When Elephants Walk: Large Investor, Information Advantage and the Fragility of the Asset Market

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Abstract

How do investors' size and information precision drive asset price fluctuations and contribute to market fragility? When investors are large, they will trade cautiously. But when they trade, their price movement will make the price more informative. We adopt the rational expectation equilibrium model where the investors are large and behave as a price maker, showing that large investors are a double-edged sword to the market: they enhance price informativeness by injecting more fundamental information into the market, yet increase the asset market fragility to shocks due to their price impact concern, making the market illiquid and inelastic. We apply this model to examine the implications of the growing market share of passive funds over active funds. Our simulation reveals that a higher passive fund share improves liquidity, reducing liquidity shock fragility, but worsens the price informativeness. Depending on the size of passive investors, our analysis suggests two distinct policy strategies to improve market efficiency and reduce fragility. When the passive fund share is low, reducing informed investors' market concentration will improve price efficiency and reduce price fragility more effectively. When the passive fund share is high, enhancing information advantage for large informed investors will be more effective in improving price efficiency and reducing price fragility.

JEL codes: G1, G2, D4, L1

Key words: Asset Market Fragility; Asset Market Competition; Information Asymmetry

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1 Introduction

The past decade has witnessed substantial growth and increasing concentration within the mutual fund industry. Figure 1 and figure 2 illustrate these dynamics visually, highlighting the growth of the domestic equity fund industry and its concentration. The rise of fund industry concentration and the rise of passive funds raise concerns about whether they affect the efficiency of resource allocation, financial market stability, and risk diversification. See the relevant discussion by Anadu et al. (2020), Ben-David et al. (2021), Fang et al. (2024), and Jiang et al. (2024). On the other hand, the rise of passive investing accelerates the exit of underperforming funds, leaving the skillful funds to stay in the market (Huang, 2024). Since the passive investment funds do not actively search and provide information to the financial market, this raises concerns about whether information concentrated on a small number of active investors will be healthy for the asset market. While existing research explores how large investors influence liquidity, price efficiency, and how passive investing alters price dynamics, few studies have simultaneously modeled the joint effects of market-size concentration and information concentration on market fragility within a strategic microstructure framework.

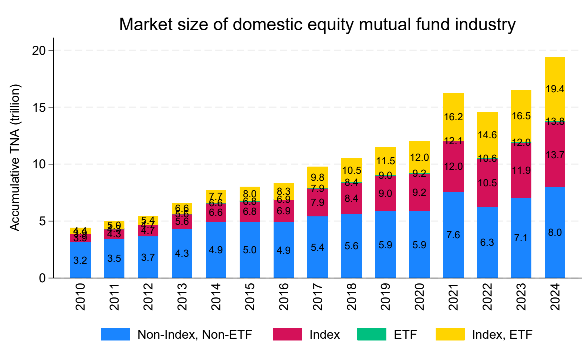


Figure 1: Mutual fund industry size expending through years

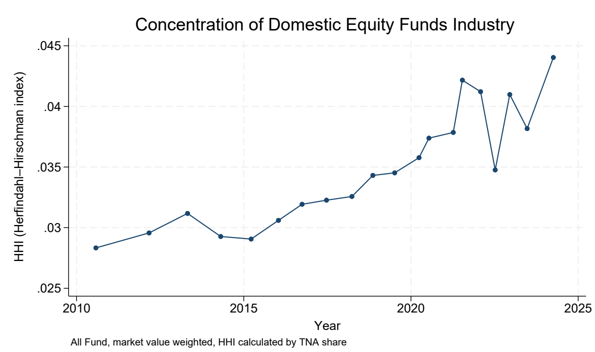


Figure 2: HHI of mutual fund industry increase through years

In this paper, we examine how market-size concentration (few investors managing large asset shares) and information concentration (few investors possessing high-quality private signals) jointly shape asset price dynamics and fragility. Market-size concentration reflects competitive intensity: fewer large players likely face less price pressure. Information concentration captures market power via superior forecasting ability: informed investors may bypass prevailing prices to extract rents. Together, both dimensions measure the distribution of market power, and we eventually answer the question of how market power distorts the asset price and makes it inefficient. We focus on fragility as it distorts resource allocation and investment decisions (see Friberg et al. (2024)).

In this paper, we adopt the rational expectation equilibrium model where investors are large and have price impact as in Kacperczyk et al. (2024) and Kyle (1989). We explicitly model how information concentration — the distribution of high-quality private signals among a subset of informed traders—impacts price fragility. Our mechanism is as follows: each informed investor faces a unique price impact when submitting an order, and they will face demand-side Cournot competition by submitting an asset demand order as in Lambert et al. (2018) and Vives (2011). This means they will strategically submit their asset demand order, considering their price impact, conditional on their private information and information inferred from a menu of possible asset prices. Once orders are submitted, a Walrasian auctioneer clears the market by setting the equilibrium price.

