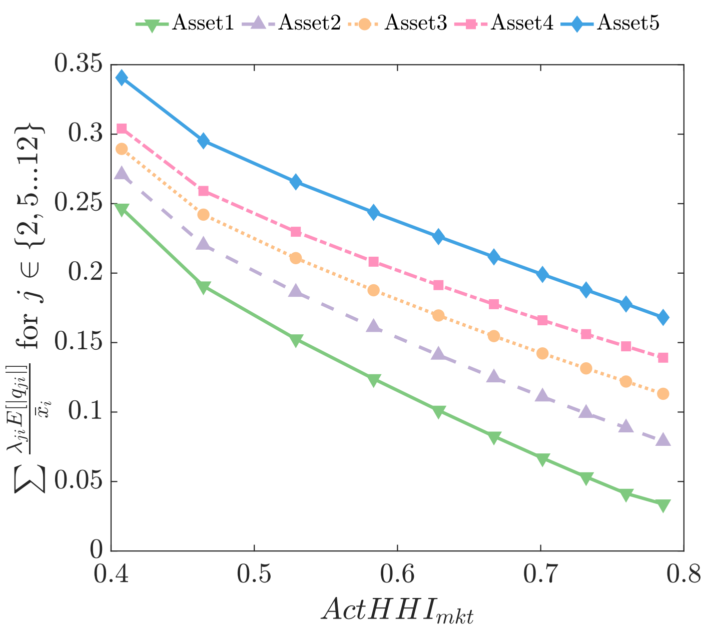
(e) Asset 5 (largest)

This figure plots individual price informativeness against different values of ownership concentration at the asset level. Price informativeness and asset-level concentrations are defined in equations (14) and (16) respectively. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5).

Figure 4: The Effect of Asset-level Ownership Concentration



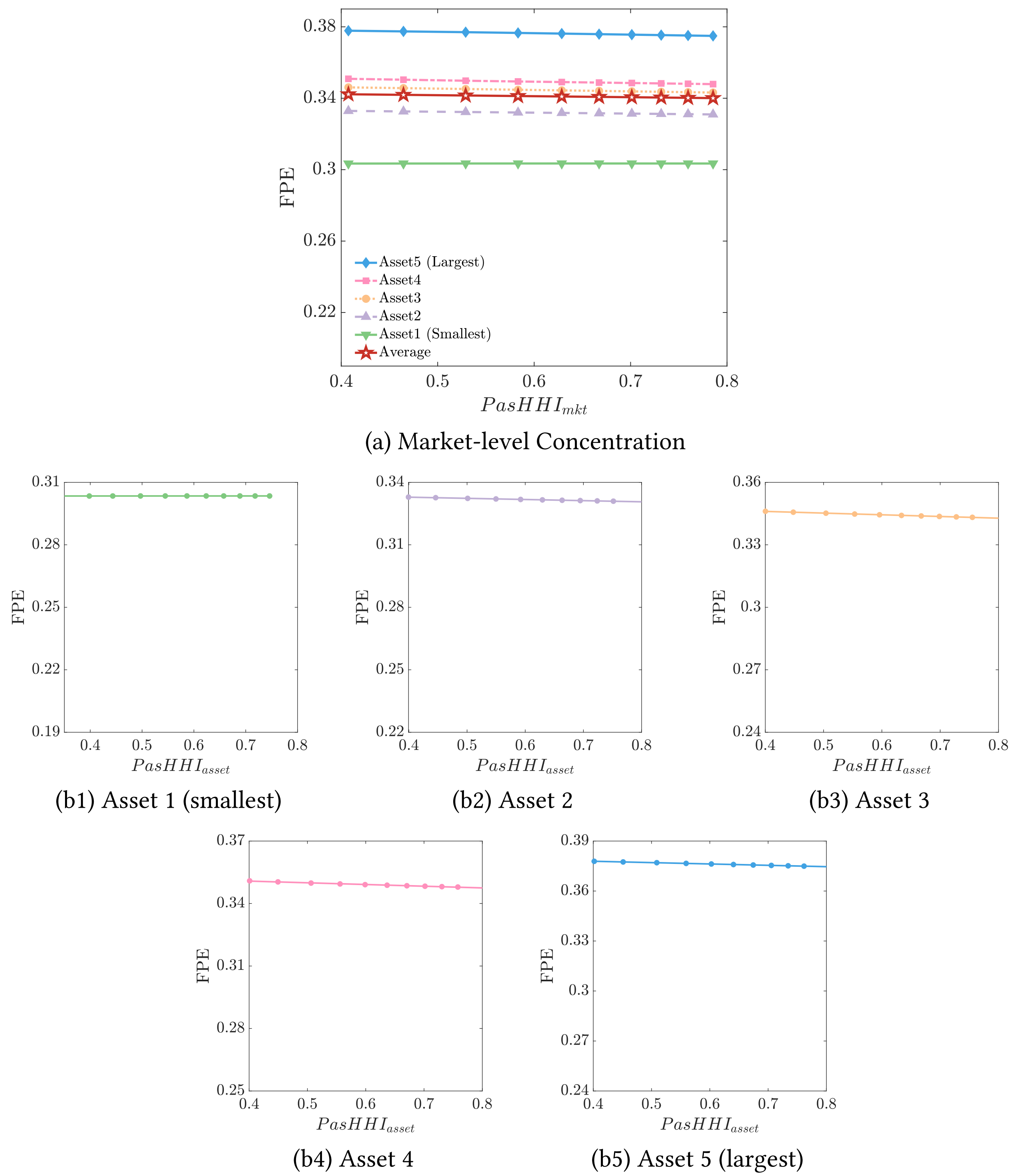
(a) Trading Percentage by the Largest Active Investors



(b) Trading Percentage by All Other Active Investors

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

Figure 5: Trading Choices by Active Investors



(a) Market-level Concentration

(b1) Asset 1 (smallest)

(b2) Asset 2

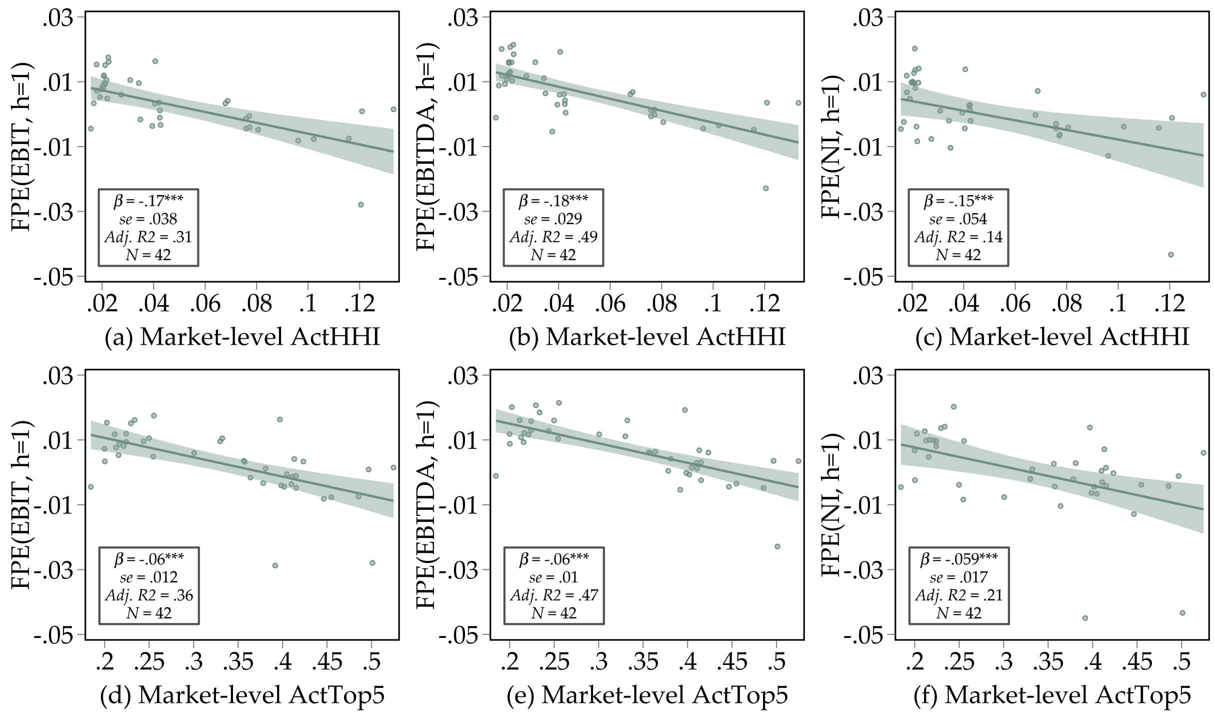
(b3) Asset 3

(b4) Asset 4

(b5) Asset 5 (largest)

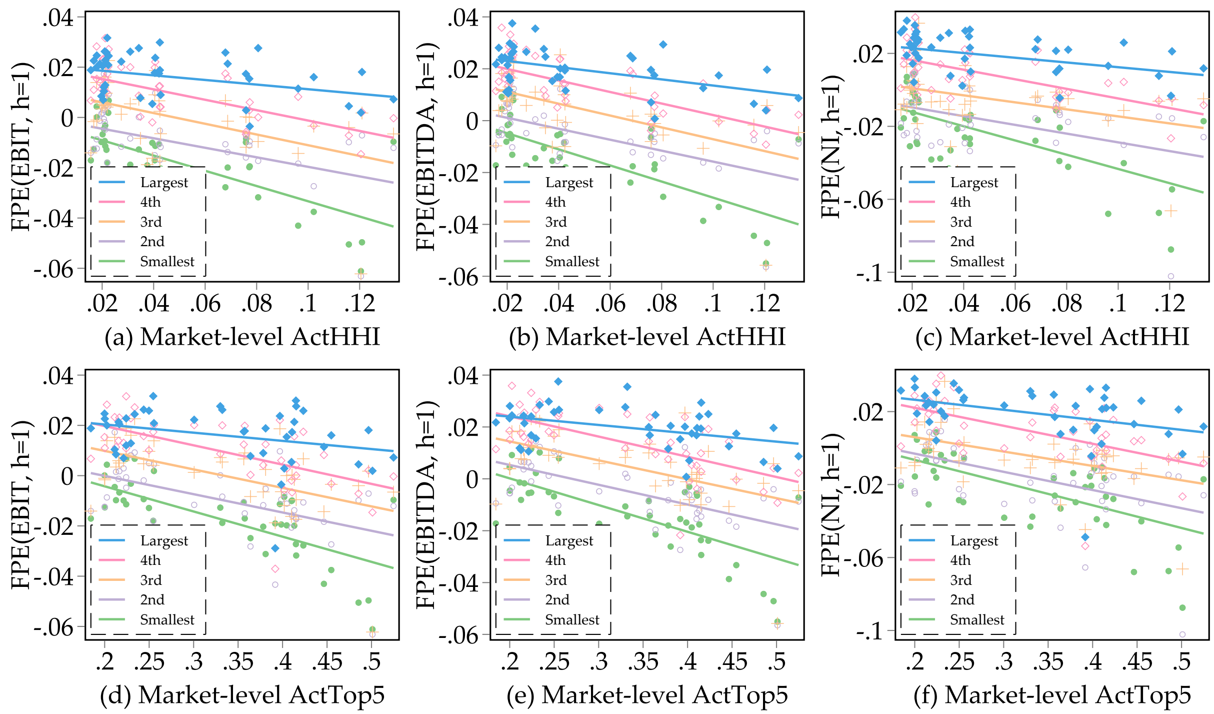
This figure illustrates the effect of ownership concentration among passive investors, with Panel (a) showing the market level and Panels (b1)-(b5) displaying different assets at the asset level. The size distribution of active investors is fixed ($\lambda_1/\lambda_2 = 1.1$ and $\sum_{j\in SA}\lambda_j/\sum_{j\in SA\cup LA}\lambda_j = 0.10$). Price informativeness is defined in equation (14). Asset-level concentration is calculated as $PasHHI_{asset} = \sum_{j\in SP\cup LP}\left(\lambda_j E[|q_{ji}|]/\sum_{k\in SP\cup LP}\lambda_k E[|q_{ki}|]\right)^2$. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5).