Intuitively, when investors are large—thus having significant price impact—they behave more cautiously, submitting smaller orders to avoid moving the market. We can see the discussion by Frazzini et al. (2018), Gârleanu and Pedersen (2013), and Jensen et al. (2024). This makes the demand curve steep and the market inelastic, increasing fragility to liquidity shocks or noisy signals. However, if a large investor possesses a high-quality private signal, confidence in their information leads them to trade more fully despite their price impact. That directly softens the demand curve, making the market more elastic and resilient. In other words, concentrating information in large investors tends to reduce price fragility. By contrast, if high-quality information is held by small investors instead, large traders become wary: without superior signals, they face higher uncertainty and require larger price concessions to trade. As a result, overall market demand remains inelastic, and susceptibility to price shocks increases. Thus, reducing market-size concentration—i.e., making asset control more dispersed—could also decrease fragility by weakening the market power of any single trader.

Our model delivers a threefold equilibrium that jointly determines prices, price impacts, and price-signal interactions. First, a Walrasian auctioneer sets the market-clearing price so that aggregate demand matches supply, just as in standard competitive models. Second, we endogenize each investor's price impact through a fixed-point condition: an investor's marginal price sensitivity depends on its own price impact, which depends on the sensitivities of all other traders, yielding a unique strategic equilibrium under heterogeneous beliefs. This equilibrium is also in the literature by Anthropelos and Kardaras (2024), Haddad et al. (2025), Kacperczyk et al. (2024), Rostek and Yoon (2023), and Vives (2011). This price impact is a part of the investor's transaction cost discussed by Frazzini et al. (2018), Gârleanu and Pedersen (2013), and Jensen et al. (2024), but they take the price impact as an exogenous. Third, we embed an equilibrium price-signal feedback channel by allowing investors to optimally weight their private information against the price signal. High-precision private signals reduce reliance on prices (and vice versa), reinforcing the endogenous quality of price informativeness.

At the investor level, our framework reveals that large traders play a dual role as both informational providers and liquidity dampeners, conditional on their information quality. When a well-informed, sizeable investor submits an order, her strategic trade moves prices toward true value, thus conveying private information. However, her concern about adverse price impact induces order suppression, shrinking market depth, and amplifying vulnerability to idiosyncratic shocks. But if his information is sufficiently precise, the information channel will outweigh the price concern. And the large investor will be the liquidity provider. This result is supported by the empirical work by Chen et al. (2024). This tension implies that the same agent both enriches and pollutes the information content of prices, and can be the creator of order and disorder.

On the aggregate market side, high market-size concentration—where a few investors control most assets—reduces overall liquidity and renders prices highly inelastic, exacerbating fragility in the face of liquidity or information shocks. By contrast, when information is concentrated among those same large players (so they hold especially precise signals), they trade more aggressively on their superior insights, which bolsters depth and attenuates fragility. Importantly, this highlights a policy trade-off: encouraging a handful of deep-pocketed, well-informed participants can improve stability, whereas diluting private information across many small investors may erode resilience.

Finally, our analysis identifies the "key investor" that drives market outcomes. They are large and uninformative investors. In settings with growing passive-fund dominance, our results suggest regulators should focus not only on size concentration but also on preserving (or enhancing) price-signal quality—perhaps via disclosure requirements or liquidity provisions—to mitigate the adverse effects of fragmented information and insulate markets against collective shocks.

To validate our theory, we calibrate and simulate the model using U.S. corporate bond mutual-fund data from Q1 2010 through Q1 2024—during which passive-fund share rose from roughly 20 percent to nearly 75 percent. Holding the distribution of private information constant, we find that greater concentration of informed investors reduces price-signal efficiency and amplifies price fragility to liquidity shocks. Conversely, for a fixed market-size concentration, concentrating information advantage in large investors makes prices more informative and markets more resilient.

The simulations also identify two distinct policy strategies for boosting efficiency and stability as passive ownership grows. When passive funds constitute a small fraction of the total market size, reducing informed-investor concentration most effectively sharpens price signals and cushions liquidity shocks. But once passive investors become dominant, centrally allocating high-quality information to the remaining large active funds substantially improves price informativeness and mitigates asset-price fragility.