Figure 6: The Effect of Ownership Concentration Among Passive Investors



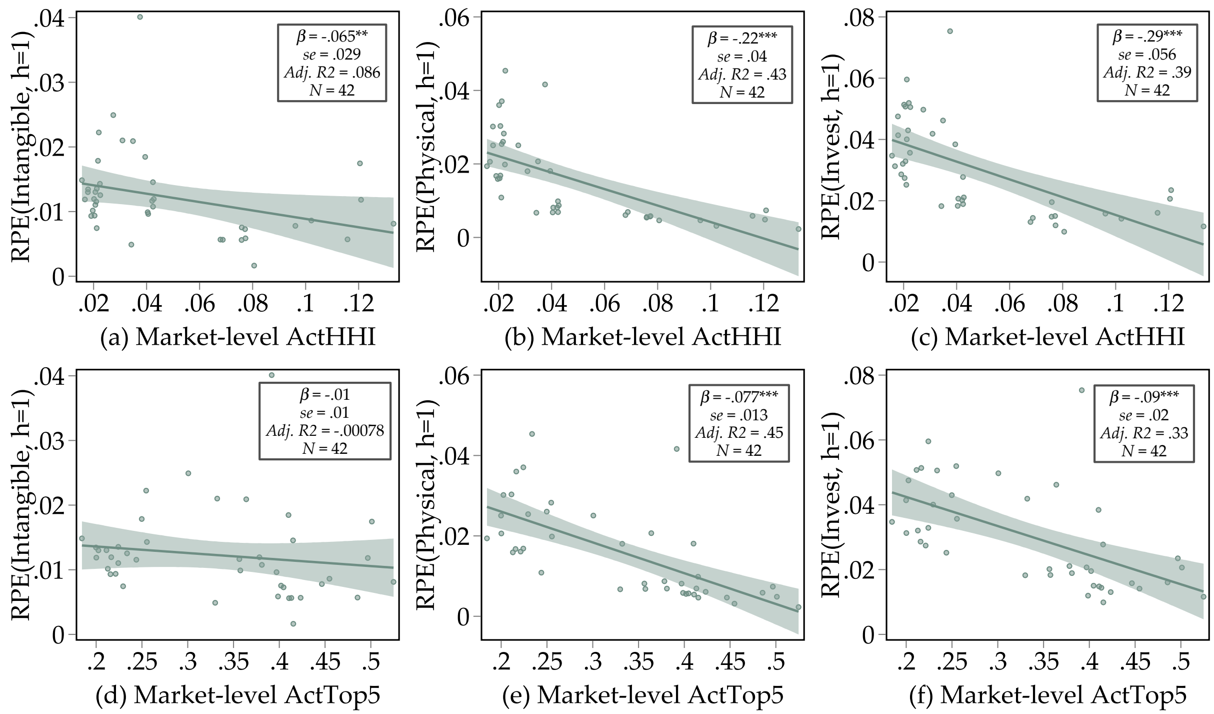
This figure presents scatter plots illustrating the relation between Forecasting Price Efficiency (FPE) and market-level ownership concentration among active institutional investors. The plots include fitted lines and 95% confidence intervals. Market-level ownership concentration is quantified using two metrics: (i) $ActHHI_{mkt}$: the Herfindahl-Hirschman Index of Assets Under Management (AUM) among active institutional investors, shown in Panels (a)-(c), and (ii) $ActTop5_{mkt}$: 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 (d)-(f). FPE is derived from equations (20) and (21) 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. See Table A1 for the complete list of variable definitions. The sample has an annual frequency and spans from 1980 to 2022. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure 7: FPE and Market-level Active Institutional Ownership Concentration



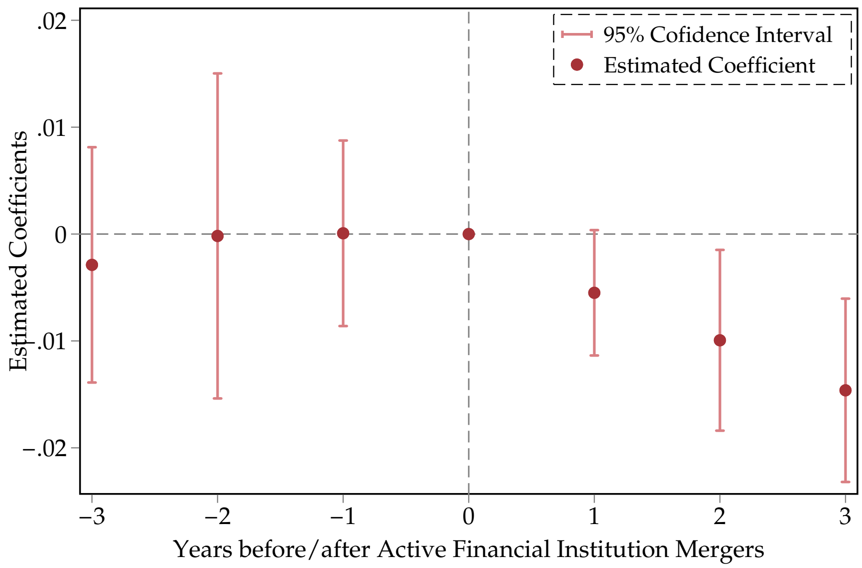
This figure presents scatter plots with fitted lines illustrating the relation between Forecasting Price Efficiency (FPE) by size group and market-level ownership concentration among active institutional investors. Market-level ownership concentration is quantified using two metrics: (i) $ActHHI_{mkt}$: the Herfindahl-Hirschman Index of Assets Under Management (AUM) among active institutional investors, shown in Panels (a)-(c), and (ii) $ActTop5_{mkt}$: 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 (d)-(f). We divide the sample firms into quintiles based on each security's market capitalization, and estimate FPE for each group according to equations (20) and (21). Future cash flows in equation (20) 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. See Table A1 for the complete list of variable definitions. The sample has an annual frequency and spans from 1980 to 2022.

Figure 8: FPE by Size Group and Market-level Active Institutional Ownership Concentration

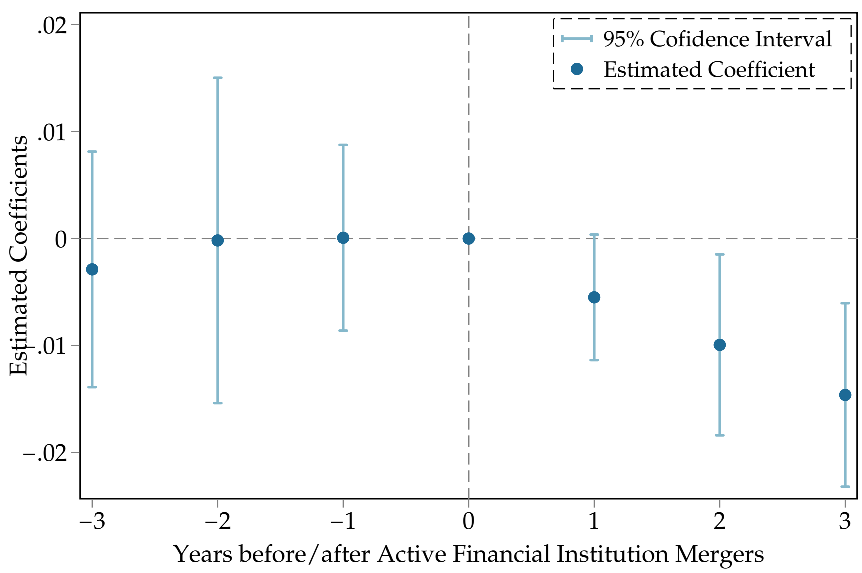


This figure presents scatter plots illustrating the relation between Revelatory Price Efficiency (RPE) and market-level ownership concentration among active institutional investors. The plots include fitted lines and 95% confidence intervals. Market-level ownership concentration is quantified using two metrics: (i) $ActHHI_{mkt}$: the Herfindahl-Hirschman Index of Assets Under Management (AUM) among active institutional investors, shown in Panels (a)-(c), and (ii) $ActTop5_{mkt}$: 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 (d)-(f). RPE is derived from equation (22) 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. See Table A1 for the complete list of variable definitions. The sample has an annual frequency and spans from 1980 to 2022. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure 9: RPE and Market-level Active Institutional Ownership Concentration



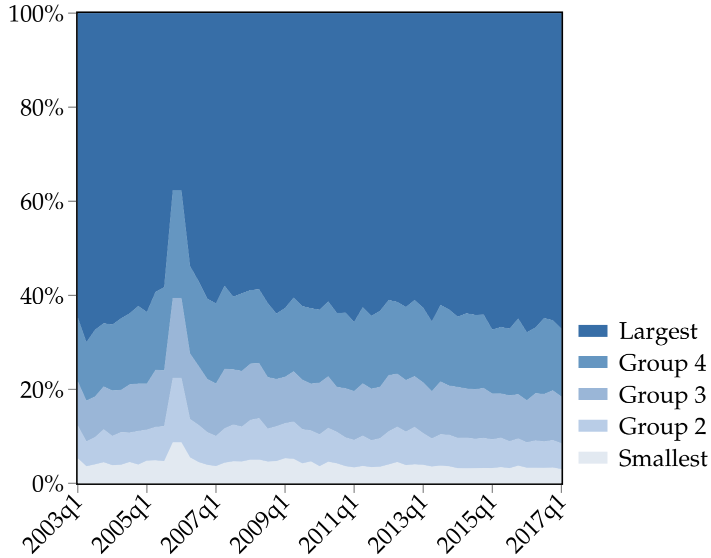
(a) FPE



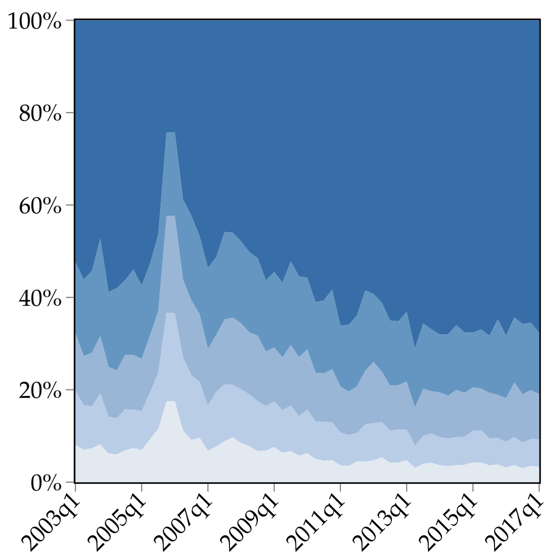
(b) RPE

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 FPE based on the earnings variable $EBITDA/A$ at the 1-year prediction horizon, while Panel (b) measures RPE 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.