Our paper makes three key contributions. To the first, we separate market-size concentration (distribution of asset shares among investors) from information-advantage concentration (who holds superior private information). Unlike traditional microstructure models that assume small, price-taking traders or homogenous, exogenous price impacts, our model endogenizes each investor's price impact. This is determined in equilibrium by both their relative asset share and the distribution of private-signal precision among investors. Second, asset market fragility. We explore how market structure amplifies shocks. Our model shows how both market and information concentration influence shock transmission and amplification. We find that large investor granularity amplifies shocks, while concentrated information advantages help mitigate this effect. To the third, asset market inelasticity. Our model could help answer the question of the origins of asset market inelasticity (Gabaix & Koijen, 2021). We argue that concerns over price impact and information disadvantages constrain investor reactions to price changes. This inelasticity emerges as an equilibrium outcome shaped by the size distribution of large investors and their information disparities. Our findings indicate that inelasticity is most severe when small, uninformed investors dominate, informed investors are size-concentrated, and information advantages lie with small informed investors. Conversely, the market is most elastic when large, uninformed investors prevail, informed investors are less size-concentrated, and information advantages are with large investors.

Literature Review Our paper builds on growing research into how large and strategic investors influence asset prices. Prior theoretical and empirical work—such as Ben-David et al. (2021), Dávila and Parlatore (2021), Haddad et al. (2025), and Kacperczyk et al. (2024) —has shown that large institutional players wield market power that can drive liquidity dynamics and impact volatility. These papers typically assume either symmetric informational structures or treat price impact exogenously. In contrast, our model highlights the joint roles of investor market-size distribution and signal precision, illustrating how concentration in both dimensions can amplify market shocks through strategic trading behavior and liquidity deterioration.

We also address debates surrounding the rise of passive investing. Research like Fang et al. (2024) and Jiang et al. (2024) argues that passive growth can distort market signals and raise correlations, raising concern about market efficiency. Regulatory analyses—such as the James et al. (2019) warn that while passive strategies lower costs, widespread adoption may undermine market quality and impair competition. Our contribution is to frame this issue through a market-microstructure lens, exploring how passive investors' presence shifts strategic equilibria and affects price fragility—not just corporate governance or proxy outcomes.

Our paper is also related to the role of large investors in providing liquidity to the market. Chen et al. (2024) and Giannetti and Jotikasthira (2024). They want to ask the question: how would the size of a mutual fund contribute to market fragility? Our difference is that they do not explain how the decision regarding heterogeneous assets is determined by their size, their opponent's size, their information, and the information of other opponents. Specifically, how would the fragility be magnified and propagated by those who own what information? We can ask whether increasing information diversity would be a good idea

Finally, we contribute to the literature on financial market fragility, including recent work by Falato et al. (2021), Friberg et al. (2024), and Goldstein et al. (2025). They highlight how shocks—including funding runs or margin spirals—can cascade through markets. We complement this by showing that fragility is not only a function of external shocks but is endogenously shaped by the distribution of investor market power and informational advantage. Specifically, we show that markets with uninformed, large passive investors are especially fragile, whereas markets where large actors hold high-quality private signals can mitigate shocks via improved elasticity and trade aggressiveness.

Our paper is structured as follows. Section 2.1 introduced our model settings, and section 2.2 solves our model and characterizes the equilibrium of the model parameters. Section 3.1 defines the price fragility in our settings. Section 3.2 and Section 3.3 discuss the determinants of individual and aggregate trading incentives. Section 4.1 discusses how we simulate our model, section 4.3 and section 4.3 discuss our simulation outcome of low passive investor environment asset price fragility, and how the simulation outcome changes when the passive investor market share increase. Section 5 conclude.

2 Model of Assets and Fund Managers

We borrow the asset-market structure setting in Grossman and Stiglitz (1980) and focus on the size and the behavior of the asset managers. The model has two periods. The investor will observe information in the first period and decide on the portfolio. And in the second period, the payoff is realized. The detail settings are the following.

2.1 Model Settings

2.1.1 Assets, market, and their signal

There is a risky asset with a price of p at time $t = 0$. It will pay v as a random payoff at $t = 1$. The payoff variable $v = \overline{v} + \epsilon_v$, with $\epsilon_v \sim \mathcal{N}(0, \sigma_v^2)$. And there is a risk-free asset, with price 1 at $t = 0$, and payoff as r at $t = 1$. The asset has a random supply with $z \sim \mathcal{N}(0, \sigma_z^2)$. There is a Walrasian auctioneer who sets the price p, thereby clearing the market.

2.1.2 Investors

There are two types of investors: informed and uninformed. Informed investors differ in terms of the signals they observe. We assume their signal structures are different, meaning they have different signal precisions. Each signal has an additive noise structure to the payoff that $s_i = v + \epsilon_i$, with $\epsilon_i \sim \mathcal{N}(0, \sigma_{e,i}^2)$. The investors' signals are correlated through their correlation to the ex-post payoff. To emphasize the price fluctuations that could arise from the self-reinforcement behavior of the investor, we adopt the structure proposed by Grossman and Stiglitz (1980), where the investor can learn from prices. Therefore their information set are $\mathcal{I}^I = \{s_p, s_i, \overline{v}\}$, representing the information learning from price s_p, from private signal s_i, and from prior $\overline{v}$.

The asset market is not fully competitive. Each informed investor is large in the sense that they have local monopoly power over their residual market. The outcome is that their asset demand decisions will have a price impact, and they will consider their price impact when making decisions. This price impact is an equilibrium outcome; we will discuss this in the next chapter. This price impact is one component of their transaction cost, as discussed in the literature Frazzini et al. (2018), Gârleanu and Pedersen (2013), and Jensen et al. (2024). We denote each investor as $I_i \in \{I_1, \ldots, I_M\}$ and their size is determined by their asset under management (AUM) amount denoted as M_i.

We have another group of uninformative investors, denoted as U. Each investor within this group is small in the sense that their asset decision does not have a price impact, and they will behave as a price taker. Their total asset size is M_U. To be consistent with the notation of informed investors, we assume the uninformed investors' private signal set is empty. This means that $s_u = v + \epsilon_u$, where $\epsilon_u \sim \mathcal{N}(0, \infty)$. Although he does not observe the private information, he can still infer the future payoff from the price. Thus, the information set for the uninformed investor is the following: $\mathcal{I}^U = \{p, s_u, \overline{v}\}$. newline For analytical convenience, we standardize the total market size to be one. Then M_i and M_U will represent the market shares for each group. It satisfy the condition $M_U + \sum_i M_i = 1$. In the subsequent analysis, we will demonstrate that only the relative size makes a difference. Therefore, it is valid to standardize the total market size to be one and use M_i and M_U to represent the market share of each group.

For each group, we examine the behavior of its representative investor. Both informed and uninformed will manage their asset with their initial amount M_i at $t = 0$. At $t = 0$, each investor competes via the demand function. This means each investor submits a demand function $q_i : \mathbb{R} \times \mathbb{R} \to \mathbb{R}$ which specifies the demand function as the market price p and the signal he observed. q_i is the quantity of asset demand. Then pq_i/M_i is the percentage of assets allocated to the risky assets. At $t = 1$, the investor will realize the total payoff W_i. The total payoff will satisfy the following relationship.

$$W_i = vq_i + (M_i - pq_i)r = M_i r + (v - rp_i)q_i \tag{1}$$

We assume that the investor's second-period utility is the Constant Absolute Risk Aversion (CARA) form with risk-averse coefficient ρ. That is $U(W_i) = -\exp(-\rho W_i)$ at $t = 1$.

2.1.3 Equilibrium concept

We borrow the equilibrium structure from Bergemann et al. (2021) and focus on the linear equilibrium. That is, each investor maximizes their second-period utility by posting a menu of demand given a price condition on their private information. Then, a Walrasian auctioneer will set the price to clear the market. The formal definition of equilibrium is as follows.

Definition 1 (Nash Equilibrium)**.** *The strategy profile $\{q_i\}_{\{i=I_1,\dots,I_N,U\}}$ is a **Nash Equilibrium** if it satisfied the following relationship*

1. *The investor will maximize his expected payoff by choosing their demand.*

$$w_i(p^*, s_i) = \arg\max_{w_i} \quad E\left[-exp(-\rho W_i) \mid p^*, s_i\right] \quad s.t.\ W_i = M_i r + (v - rp_i)q_i \tag{2}$$

2. *The price meets the market clearing condition that there exists a p^* such that.*

$$\sum_i M_i q_i(p^*, s_i) = z \tag{3}$$

2.2 Solving the model

To solve the model, we first conjecture that the demand function is linear. Then we derive that the pricing function will also be linear, given that everyone uses the linear demand strategy. Finally, we rationalize this linear demand function by noting that given this linear pricing function, the investor will also have a linear optimal asset demand function.