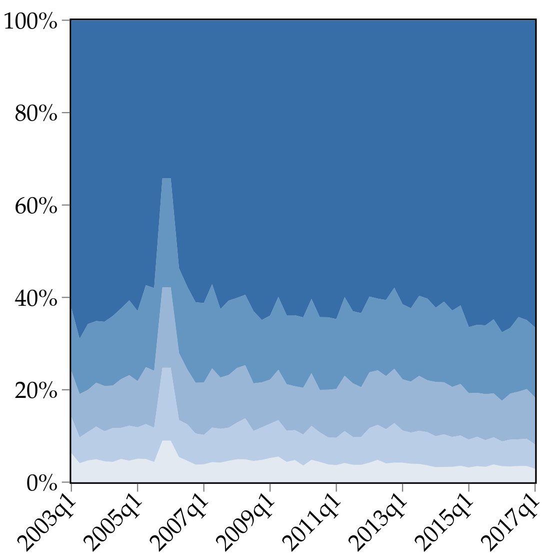
Figure 10: Event-Study Estimates for FPE and RPE



(a) All Active Investors



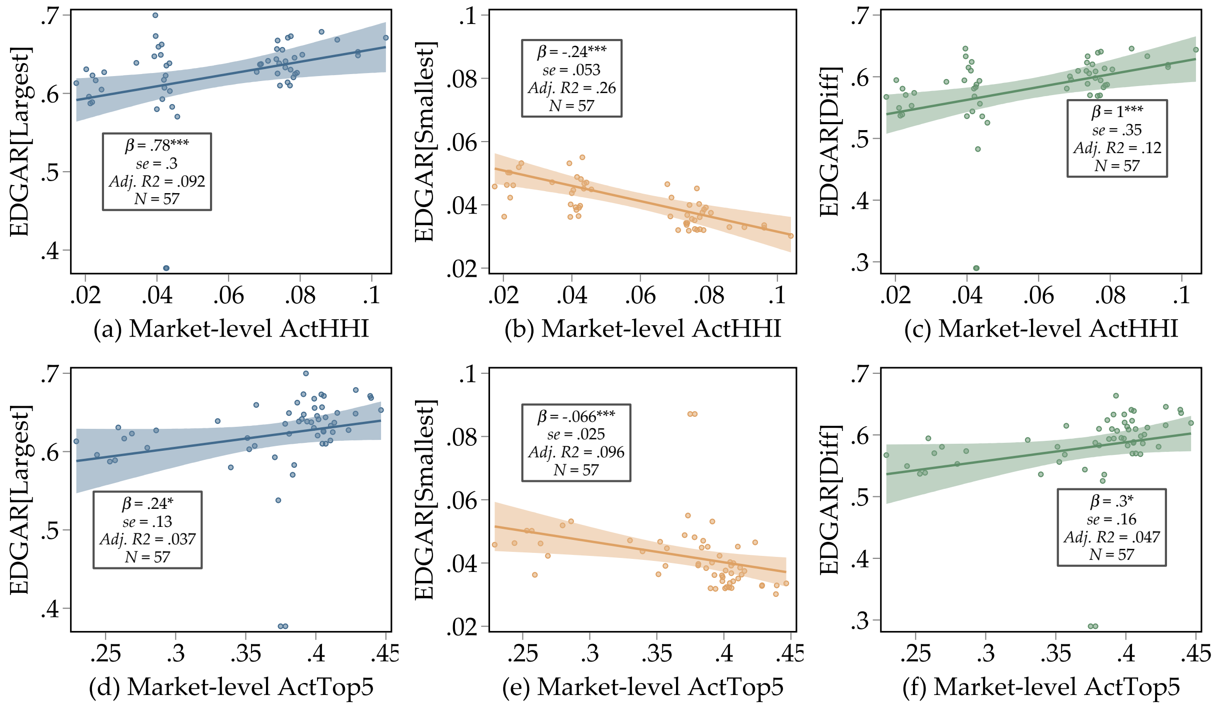
(b) Large Active Investors



(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 11: EDGAR Downloads for Each Group



This figure presents scatter plots illustrating the relation between EDGAR downloads (in percentage) by size group and market-level active institutional ownership concentration, as measured by $ActHHI_{mkt}$ in Panels (a)-(c) and $ActTop5_{mkt}$ in Panels (d)-(f). Each plot includes fit lines and 95% confidence intervals. Panel (a) focuses on the weighted average EDGAR downloads in the group with the largest market capitalization, while Panel (b) focuses on the weighted average EDGAR downloads in the group with the smallest market capitalization. Panel (c) examines 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 12: Market-level 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 $j \in SA$
Fringe 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 A1.

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

Table 3: FPE and Active Institutional Ownership Concentration

This table reports OLS estimates on the relation between Forecasting Price Efficiency (FPE), which measures the predictability of future cash flows from current market prices, and firm-level ownership concentration among active institutional investors. The dependent variable is future earnings, calculated as one of the three cash flow variables (EBIT, EBITDA, and NI) in year $t+h$ divivded 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 Panels A, representing the Herfindahl-Hirschman index of active institutional ownership, and by $ActTop5$ in Panels 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 A1 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: FPE and $ActHHI$						
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
$\log(M/A)$	0.030***	0.041***	0.041***	0.013	0.048***	-0.028
	(0.011)	(0.007)	(0.013)	(0.011)	(0.010)	(0.018)
E/A	0.539***	0.559***	0.288***	0.314***	0.322***	0.159***
	(0.024)	(0.020)	(0.031)	(0.036)	(0.032)	(0.036)
$\log(M/A)$*$ActHHI$	**-0.026*** **	**-0.030*** **	**-0.027*** **	**-0.052*** **	**-0.059*** **	**-0.035*** **
	(0.005)	**(0.004)**	**(0.004)**	**(0.010)**	**(0.009)**	**(0.011)**
$\log(M/A)$*$PasHHI$	-0.036***	-0.034***	-0.036***	-0.035**	-0.028**	-0.029*
	(0.008)	(0.008)	(0.010)	(0.013)	(0.013)	(0.015)
$\log(M/A)$*IO	0.025***	0.019***	0.028***	0.027***	0.015*	0.041***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
$\log(M/A)$*$Leverage$	-0.037***	-0.037***	-0.047***	-0.004	-0.013	-0.003
	(0.005)	(0.004)	(0.009)	(0.013)	(0.011)	(0.019)
$\log(M/A)$*$Sale$	0.021***	0.019***	0.019***	0.026***	0.023***	0.029***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)
$\log(M/A)$*$Cash$	-0.069***	-0.060***	-0.083***	-0.097***	-0.085***	-0.107***
	(0.012)	(0.008)	(0.011)	(0.012)	(0.009)	(0.014)
$ActHHI$	-0.012***	-0.010***	-0.022***	-0.013	-0.004	-0.023**
	(0.003)	(0.004)	(0.004)	(0.009)	(0.008)	(0.011)
$PasHHI$	0.030***	0.034***	0.015	0.076***	0.108***	0.010
	(0.009)	(0.009)	(0.011)	(0.019)	(0.018)	(0.021)
IO	-0.005	-0.007*	0.002	-0.028**	-0.041***	-0.012
	(0.004)	(0.004)	(0.006)	(0.011)	(0.011)	(0.009)
$Leverage$	0.054***	0.052***	0.064***	0.035**	0.025*	0.041**
	(0.005)	(0.005)	(0.010)	(0.014)	(0.013)	(0.017)
$Sale$	0.026***	0.024***	0.049***	0.049***	0.057***	0.046***
	(0.003)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
$Cash$	0.011	-0.010	0.068***	0.061***	0.058***	0.067***
	(0.010)	(0.009)	(0.012)	(0.015)	(0.015)	(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: FPE and $ActTop5$			
$\log(M/A)$	0.056***	0.070***	0.059***	0.048***	0.084***	-0.004
	(0.012)	(0.007)	(0.014)	(0.016)	(0.013)	(0.023)
E/A	0.540***	0.560***	0.288***	0.322***	0.334***	0.162***
	(0.024)	(0.020)	(0.031)	(0.036)	(0.032)	(0.037)
$\log(M/A)$*$ActTop5$	**-0.033*** **	**-0.040*** **	**-0.029*** **	**-0.045*** **	**-0.063*** **	**-0.022* **
	(0.006)	**(0.005)**	**(0.005)**	**(0.010)**	**(0.009)**	**(0.012)**
$\log(M/A)$*$PasTop5$	-0.016**	-0.013*	-0.013*	-0.025**	-0.005	-0.028**
	(0.006)	(0.006)	(0.007)	(0.012)	(0.011)	(0.013)
$\log(M/A)$*IO	0.021**	0.016**	0.027***	0.023***	0.014*	0.037***
	(0.008)	(0.007)	(0.008)	(0.008)	(0.008)	(0.009)
$\log(M/A)$*$Leverage$	-0.035***	-0.035***	-0.046***	-0.001	-0.010	-0.001
	(0.005)	(0.004)	(0.009)	(0.013)	(0.011)	(0.019)
$\log(M/A)$*$Sale$	0.022***	0.019***	0.019***	0.027***	0.024***	0.029***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.003)	(0.004)
$\log(M/A)$*$Cash$	-0.070***	-0.062***	-0.084***	-0.097***	-0.087***	-0.105***
	(0.012)	(0.008)	(0.011)	(0.011)	(0.010)	(0.014)
$ActTop5$	-0.026***	-0.023***	-0.036***	-0.004	0.006	-0.023**
	(0.004)	(0.004)	(0.005)	(0.007)	(0.007)	(0.009)
$PasTop5$	0.045***	0.050***	0.026***	0.103***	0.138***	0.048***
	(0.006)	(0.006)	(0.006)	(0.013)	(0.015)	(0.012)
IO	-0.000	-0.001	0.003	-0.005	-0.011	0.000
	(0.004)	(0.004)	(0.006)	(0.010)	(0.010)	(0.009)
$Leverage$	0.052***	0.050***	0.062***	0.031**	0.019	0.039**
	(0.005)	(0.005)	(0.010)	(0.015)	(0.013)	(0.017)
$Sale$	0.025***	0.022***	0.049***	0.046***	0.053***	0.045***
	(0.003)	(0.002)	(0.005)	(0.005)	(0.005)	(0.005)
$Cash$	0.010	-0.011	0.067***	0.058***	0.054***	0.064***
	(0.010)	(0.009)	(0.012)	(0.014)	(0.015)	(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: RPE and Active Institutional Ownership Concentration

This table reports OLS estimates on the relation between Revelatory Price Efficiency (RPE), which measures the predictability of future investments from current market prices, and firm-level ownership concentration among active institutional investors. The dependent variable is future investment rate, calculated as investment volume in year $t+h$ divivded 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 $Intangible$. Concentration is measured by $ActHHI$ in Panels A, representing the Herfindahl-Hirschman index of active institutional ownership, and by $ActTop5$ in Panels 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 A1 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: RPE and $ActHHI$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
$\log(M/A)$	0.033***	0.054***	0.085***	0.074***	0.070***	0.139***
	(0.006)	(0.004)	(0.008)	(0.007)	(0.007)	(0.011)
I/K	1.091***	0.653***	0.927***	1.245***	0.378***	0.917***
	(0.049)	(0.025)	(0.039)	(0.084)	(0.041)	(0.062)
log(M/A)*$ActHHI$	**-0.022***	**-0.023***	**-0.044***	**-0.042***	**-0.025***	**-0.070***
	(0.007)	**(0.003)**	**(0.007)**	**(0.009)**	**(0.004)**	**(0.010)**
$\log(M/A)$*$PasHHI$	0.013***	-0.001	0.016*	0.030**	-0.004	0.027
	(0.005)	(0.004)	(0.009)	(0.012)	(0.010)	(0.021)
$\log(M/A)$*IO	-0.022***	-0.028***	-0.050***	-0.054***	-0.038***	-0.094***
	(0.004)	(0.003)	(0.006)	(0.006)	(0.007)	(0.012)
$\log(M/A)$*$Leverage$	-0.016***	-0.006**	-0.024***	-0.043***	-0.005	-0.046***
	(0.003)	(0.003)	(0.004)	(0.008)	(0.006)	(0.013)
$\log(M/A)$*$Sale$	-0.003	-0.004***	-0.007**	0.003	-0.000	0.003
	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.004)
$\log(M/A)$*$Cash$	0.072***	0.005	0.084***	0.136***	0.001	0.158***
	(0.013)	(0.006)	(0.020)	(0.013)	(0.009)	(0.022)
$ActHHI$	-0.014***	-0.015***	-0.025***	-0.001	0.006	0.014
	(0.003)	(0.003)	(0.005)	(0.007)	(0.005)	(0.010)
$PasHHI$	0.031***	0.030***	0.064***	0.142***	0.100***	0.256***
	(0.006)	(0.005)	(0.010)	(0.020)	(0.018)	(0.038)
IO	-0.010***	-0.013***	-0.025***	-0.063***	-0.059***	-0.137***
	(0.003)	(0.003)	(0.005)	(0.008)	(0.008)	(0.015)
$Leverage$	-0.008**	-0.015***	-0.026***	-0.031***	-0.036***	-0.071***
	(0.003)	(0.004)	(0.006)	(0.009)	(0.009)	(0.016)
$Sale$	-0.020***	-0.007***	-0.021***	-0.025***	0.004	-0.009
	(0.003)	(0.001)	(0.004)	(0.005)	(0.003)	(0.006)
$Cash$	0.018**	0.064***	0.100***	0.077***	0.100***	0.209***
	(0.008)	(0.007)	(0.013)	(0.017)	(0.013)	(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: RPE and $ActTop5$			
$\log(M/A)$	0.040***	0.060***	0.096***	0.074***	0.067***	0.136***
	(0.010)	(0.006)	(0.014)	(0.011)	(0.008)	(0.015)
I/K	1.091***	0.655***	0.929***	1.242***	0.384***	0.921***
	(0.049)	(0.025)	(0.038)	(0.083)	(0.040)	(0.061)
log(*M/A*)*ActTop5	**-0.027***	**-0.024***	**-0.050***	**-0.049***	**-0.028***	**-0.082***
	(0.009)	**(0.005)**	**(0.012)**	**(0.011)**	**(0.004)**	**(0.013)**
$\log(M/A)$*$PasTop5$	0.016***	0.011**	0.030***	0.050***	0.025***	0.081***
	(0.004)	(0.004)	(0.007)	(0.011)	(0.009)	(0.021)
$\log(M/A)$*IO	-0.022***	-0.027***	-0.048***	-0.045***	-0.028***	-0.074***
	(0.005)	(0.003)	(0.007)	(0.006)	(0.005)	(0.010)
$\log(M/A)$*$Leverage$	-0.017***	-0.007**	-0.025***	-0.045***	-0.006	-0.049***
	(0.003)	(0.003)	(0.004)	(0.008)	(0.006)	(0.012)
$\log(M/A)$*$Sale$	-0.003	-0.004***	-0.007**	0.002	-0.000	0.002
	(0.002)	(0.001)	(0.003)	(0.003)	(0.002)	(0.004)
$\log(M/A)$*$Cash$	0.071***	0.003	0.080***	0.130***	-0.004	0.147***
	(0.013)	(0.006)	(0.020)	(0.013)	(0.008)	(0.021)
$ActTop5$	-0.014***	-0.017***	-0.027***	-0.003	0.006	0.012
	(0.003)	(0.003)	(0.005)	(0.007)	(0.005)	(0.011)
$PasTop5$	0.029***	0.034***	0.067***	0.130***	0.114***	0.262***
	(0.004)	(0.005)	(0.008)	(0.014)	(0.015)	(0.030)
IO	-0.007**	-0.008***	-0.016***	-0.042***	-0.036***	-0.087***
	(0.003)	(0.003)	(0.005)	(0.007)	(0.006)	(0.012)
$Leverage$	-0.009***	-0.016***	-0.029***	-0.036***	-0.041***	-0.082***
	(0.003)	(0.004)	(0.007)	(0.009)	(0.009)	(0.017)
$Sale$	-0.021***	-0.007***	-0.022***	-0.027***	0.002	-0.013**
	(0.003)	(0.001)	(0.004)	(0.005)	(0.003)	(0.006)
$Cash$	0.018**	0.064***	0.099***	0.076***	0.098***	0.205***
	(0.008)	(0.007)	(0.013)	(0.016)	(0.013)	(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: 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

	$BHAR[0,2]$	$BHAR[0,2]$	$BHAR[3,24]$	$BHAR[3,24]$
	(1)	(2)	(3)	(4)
$Rank$	0.0029***	0.0037***	0.0017***	0.0007
	(0.001)	(0.001)	(0.001)	(0.001)
$Rank$*$ActHHI$	-0.0027***		0.0015*	
	(0.001)		(0.001)	
$Rank$*$ActTop5$		-0.0049***		0.0016**
		(0.001)		(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

Panel B: Conditional Probability of An Information Event

	$CPIE$	$CPIE$	$CPIE$	$CPIE$	$CPIE$	$CPIE$	$CPIE$	$CPIE$
Model:	PIN	APIN	GPIN	OWR	PIN	APIN	GPIN	OWR
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$ActHHI$	-0.088***	-0.054***	-0.036***	-0.007				
	(0.012)	(0.008)	(0.012)	(0.014)				
$ActTop5$					-0.123***	-0.064***	-0.064***	-0.001
					(0.013)	(0.008)	(0.012)	(0.014)
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

Continued on next page

Table 5 – *Continued*

Panel C: Informed Trading Intensity

Training	ITI 13D (1)	ITI Insider (2)	ITI Short Sale (3)	ITI 13D (4)	ITI Insider (5)	ITI Short Sale (6)
$ActHHI$	-0.049***	-0.055***	-0.026***			
	(0.002)	(0.002)	(0.001)			
$ActTop5$				-0.057***	-0.075***	-0.035***
				(0.003)	(0.002)	(0.001)
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

Panel D: Variance Ratio

	$VR(5)$ (1)	$VR(10)$ (2)	$VR(15)$ (3)	$VR(20)$ (4)	$VR(5)$ (5)	$VR(10)$ (6)	$VR(15)$ (7)	$VR(20)$ (8)
$ActHHI$	0.045***	0.049***	0.043***	0.036***				
	(0.003)	(0.005)	(0.006)	(0.007)				
$ActTop5$					0.045***	0.052***	0.042***	0.040***
					(0.004)	(0.006)	(0.007)	(0.008)
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	t-value	Obs.
(1) $ActHHI$	-0.018620***	0.000412	-45.22	2960
(2) $ActTop5$	-0.020837***	0.000319	-65.22	2960
(3) $ActHHI(Residual)$	-0.003438***	0.000390	-8.82	2960
(4) $ActTop5(Residual)$	-0.001325***	0.000326	-4.07	2960

Table 6: 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 A1 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: FPE and $ActHHI$						
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
$\log(M/A)$*$ActHHI$	-0.027***	-0.034***	-0.024**	-0.049***	-0.054***	-0.028*
	(0.008)	(0.006)	(0.010)	(0.011)	(0.010)	(0.016)
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: FPE and $ActTop5$						
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
$\log(M/A)$*$ActTop5$	-0.030***	-0.041***	-0.017*	-0.047***	-0.058***	-0.022
	(0.008)	(0.004)	(0.010)	(0.013)	(0.014)	(0.022)
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
Panel C: RPE and $ActHHI$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
$\log(M/A)$*$ActHHI$	-0.032***	-0.022***	-0.054***	-0.049***	-0.022***	-0.072***
	(0.012)	(0.005)	(0.014)	(0.010)	(0.006)	(0.012)
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

Continued on next page

Table 6 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
	Panel D: RPE and $ActTop5$					
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
$\log(M/A)$*$ActTop5$	-0.031**	-0.023***	-0.053***	-0.047***	-0.017**	-0.063***
	(0.012)	(0.006)	(0.017)	(0.012)	(0.007)	(0.013)
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 7: 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 on two measures of ownership concentration among active institutional investors: $ActHHI$ 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). Panels B and C present the relation between price informativeness (FPE and RPE) and firm-level ownership concentration among active institutional investors using DiD models. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Panel A: Active Institutional Ownership Concentration and Active Institutional Mergers

Event window	$(-8, +8)$ quarters		$(-12, +12)$ quarters	
Dependent variable	$ActHHI$	$ActTop5$	$ActHHI$	$ActTop5$
	(1)	(2)	(3)	(4)
$Treat$*$Post$	0.021***	0.034***	0.021***	0.034***
	(0.004)	(0.005)	(0.005)	(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 FPE within $(-2, +2)$ years

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
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(M/A)$*$Treat$*$Post$	-0.014***	-0.013***	-0.012***	-0.029***	-0.034***	-0.011
	(0.003)	(0.004)	(0.004)	(0.010)	(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 RPE within $(-2, +2)$ years

where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
	(1)	(2)	(3)	(4)	(5)	(6)
$\log(M/A)$*$Treat$*$Post$	-0.001	-0.010***	-0.010**	-0.023**	-0.016***	-0.042***
	(0.002)	(0.002)	(0.004)	(0.008)	(0.006)	(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 8: International Evidence

This table utilizes the international sample to re-examine the relation between price informativeness and firm-level ownership concentration among active institutional investors. The international sample is constructed by amalgamating data on global institutional ownership from FactSet, accounting data from Worldscope, and stock market data from DataStream. Price informativeness is assessed using FPE in Panels A and B, and RPE in Panels C and D. FPE measures the predictability of future cash flows based on current market prices, while RPE evaluates the extent to which current market prices reveal the information necessary for future investment decisions. Active institutional 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 A1 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: FPE and $ActHHI$			
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
$\log(M/A)$*$ActHHI$	-0.021***	-0.021***	-0.018***	-0.025***	-0.026***	-0.022***
	(0.003)	(0.003)	(0.003)	(0.005)	(0.006)	(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: FPE and $ActTop5$			
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
$\log(M/A)$*$ActTop5$	-0.029***	-0.029***	-0.024***	-0.037***	-0.041***	-0.031***
	(0.003)	(0.003)	(0.003)	(0.006)	(0.006)	(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
			Panel C: RPE and $ActHHI$			
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
$\log(M/A)$*$ActHHI$	-0.007***	-0.015***	-0.022***	-0.022**	-0.023***	-0.049***
	(0.003)	(0.004)	(0.006)	(0.008)	(0.006)	(0.013)
Observations	178,293	177,640	177,992	146,622	146,034	146,391

Continued on next page

Table 8 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
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: RPE and $ActTop5$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
log(M/A)*$ActTop5$	-0.010***	-0.022***	-0.032***	-0.032***	-0.038***	-0.074***
	(0.003)	(0.004)	(0.005)	(0.008)	(0.008)	(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 9: 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 with Column (1) showing the results of PTR regressed on the dummy variable $DumTop5$, which is set to one for investor's Top5 subgroup, and zero for her Non-Top5 subgroup. Column (2) incorporates a set of portfolio-level control variables, and Column (3) includes investor-quarter fixed effects. Columns (4) through (6) substitute 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) PTR	(2) PTR
$DumTop5$	-0.143***	
	(0.004)	
$DumTop10$		-0.125***
		(0.003)
PIO	0.046***	0.050***
	(0.010)	(0.010)
$PRet$	0.027***	0.037***
	(0.010)	(0.011)
$PRetStd$	-0.108***	-0.095***
	(0.019)	(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 10: Information Content of Earnings Announcements