2.2.1 Asset market equilibrium and price

We first conjecture here and verify later that the demand is linear. It is linear in the asset price p and the observing signal s_i. We assume the function form to be as follows.

$$q_i = c_i^0 \bar{v} + c_s^i s_i - c_p^i r p \tag{4}$$

From the market-clearing condition, (3), the price will make the total demand equal to the total supply. Given our conjectured linear demand system, the price will be linear to the expected asset payoff $\bar{v}$ and all available signals in the market. The equilibrium price will have the following expression.

$$rp = \hat{c}_p^{-1} \hat{c}_0 \bar{v} + \sum_{i \in I} \hat{c}_p^{-1} c_s^i s_i - \hat{c}_p^{-1} z \tag{5}$$

Here $\hat{c}_0$, $\hat{c}_s$, and $\hat{c}_p$ are the aggregate trading intensity of all investors' private signals and prices as the weighted sum of individual trading intensities. This trading intensity can be expressed as the following

$$\hat{c}_0 = \sum_i M_i c_0^i, \quad \hat{c}_s = \sum_i M_i c_s^i, \quad \hat{c}_p = \sum_i M_i c_p^i \tag{6}$$

2.2.2 The linear optimal asset demand

To rationalize the linear demand function, we adopt the framework from Kacperczyk et al. (2024) and Vives (2011), where each investor initially observes a private signal s_i and then updates their beliefs based on available price menus p. A surprising price suggests that other investors likely received favorable signals, indicating that the price not only reflects scarcity but also conveys information. This mechanism produces outcomes of flexible sustainability and complementarity. Formally, the informed investor solves the following problem.

$$\max_{q_i} E(u_i(W_i(w_i)) \mid \mathcal{I}) = \max_{q_i} \rho \left(E(v|\mathcal{I}) - rp(q_i)\right) q_i - \frac{1}{2} q_i^2 \rho^2 Var(v|\mathcal{I}) \tag{7}$$

The optimal asset demand is to the point where the marginal cost of acquiring an additional unit equals the risk-adjusted expected payoff. The risk-adjusted expected payoff is $E(v|\mathcal{I}) - \rho Var(v|\mathcal{I})q$. It is the expected future payoff net of the expected future uncertainty. The marginal cost of acquiring the asset is $rp(q) + r\frac{\partial p}{\partial q}q$. Here, the first term $rp(q)$ reflects the current market price, while the second term $r\frac{\partial p}{\partial q}q$ is the price increase for an additional unit of asset. That is the residual supply curve that the individual faced. Finally, the optimal demand for the asset is as follows.

$$q_i^* = \frac{E(v|\mathcal{I}) - rp}{\rho Var(v|\mathcal{I}) + r\frac{\partial p}{\partial q_i}} \tag{8}$$

This optimal demand function tells us that the investor would consider their price impact when making an investment decision if they have a price impact. The price impact is an equilibrium concept, but the investor does not need to know how this equilibrium price is formed. He only needs to know how his additional unit of asset demand will move the price. The price impact is sufficient statistics for investors to make asset demand decisions. We assume the investor knows his price impact.

This function deviates from the classic CARA optimal asset decision by adding the price impact terms, $r\frac{\partial p}{\partial q_i}$ to its denominator. We assume the price impact is a positive, non-decreasing function, meaning that the larger quantity you submit to the market, the larger price impact you will have. The is means $\frac{\partial p}{\partial q} > 0$, and $\frac{\partial^2 p}{\partial q^2} \geq 0$. [1] This assumption will also guarantee a maximization result.

[1]The second order condition is given by $\frac{\partial^2 U_i}{\partial q^2} = -r(2\frac{\partial p}{\partial q} + \frac{\partial^2 p}{\partial q^2}q) - \rho Var(v|\mathcal{I})$. Therefore, a positive, non-decreasing price impact function would guarantee an optimal demand result.

2.2.3 Equilibrium price impact

Given the market-clearing condition, (3), the price impact is in equilibrium. One investor's price impact is determined by how easily he can induce his trade counterparty to trade, and how large his trade counterparty is compared to him. If his trade counterparties are sensitive to the price, he only needs to concede a small amount of price to induce a unit of trade. Therefore, his price impact is low. Also, the order will first satisfy the easy-to-trade counterparties. And the market clearing mechanism will make the price concession to trade the same across all trade counterparty groups. From our model, the price impact is a number given by the weighted harmonic mean of all its counter parties' price sensitivities. This harmonic price impact would put more weight on the price sensitivity for the relatively large groups. The expression is as follows.

$$\lambda_i \equiv \frac{\partial p}{\partial q_i} = \frac{M_i}{r \sum_{j \neq i} M_j c_p^j} \tag{9}$$

We can understand this equation from another aspect. We flip the expression of this equation and yield $\partial q_i / \partial p = r \sum_j \frac{M_j}{M_i} c_p^j$. The left-hand side, $\frac{\partial q_i}{\partial p}$, can be viewed as the liquidity demand. That is how much price concession an investor is willing to pay to demand a unit of the asset. The right-hand side can be viewed as the aggregate liquidity supply. That is how much price concession an investor is willing to take in order to give up a unit of asset.