This table examines the relation between information content of earnings announcements and firm-level ownership concentration among active institutional investors, 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). Speifically, $AVOL$ 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 annoucement date; $AVAR$ is calculated as the 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. See Table A.1 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)
Panel A: Baseline Regression				
	$AVOL$	$AVOL$	$AVAR$	$AVAR$
$ActHHI$	-0.167***		-0.302***	
	(0.018)		(0.034)	
$ActTop5$		-0.169***		-0.301***
		(0.018)		(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				
	$AVOL$	$AVOL$	$AVAR$	$AVAR$
$ActHHI$	-0.141***		-0.207***	
	(0.024)		(0.057)	
$ActTop5$		-0.101***		-0.125**
		(0.022)		(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

Table 11: 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 FPE

where E =	$E_{h=1}/A$ $EBIT$ (1)	$E_{h=1}/A$ $EBITDA$ (2)	$E_{h=1}/A$ NI (3)	$E_{h=1}/A$ $EBIT$ (4)	$E_{h=1}/A$ $EBITDA$ (5)	$E_{h=1}/A$ NI (6)
$\log(M/A)$*$ActHHI$	-0.017**	-0.019***	-0.017**			
	(0.006)	(0.006)	(0.006)			
$\log(M/A)$*$ActTop5$				-0.031***	-0.033***	-0.027***
				(0.005)	(0.005)	(0.007)
$\log(M/A)$*$Supply$	-0.001	-0.004	0.028***	0.003	-0.000	0.032***
	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(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 RPE

where I=	$I_{h=1}/K$ $Intangible$ (1)	$I_{h=1}/K$ $Physical$ (2)	$I_{h=1}/K$ $Invest$ (3)	$I_{h=1}/K$ $Intangible$ (4)	$I_{h=1}/K$ $Physical$ (5)	$I_{h=1}/K$ $Invest$ (6)
$\log(M/A)$*$ActHHI$	-0.006**	-0.007**	-0.016***			
	(0.003)	(0.003)	(0.005)			
$\log(M/A)$*$ActTop5$				-0.010***	-0.010***	-0.022***
				(0.003)	(0.003)	(0.005)
$\log(M/A)$*$Supply$	-0.018***	-0.004	-0.024***	-0.018***	-0.004	-0.023***
	(0.005)	(0.005)	(0.008)	(0.005)	(0.004)	(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 11 – *Continued*

Panel C: Liquidity Shock and FPE						
where E =	$E_{h=1}/A$ $EBIT$ (1)	$E_{h=1}/A$ $EBITDA$ (2)	$E_{h=1}/A$ NI (3)	$E_{h=1}/A$ $EBIT$ (4)	$E_{h=1}/A$ $EBITDA$ (5)	$E_{h=1}/A$ NI (6)
$\log(M/A)$*$ActHHI$	-0.026***	-0.030***	-0.027***			
	(0.005)	(0.004)	(0.004)			
$\log(M/A)$*$ActTop5$				-0.033***	-0.040***	-0.028***
				(0.006)	(0.005)	(0.005)
$\log(M/A)$*$Pressure$	0.017*	0.011	0.054***	0.019	0.012	0.056***
	(0.010)	(0.009)	(0.012)	(0.012)	(0.011)	(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 RPE						
where I=	$I_{h=1}/K$ $Intangible$ (1)	$I_{h=1}/K$ $Physical$ (2)	$I_{h=1}/K$ $Invest$ (3)	$I_{h=1}/K$ $Intangible$ (4)	$I_{h=1}/K$ $Physical$ (5)	$I_{h=1}/K$ $Invest$ (6)
$\log(M/A)$*$ActHHI$	-0.022***	-0.023***	-0.044***			
	(0.007)	(0.003)	(0.007)			
$\log(M/A)$*$ActTop5$				-0.027***	-0.024***	-0.050***
				(0.009)	(0.005)	(0.012)
$\log(M/A)$*$Pressure$	-0.013	-0.015*	-0.024	-0.015	-0.016*	-0.027*
	(0.012)	(0.009)	(0.015)	(0.012)	(0.008)	(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

Panel E: Concentration and Voluntary Disclosure (Management Forecast)				
	$GuideFreq$		$GuideDummy$	
	(1)	(2)	(3)	(4)
$ActHHI$	-0.259		0.005	
	(0.350)		(0.025)	
$ActTop5$		0.016		0.050*
		(0.427)		(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

Continued on next page

Table 11 – *Continued*

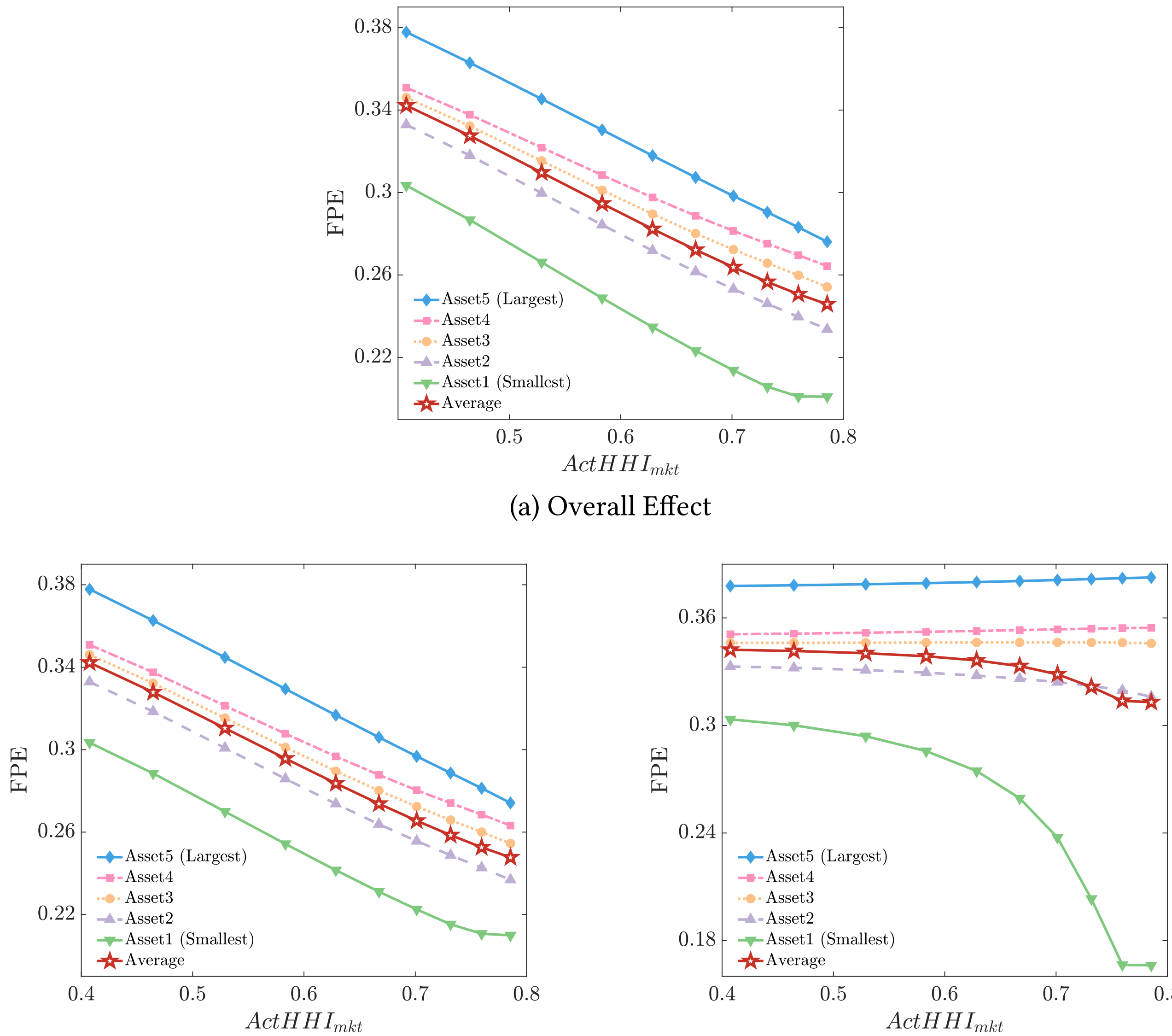
Industry-Year	Y	Y	Y	Y

Panel F: Concentration and Voluntary Disclosure (Management Earnings Forecast)

	$EPSGuideFreq$		$EPSGuideDummy$	
	(1)	(2)	(3)	(4)
$ActHHI$	-0.107		0.011	
	(0.144)		(0.022)	
$ActTop5$		0.087		0.072***
		(0.180)		(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

Internet Appendix to "Institutional Ownership Concentration and Informational Efficiency"

A Additional Figures and Tables



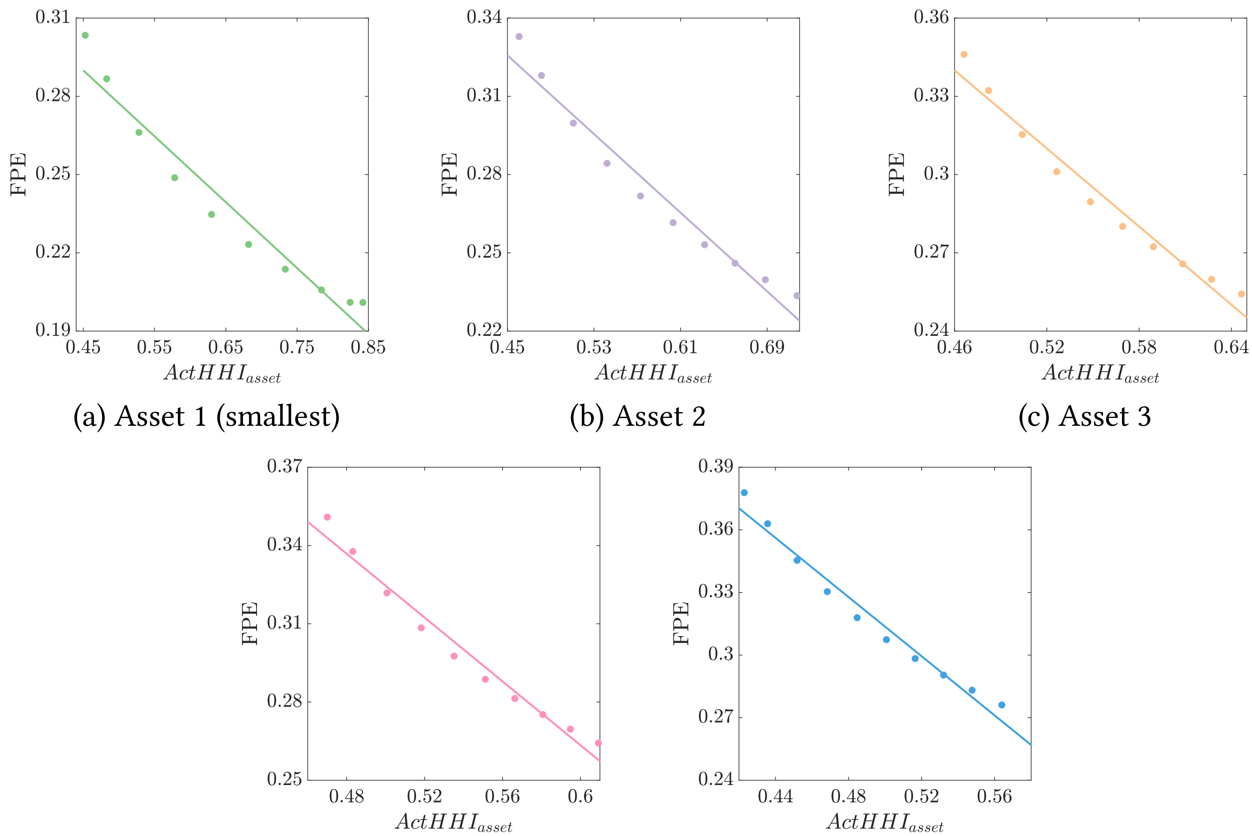
(a) Overall Effect

(b) Fixed Learning

(c) Fixed Information Pass-through

Panel (a) of this figure plots the average and individual price informativeness against different values of market-level ownership concentration among active investors. The experiment is similar to that in Figure 2, with the distinction that the size distribution of passive investors is fixed ($\lambda_3/\lambda_4 = 1.1$ and $\frac{\sum_{j\in SP}\lambda_j}{\sum_{j\in SP\cup LP}\lambda_j} = 0.10$). Price informativeness and market-level concentrations are defined in equations (14) and (15) respectively. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5). Panels (b) and (c) decompose the overall effect of active ownership concentration by respectively fixing the degree of learning (α_{ji}) and fixing the information pass-through (ω_{ji}).

Figure A1: The Effect of Market-level Ownership Concentration Among Active Investors

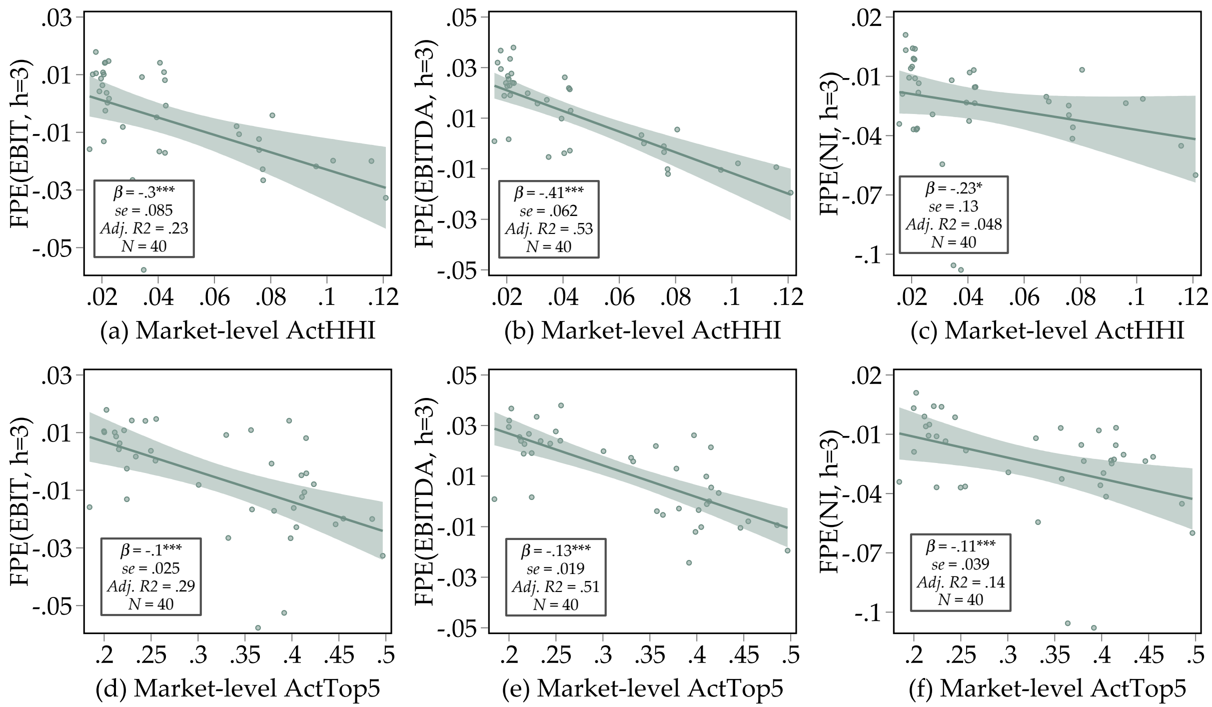


(a) Asset 1 (smallest) (b) Asset 2 (c) Asset 3

(d) Asset 4 (e) Asset 5 (largest)

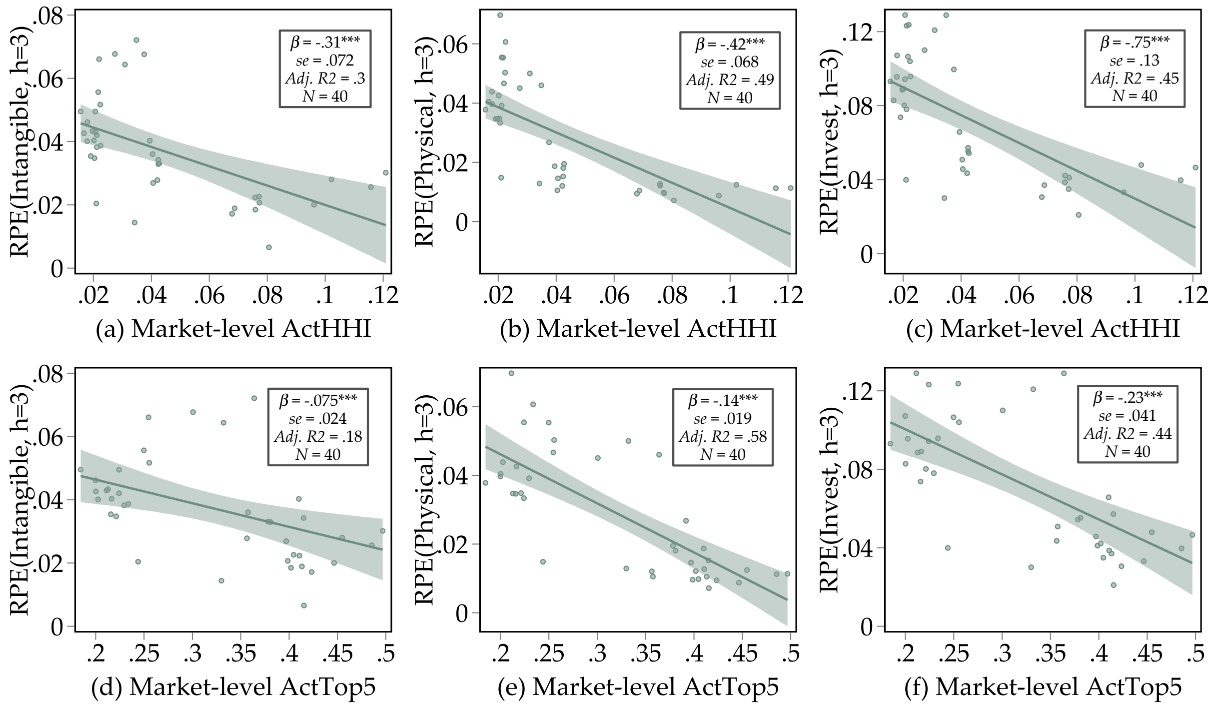
This figure plots individual price informativeness against different values of asset-level ownership concentration among active investors. The experiment is similar to that in Figure 4, with the distinction that the size distribution of passive investors is fixed ($\lambda_3/\lambda_4 = 1.1$ and $\frac{\sum_{j\in SP}\lambda_j}{\sum_{j\in SP\cup LP}\lambda_j} = 0.10$). Price informativeness and asset-level concentrations are defined in equations (14) and (16) respectively. The individual assets are ranked by their supply $\bar{x}$, from the smallest (asset 1) to the largest (asset 5).

Figure A2: The Effect of Asset-level Ownership Concentration Among Active Investors



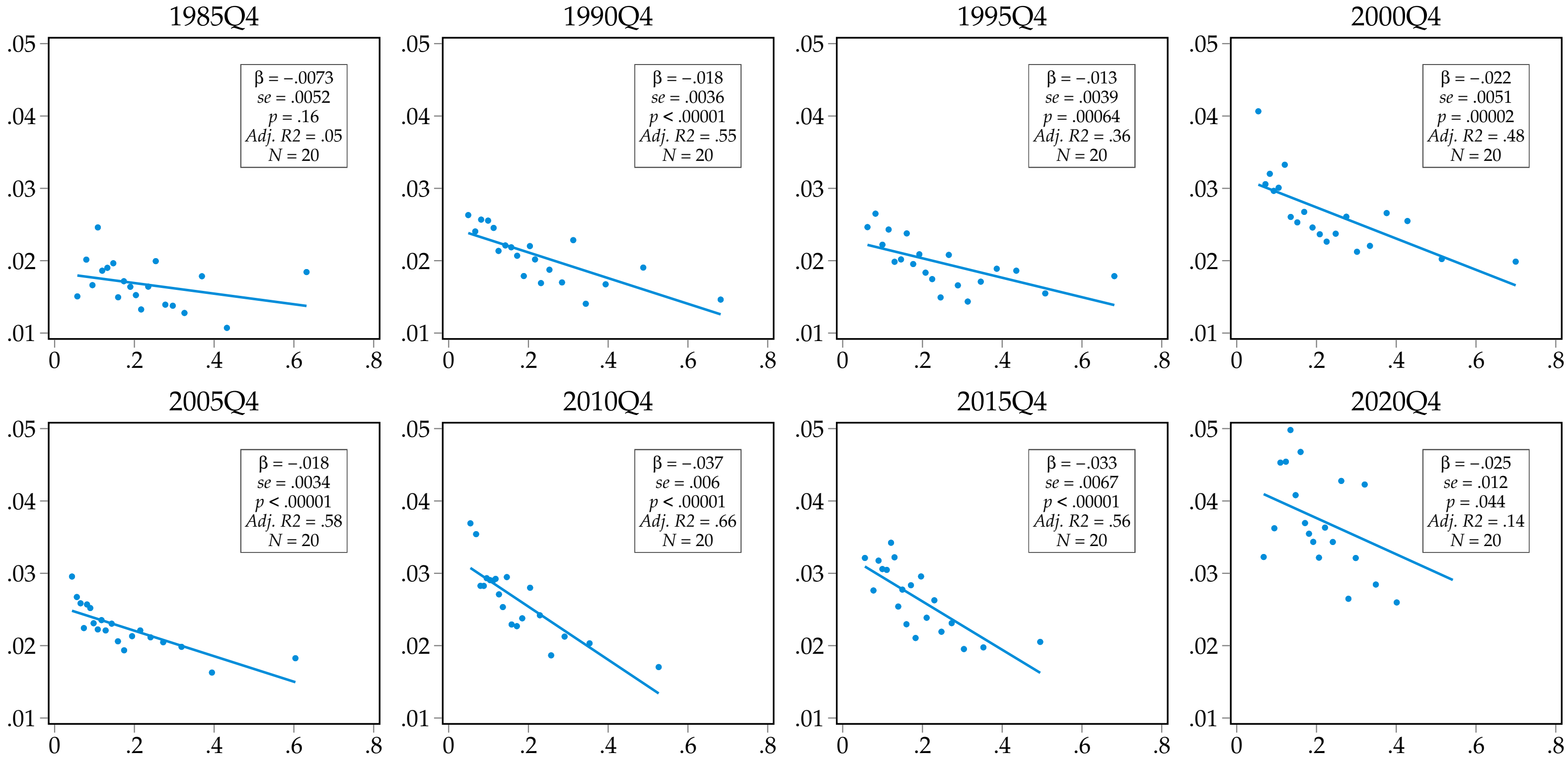
This figure presents scatter plots illustrating the relation between Forecasting Price Efficiency (FPE) and market-level ownership concentration among active institutional investors. The plots include fit lines and 95% confidence intervals. Market-level ownership concentration is quantified using $ActHHI_{mkt}$ in Panels (a)-(c), and $ActTop5_{mkt}$ in Panels (d)-(f). FPE is derived from equations (20) and (21) 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. See Table A1 for the complete list of variable definitions. The sample has an annual frequency and spans from 1980 to 2022. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure A3: FPE and Market-level Active Institutional Ownership Concentration: 3-year Prediction Horizon