The equilibrium price impact is a sufficient statistic for measuring the individual market power. To see this, recall that the price impact is the inverse slope of the individual residual supply curve $\partial q_i / \partial p = 1/\lambda_i$. If an investor faces an inelastic residual supply, he will have a large price impact. Then, to formally examine the relationship, we adopt the definition of an investor's market power as in Bergemann et al. (2021), which is the marginal benefit minus the price, divided by the price, in purchasing q shares of an asset.

$$l_i \equiv \frac{E(v|\mathcal{I}) - \rho Var(v|\mathcal{I}) q - rp}{rp} \tag{10}$$

After substituting in the first order condition, we can see $\frac{E(v|\mathcal{I})-\rho Var(v|\mathcal{I})q-rp}{rp} = r\frac{\partial p}{\partial q_i}\frac{q_i}{p} = r\lambda_i\frac{q_i}{p}$. The individual market power is equal to the inverse price elasticity that the individual faced for the residual market. This means that when investors faces an inelastic residual supply, they will have a significant price impact, and thus can more easily move the price in his favor. This means he has greater market power. From the previous analysis, we can see the price impact determined on the relative size of the investor to his opponents, and their opponents' price sensitivity. Thus this investor's market power is large when he is relatively large to his opponents and his opponents is less sensitive to the price change. We will argue in the later session that this low elasticity trading environment will be reinforced by the polarized size distribution and the poor information environment.

2.2.4 Signal and Bayesian updating demand

We begin working through the mechanism of Bayesian updating to derive how private information and price information would affect the demand. The individual investor observed both their price signal and their private signal. The price signal is heterogeneous for different investors. For an investor observing signal s_i, the pricing function can be seen as a noisy information-revealing mechanism that can help the investor know what others may know. Condition on seeing signal s_i, we can decompose price as $rp = \hat{c}_p^{-1}\hat{c}_0\bar{v} + M_i\hat{c}_p^{-1}c_s^i s_i + \sum_{j\neq i} M_j\hat{c}_p^{-1}c_s^j s_j - \hat{c}_p^{-1}z$. We define the price signal for investor i as $s_p^i \equiv \frac{rp-\left(\hat{c}_p^{-1}\hat{c}_0\bar{v}+M_i\hat{c}_p^{-1}c_s^i s_i\right)}{\sum_{j\neq i} M_j\hat{c}_p^{-1}c_s^j} = v + \frac{\sum_{j\neq i} M_j\hat{c}_p^{-1}c_s^j\epsilon_j}{\sum_{j\neq i} M_j\hat{c}_p^{-1}c_s^j} - \frac{\hat{c}_p^{-1}}{\sum_{j\neq i} M_j\hat{c}_p^{-1}c_s^j}z = v + \eta_p^i$.

The individual price signal is also an added noise structure. η_p^i has two parts. (1) the weighted average of the unobserved signals' noise, (2) the scaled supply shock. The first part depends on one's opponent's trading incentive and their signal noise itself. This part puts more weight on its large trade counter parties, and their trading incentive. If one of his opponents is large and strongly motivated to trade signals, his price signal would be overwhelmed by the noise from that opponent. This decomposition also reveals that an individual's trading activities can create externalities for others by introducing noise into their signals. This effect is more pronounced when investors are large and actively trading their signals. The second part is the scaled liquidity shock. It also depends on the size and trading incentives of the other opponents. If one's opponents are large and actively trade on their signal, it will reduce the impact of the liquidity shocks.

Then by the Bayesian updating mechanism, the precision of future payoff condition on private information and price signal is $Var(v \mid s_i, s_p)^{-1} = \sigma_v^{-2} + \sigma_{e,i}^{-2} + \sigma_{s_p,i}^{-2}$. And the expected future payoff will be given by $E(v \mid s_i, s_p) = Var(v \mid s_i, s_p)\left(\sigma_v^{-2}\bar{v} + \sigma_{e,i}^{-2}\beta_i s_i + \sigma_{s_p,i}^{-2} s_p^i\right)$. Using the optimal asset demand result, (8). We can have the optimal demand function in the following linear function form.

$$
\begin{aligned}
q_i = & \underbrace{\frac{Var(v|s_i,p)}{Var(v|s_i,p)+\lambda_i}}_{\text{Demand shrinkage}}\Bigg\{\left[\sigma_v^{-2} - \frac{\sigma_{s_p,i}^{-2}\hat{c}_0}{\sum_{j\neq i} M_j c_s^j}\right]\bar{v} + \left[\sigma_{e,i}^{-2} - \frac{\sigma_{s_p,i}^{-2} M_i c_s^i}{\sum_{j\neq i} M_j c_s^j}\right] s_i \\
& - \left(\sigma_v^{-2} + \sigma_{e,i}^{-2} + \sigma_{s_p,i}^{-2} - \frac{\sigma_{s_p,i}^{-2}\hat{c}_p}{\sum_{j\neq i} M_j c_s^j}\right) pr\Bigg\} \\
& = c_0^i \bar{v} + c_s^i s_i - c_p^i r p
\end{aligned} \tag{11}
$$

To further simplify the notation, we define $\tilde{\sigma}_{s_p,i}^{-2} := \frac{\sigma_{s_p,i}^{-2}}{\sum_{j\neq i} M_j c_s^j}$. It measures the effective price signal noise that an individual investor can use to infer information. Then, by comparing our initial assumption (4), we can express the previous undetermined coefficient as follows.

$$c_i^0 = \Lambda_i \Big[\sigma_v^{-2} - \underbrace{\tilde{\sigma}_{s_p,i}^{-2}\hat{c}_0}_{\text{Price sig. eff.}}\Big], \tag{12}$$

$$c_s^i = \Lambda_i \Big[\sigma_{e,i}^{-2} - \underbrace{\tilde{\sigma}_{s_p,i}^{-2} M_i c_s^i}_{\text{Price sig. eff.}}\Big], \tag{13}$$

$$c_p^i = \Lambda_i \Big[\underbrace{Var(v \mid \mathbf{s}_i, s_p)^{-1}}_{\text{Resource allocation effct}} - \underbrace{\tilde{\sigma}_{s_p,i}^{-2}\hat{c}_p}_{\text{Price sig. eff.}}\Big], \tag{14}$$

$$\Lambda_i = \frac{1}{1 + \lambda_i Var(v|s_i, p)^{-1}} \tag{15}$$

Here $\Lambda_i = \frac{1}{1+\lambda_i Var(v|s_i,p)^{-1}}$ is the demand shrinkage. Recall that in the classic rational expectation equilibrium model, there is no demand shrinkage and thus $\Lambda_i = 1$. When an investor has a small price impact, $\lambda_i \to 0$, this demand shrinkage reaches its supreme $\Lambda_i \to 1$, as in the classic full competitive environment.

Additionally, the uncertainty, $Var(v|s_i, p)$, will influencing the degree of demand shrinkage. When the investor's information precision is high, small $Var(v|s_i, p)$, he will concern whether his trading will reveal his information. Then, the investor becomes more cautious when placing orders. This phenomenon aligns with the endogenous limits to the arbitrage mechanism described by Edmans et al. (2015), although we do not explicitly model the directional flow of information in this context. Furthermore, if the investors have a even higher price impact this demand shrinkage effect will be even worse.
This demand function extends the class rational expectation equilibrium demand model (Grossman & Stiglitz, 1980), accounting for investor size and price impact concerns. We conclude this session by the following definition of linear equilibrium.

Definition 2. *(Linear Equilibrium) Let* $\{c_0^i, c_p^i, c_s^i\}_{i=I_1,\ldots,I_M,U}$ *be the solution to* (12) - (14). *And the aggregate intensity satisfied* $\{\hat{c}_0, \hat{c}_p, \hat{c}_s\}$ *satisfied the aggregate relationship* (6)*, For each investor* $i = \{I_1, \ldots, I_M, U\}$*, the equilibrium consist of demand schedules choice* q_i*, and equilibrium price* p*, such that*

1. *q_i is given by $q_i = c_0^i + c_s^i s_i - c_p^i rp$*

2. *For all realization of private signal s_i and supply shock z, the price p clear the market. That is*

$$rp = \hat{c}_p^{-1} \hat{c}_0 \bar{v} + \hat{c}_p^{-1} \sum_{i \in I} c_s^i s_i - \hat{c}_p^{-1} z \tag{16}$$

3 Large Investor and Asset Fragility

In this session, we'll explore how large investors can influence the market and potentially create fragility. We'll start by defining fragility as outlined in our paper. Next, we'll discuss the mechanics behind the formation of asset market fragility. Finally, we'll examine how the size of investors and the concentration of information can impact asset fragility.

3.1 Where is the fragility coming from

According to the definition by Goldstein et al. (2025), the fragility of financial markets occurs when market prices respond excessively to shocks, whether these shocks are fundamental or non-fundamental. Inspired by their definition, we propose a stricter definition of fragility as the change in asset price resulting from the realization of one unit of shock. The purpose here is to highlight the role of aggregate trading intensity in the overall market liquidity. We argue that if the market is sufficiently liquid, the price will respond to the occurrence of new information, but not excessively. If the market is not sufficiently liquid, the normal trading intensity would cause the price to overreact to the information. Furthermore, we refine the definition of Goldstein et al. (2025) by separating the fragility due to nonfundamental shocks into two groups: fragility from signal noise and fragility to liquidity shocks. The difference is that the liquidity shock is pure noise to the market and has no investor trading behavior. Thus, it is purely determined by the market liquidity condition. However, the signal noise is embedded in the investor's trading behavior, and thus it is determined by the investor's trading strategy. Formally, we define three types of fragility as follows.