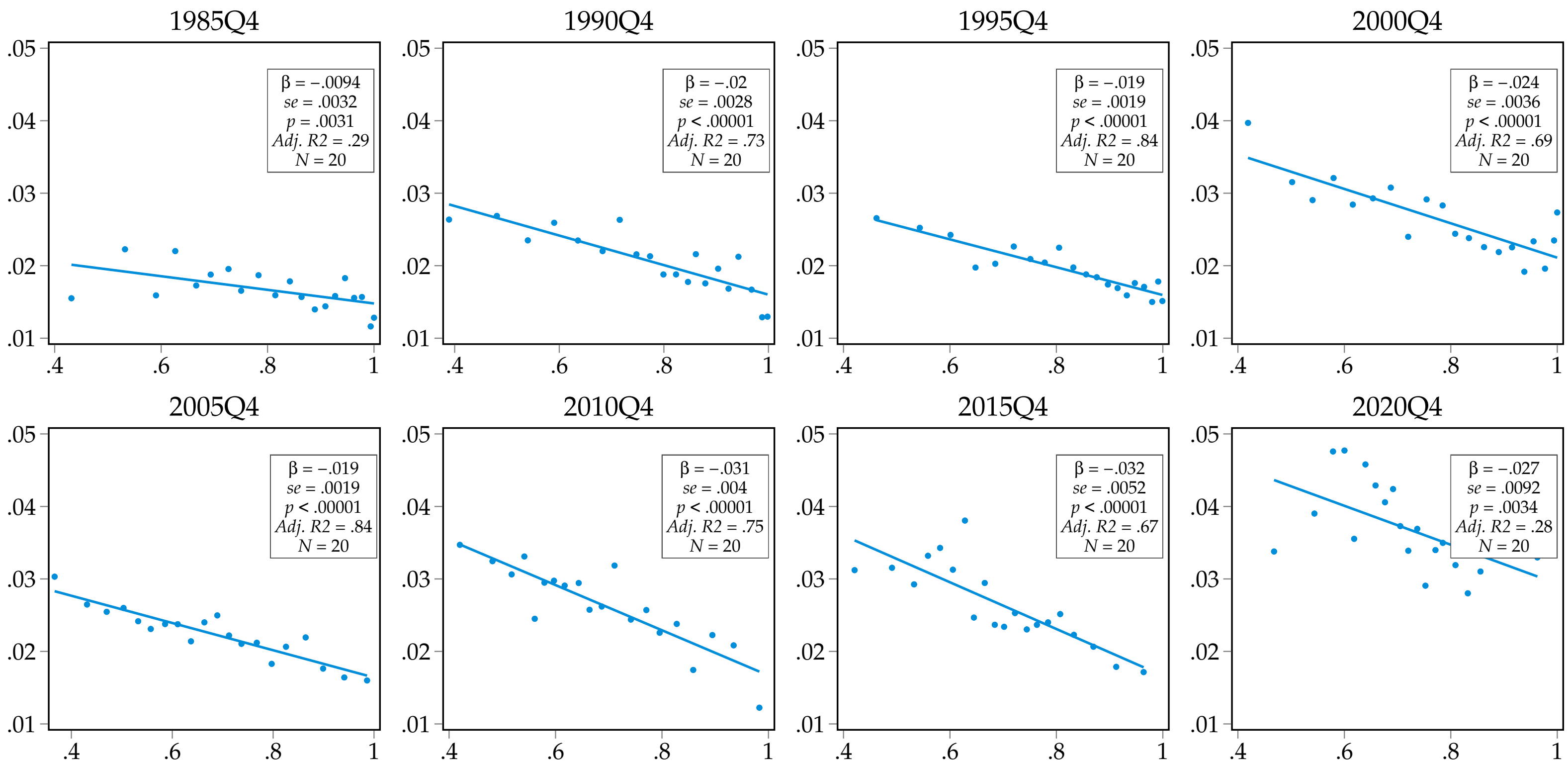
This figure presents scatter plots illustrating the relation between Revelatory Price Efficiency (RPE) and market-level ownership concentration among active institutional investors. The plots include fit lines and 95% confidence intervals. Market-level ownership concentration is quantified using $ActHHI_{mkt}$ in Panels (a)-(c), and $ActTop5_{mkt}$ in Panels (d)-(f). RPE is derived from equation (22) 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. See Table A1 for the complete list of variable definitions. The sample has an annual frequency and spans from 1980 to 2022. ***, **, and * indicate statistical significance at 1%, 5%, and 10%, respectively.

Figure A4: RPE and Market-level Active Institutional Ownership Concentration: 3-year Prediction Horizon



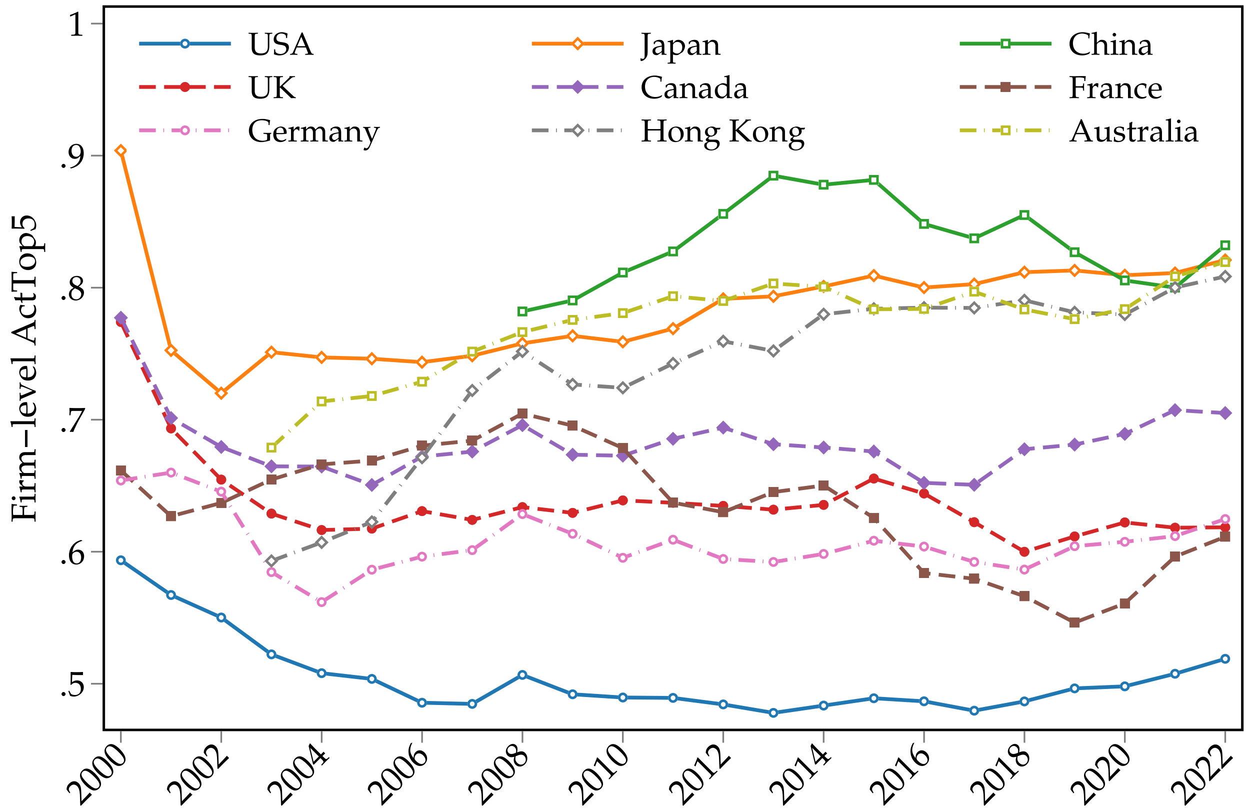
This figure shows quarter-by-quarter cross-sectional regressions of relative price informativeness (in twentiles) on firm-level ownership concentration among active institutional investors, as measured by $ActHHI$. The estimate result reported in the first row in Panel E of Table 5 can be interpreted as a weighted average of the quarter-by-quarter slope coefficient illustrated here.

Figure A5: Relative Price Informativeness and Active Institutional Ownership Concentration: HHI Index



This figure shows quarter-by-quarter cross-sectional regressions of relative price informativeness (in twentiles) on firm-level ownership concentration among active institutional investors, as measured by $ActTop5$. The estimate result reported in the second row in Panel E of Table 5 can be interpreted as a weighted average of the quarter-by-quarter slope coefficient illustrated here.

Figure A6: Relative Price Informativeness and Active Institutional Ownership Concentration: Top-5 Holdings



This figure displays the time-series average firm-level $ActTop5$ values for the largest equity markets worldwide, including the United States, the United Kingdom, Germany, Japan, Canada, Hong Kong, China, France, and Australia.

Figure A7: Top-5 Active Investors' Share

Table A1: Variable Definitions

Variable	Description
$ActHHI_{mkt}$	Market-level Herfindahl-Hirschman index of Assets Under Management (AUM) among active institutional investors: $$ActHHI_{mkt,q} = \frac{\sum_{j=1}^{N_{mkt}} \left(AUM_{j,q}^2\right)}{\left(\sum_{j=1}^{N_{mkt}} AUM_{j,q}\right)^2},$$ where N_{mkt} 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 classfication scheme of Bushee (1998).
$ActTop5_{mkt}$	The proportion of AUM held by the top five active institutional investors relative to the total AUM of all active institutional investors: $$ActTop5_{mkt,q} = \frac{\sum_{j=1}^{\text{Top 5}} AUM_{j,q}}{\sum_{j=1}^{N_{mkt}} AUM_{j,q}},$$ where N_{mkt} is the total number of institutional investors; $AUM_{j,q}$ is the AUM of institution j in quarter q.
$ActHHI$	Firm-level Herfindahl-Hirschman index of active institutional ownership: $$ActHHI_{i,q} = \frac{\sum_{j=1}^{N_i} \left(S_{i,j,q}^2\right)}{(\sum_{j=1}^{N_i} S_{i,j,q})^2},$$ 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.: $$ActTop5_{i,q} = \frac{\sum_{j=1}^{\text{Top 5}} S_{i,j,q}}{\sum_{j=1}^{N_i} S_{i,j,q}},$$ 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 A1 – *Continued*

Variable	Description
$Intangible/K$	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)).
$Physical/K$	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)).
$Invest/K$	Total investment rate, defined as the sum of $Physical$ and $Intangible$.
$\log(M/A)$	The log-ratio of market capitalization at the end of March to the total asset value in the previous fiscal year.
$PasHHI$	Firm-level Herfindahl-Hirschman index of passive institutional ownership. The calculation method closely resembles that of $ActHHI$, with the key distinction being the transition from active to passive investors within the cohort considered.
$PasTop5$	Firm-level holding percentage of the largest five passive shareholders. The calculation method closely resembles that of $ActTop5$, with the key distinction being the transition from active to passive investors within the cohort considered.
IO	Institutional ownership, calculated as the total institution holding divided by the market capitalization.
$Leverage$	Ratio of book debt to total assets.
$Sale$	Total sales scaled by total assets.
$Cash$	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.
$Rank$	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.
$CPIE$	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 A1 – *Continued*

Variable	Description
ITI	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.
$VR(q)$	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 Parlatore (2025), which corresponds to the Kalman gain of a Bayesian external observer who only learns from the price under a Gaussian environment.
PTR	Portfolio turnover, calculated as $$PTR_{k,g,q} = \frac{\min\left(AgBuy_{k,g,q}, AgSell_{k,g,q}\right)}{\sum_{i \in N_{k,g}} (S_{k,g,i,q}P_{i,q} + S_{k,g,i,q-1}P_{i,q-1})/2},$$ 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.
$AVAR$	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.
$AVOL$	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 A2: 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. Price informativeness is assessed using FPE in Panels A and B, and RPE in Panels C and D. FPE gauges the predictability of future cash flows based on current market prices, while RPE evaluates the extent to which current market prices reveal the information necessary for future investment decisions. Active institutional 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 A1 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: FPE and $ActHHI$						
	$E_{h=1}/A$	$E_{h=1}/A$	$E_{h=1}/A$	$E_{h=3}/A$	$E_{h=3}/A$	$E_{h=3}/A$
where E =	$EBIT$	$EBITDA$	NI	$EBIT$	$EBITDA$	NI
$\log(M/A)$*$ActHHI$	-0.026***	-0.030***	-0.027***	-0.052***	-0.059***	-0.035***
	(0.005)	(0.004)	(0.004)	(0.010)	(0.009)	(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: FPE and $ActTop5$						
	$E_{h=1}/A$	$E_{h=1}/A$	$E_{h=1}/A$	$E_{h=3}/A$	$E_{h=3}/A$	$E_{h=3}/A$
where E =	$EBIT$	$EBITDA$	NI	$EBIT$	$EBITDA$	NI
$\log(M/A)$*$ActTop5$	-0.033***	-0.040***	-0.029***	-0.045***	-0.063***	-0.022*
	(0.006)	(0.005)	(0.005)	(0.010)	(0.009)	(0.012)
Obs	83,054	83,794	83,952	69,612	70,250	70,402
R2	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
Panel C: RPE and $ActHHI$						
	$I_{h=1}/K$	$I_{h=1}/K$	$I_{h=1}/K$	$I_{h=3}/K$	$I_{h=3}/K$	$I_{h=3}/K$
where I=	$Intangible$	$Physical$	$Invest$	$Intangible$	$Physical$	$Invest$
$\log(M/A)$*$ActHHI$	-0.022***	-0.023***	-0.044***	-0.042***	-0.025***	-0.070***
	(0.007)	(0.003)	(0.007)	(0.009)	(0.004)	(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

Continued on next page

Table A2 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Controls	Y	Y	Y	Y	Y	Y
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y

Panel D: RPE and $ActTop5$

where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
log(M/A)*$ActTop5$	-0.027***	-0.024***	-0.050***	-0.049***	-0.028***	-0.082***
	(0.009)	(0.005)	(0.012)	(0.011)	(0.004)	(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 A3: 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 active institutional 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. Price informativeness is assessed using FPE in Panels A and B, and RPE in Panels C and D. FPE gauges the predictability of future cash flows based on current market prices, while RPE evaluates the extent to which current market prices reveal the information necessary for future investment decisions. The sample has an annual frequency and spans from 1980 to 2022. The coefficients of the control variables are suppressed for brevity. See Table A1 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: FPE and $ActHHI$						
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
$\log(M/A)$*$ActHHI$	-0.013***	-0.016***	-0.015**	-0.033***	-0.035***	-0.029***
	(0.005)	(0.004)	(0.005)	(0.010)	(0.009)	(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: FPE and $ActTop5$						
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
$\log(M/A)$*$ActTop5$	-0.024***	-0.027***	-0.027***	-0.035***	-0.041***	-0.028***
	(0.005)	(0.004)	(0.007)	(0.008)	(0.008)	(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
Panel C: RPE and $ActHHI$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
$\log(M/A)$*$ActHHI$	-0.017***	-0.014***	-0.031***	-0.025***	-0.011***	-0.037***
	(0.006)	(0.003)	(0.009)	(0.007)	(0.004)	(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

Continued on next page

Table A3 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
Firm	Y	Y	Y	Y	Y	Y
Industry-Year	Y	Y	Y	Y	Y	Y
Panel D: RPE and $ActTop5$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
$\log(M/A)$*$ActTop5$	-0.012*	-0.008*	-0.021**	-0.014*	-0.003	-0.021*
	(0.007)	(0.004)	(0.010)	(0.008)	(0.005)	(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 A4: Concentration Measures Without Distinguishing Active/Passive Investors

This table replicates Tables 3-4, with the distinction that we reconstruct the 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 firm-level HHI of institutional shares, where N_{tot} denotes the number of institutions holding stock i; $TotTop5_{i,q} = \frac{\sum_{j=1}^{\text{Top 5}} S_{i,j,q}}{\sum_{j=1}^{N_{tot}} S_{i,j,q}}$ measures the proportion of shares held by the top five largest institutional investors relative to the total shares held by all institutional investors. Price informativeness is assessed using FPE in Panels A and B, and RPE in Panels C and D. FPE gauges the predictability of future cash flows based on current market prices, while RPE evaluates the extent to which current market prices reveal the information necessary for future investment decisions. The sample has an annual frequency and spans from 1980 to 2022. The coefficients of the control variables are suppressed for brevity. See Table A1 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: FPE 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***	-0.046***	-0.047***	-0.081***	-0.078***	-0.075***
	(0.006)	(0.006)	(0.009)	(0.016)	(0.014)	(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: FPE 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***	-0.041***	-0.037***	-0.066***	-0.066***	-0.052***
	(0.005)	(0.004)	(0.006)	(0.010)	(0.010)	(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
Panel C: RPE and $TotHHI$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
log(M/A)*$TotHHI$	-0.020***	-0.021***	-0.040***	-0.033***	-0.033***	-0.068***
	(0.006)	(0.005)	(0.011)	(0.009)	(0.007)	(0.012)
Observations	109,450	108,359	109,304	91,771	90,687	91,613

Continued on next page

Table A4 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
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: RPE and $TotTop5$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
$\log(M/A)$*$TotTop5$	-0.015***	-0.018***	-0.032***	-0.018**	-0.021***	-0.041***
	(0.006)	(0.004)	(0.009)	(0.007)	(0.006)	(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 A5: Alternative Measure of RPE: Investment-Q 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). Active institutional 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 A1 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: $ActHHI$			
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
Q*ActHHI	-0.025***	-0.029***	-0.051***	-0.051***	-0.027***	-0.076***
	(0.007)	(0.003)	(0.008)	(0.009)	(0.005)	(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: $ActTop5$			
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
Q*ActTop5	-0.035***	-0.036***	-0.069***	-0.066***	-0.035***	-0.102***
	(0.010)	(0.005)	(0.013)	(0.011)	(0.006)	(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

Table A6: 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.

Announcement 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 A7: DiD Estimation Using Active Institutional Mergers: Alternative Control Group

This table replicates our DID results from Table 7, 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. Price informativeness is assessed using FPE in Panels A, and RPE in Panels B. FPE gauges the predictability of future cash flows based on current market prices, while RPE evaluates the extent to which current market prices reveal the information necessary for future investment decisions. $Treat$ 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. $After$ 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 A1 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: FPE within $(-2, +2)$ years						
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)*$Treat$*$After$	-0.016***	-0.015***	-0.013***	-0.031***	-0.035***	-0.014
	(0.003)	(0.004)	(0.004)	(0.010)	(0.011)	(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: RPE within $(-2, +2)$ years						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
log(M/A)*$Treat$*$After$	-0.000	-0.010***	-0.009**	-0.020**	-0.017***	-0.039***
	(0.002)	(0.002)	(0.004)	(0.009)	(0.006)	(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 A8: DiD Estimation Using Active Institutional Mergers: Alternative Event Window

This table replicates our DID results from Table 7, with the key distinction that the estimation window is extended to (-3, +3) years, with year-0 denoting the merger completion year. Price informativeness is assessed using FPE in Panels A, and RPE in Panels B. FPE gauges the predictability of future cash flows based on current market prices, while RPE evaluates the extent to which current market prices reveal the information necessary for future investment decisions. $Treat$ 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. $After$ 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 A1 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: FPE within $(-3, +3)$ years						
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)*$Treat$*$After$	-0.012**	-0.012***	-0.009**	-0.038***	-0.042***	-0.019*
	(0.005)	(0.004)	(0.004)	(0.010)	(0.011)	(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 FE	Y	Y	Y	Y	Y	Y
Panel B: RPE within $(-3, +3)$ years						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
log(M/A)*$Treat$*$After$	0.000	-0.008**	-0.007	-0.025**	-0.022***	-0.046***
	(0.002)	(0.004)	(0.005)	(0.010)	(0.007)	(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 A9: 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 amalgamating 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 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 A1.

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

Table A10: 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 firm-level ownership concentration among active institutional investors. The international sample is constructed by amalgamating data on global institutional ownership from FactSet, accounting data from Worldscope, and stock market data from DataStream. Price informativeness is assessed using FPE in Panels A and B, and RPE in Panels C and D. FPE gauges the predictability of future cash flows based on current market prices, while RPE evaluates the extent to which current market prices reveal the information necessary for future investment decisions. Active institutional 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 A1 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: FPE and $ActHHI$						
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)*$ActHHI$	-0.020***	-0.020***	-0.014***	-0.020***	-0.021***	-0.015***
	(0.003)	(0.003)	(0.002)	(0.005)	(0.006)	(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: FPE and $ActTop5$						
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)*$ActTop5$	-0.030***	-0.030***	-0.022***	-0.042***	-0.046***	-0.034***
	(0.004)	(0.004)	(0.003)	(0.006)	(0.007)	(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
Panel C: RPE and $ActHHI$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
log(M/A)*$ActHHI$	-0.005***	-0.011**	-0.017***	-0.015**	-0.015*	-0.031**
	(0.002)	(0.004)	(0.005)	(0.007)	(0.008)	(0.014)
Observations	123,162	122,660	122,906	102,078	101,598	101,867

Continued on next page

Table A10 – *Continued*

	(1)	(2)	(3)	(4)	(5)	(6)
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: RPE and $ActTop5$						
where I=	$I_{h=1}/K$ $Intangible$	$I_{h=1}/K$ $Physical$	$I_{h=1}/K$ $Invest$	$I_{h=3}/K$ $Intangible$	$I_{h=3}/K$ $Physical$	$I_{h=3}/K$ $Invest$
log(M/A)*$ActTop5$	-0.008***	-0.019***	-0.027***	-0.023***	-0.033***	-0.055***
	(0.002)	(0.005)	(0.005)	(0.007)	(0.009)	(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

B 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 assoc iated 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.[13] 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 following 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 A11 reports regression results of the aforementioned proxies on active ownership con-

[13]Gaining 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.

centration. 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 A11: Competing Hypothesis: Corporate Governance

This table reports regression results of shareholder activism and corporate fraud proxies on active 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. Active institutional 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.

	(1)	(2)	(3)	(4)	(5)	(6)
	$Activism$		$HardActivism$		$Fraud$	
$ActHHI$	-0.003		0.004		-0.011	
	(0.020)		(0.009)		(0.007)	
$ActTop5$		0.015		0.021**		-0.000
		(0.019)		(0.009)		(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