Definition 3. *(Financial market fragility)*

1. *The asset price exhibits fragility to the asset fundamentals if* $\partial p/\partial v > 1$
2. *The asset price exhibits fragility to the signal noise if* $\partial p/\partial \epsilon_i > 1$
3. *The asset price exhibits fragility to the liquidity shock if* $\partial p/\partial z > 1$

In our framework, we can decompose the equilibrium price as exposed to different shocks as follows

$$rp = \hat{c}_p^{-1}\hat{c}_0\bar{v} + \underbrace{\hat{c}_p^{-1}\hat{c}_s}_{\textit{frag. fundtl.}} \cdot v + \underbrace{\hat{c}_p^{-1}\sum_{i\in I} M_i c_s^i \epsilon_k}_{\textit{frag. sig. noise}} - \underbrace{\hat{c}_p^{-1}}_{\textit{frag. liq. shk.}} z \tag{17}$$

From this decomposition, we can see that the fragility is coming from the inelasticity of the aggregate demand $dQ/dp = \hat{c}_p$. This definition is also used by Van der Beck (2022). This is the amount of price concession the overall market needs to have to induce one unit of aggregate trade. This is a Kyle (1989)-λ measure of the market liquidity. If the market is illiquid, you need to concede a large price to induce a unit of trade. Thus $\hat{c}_p$ is small. If we follow the analysis method by Van der Beck (2022) and define the aggregate market elasticity in absolute terms, $\zeta = -dQ/dp = \hat{c}_p$. $\hat{c}_p$ is the asset market elasticity. Here, we can see that the market elasticity plays an essential role. If the aggregate market is extremely inelastic, any signal shock, fundamental or non-fundamental, would require the investor to concede a huge amount of price to settle the trade. Thus, the asset price is fragile.

3.2 What determines the individual trading incentive

From the previous session, we can see that the aggregate trading incentive is a key factor in the asset's fragility. And the aggregate trading incentive is determined by the individual trading incentive. In this session, we discuss the price trading sensitivity and the signal trading sensitivity. The price trading sensitivity is how an individual would trade in response to a change in one price. And the signal trading sensitivity is how much the quantity of demand changes after seeing one unit of signal realization. Specifically, we aim to answer how the investors' price impact and their information would affect their trading incentives.

Pice sensitivity Price sensitivity is the core of the analysis. And the aggregate price sensitivity is weighted sum of the individual price sensitivity. Recall from previous analysis, the individual price sensitivity reflect how much of the investor will change his demand if the price increases by one unit. This is given by the following expression.

$$c_p^i = \Lambda_i \Big[\underbrace{Var(v \mid s_i, s_p)^{-1}}_{\textit{Resource scarcity eff.}} - \underbrace{\tilde{\sigma}_{s_p,i}^{-2} \hat{c}_p}_{\textit{Price sig. eff.}} \Big] \tag{18}$$

This price sensitivity incorporates two key functions: (i) The resource scarcity effect, where higher prices signal increased competition, leading investors to reduce demand behaving as strategic substitutes. This effect is moved by the total uncertainty of future payoff. If the investors are very certain about the future payoff, this effect makes the demand curve deeper, meaning that the investor would be more actively respond to the price change. (ii) The information effect, price conveying information through $\tilde{\sigma}_{s_p,i}^{-2} \hat{c}_p$, where higher prices suggest positive private signals observed by others, fostering strategic complementarity in demand. This effect is determined by the how price means for the investor, price signal accuracy $\tilde{\sigma}_{s_p,i}^{-2}$, and how active the overall market participant is $\hat{c}_p$. If the price signal is clear to the investor, and the overall market is sensitive to the price change, the price information effect will be large. The net effect depends on the relative strength of these forces. Ex-ante evidence indicates a downward-sloping asset demand curve, suggesting that resource allocation effects generally outweigh price signaling effects. We conclude it with the following proposition.

Proposition 1. *The investor's price impact and his information would change the investor's price sensitivity in the following way.*

1. *If the investor has a large price impact, they will have small price sensitivity.*

2. *If the investor has better information, they will respond more aggressively to price changes.*

Signal trading incentive In the previous session analysis, we know that price is fragile to signal noise and to the fundamentals, which all depend on how investor are willing to trade their signal. From the equation (13), and thus the following, we can see that besides the systematic demand shrinkage that reduces the trading incentive, the investors' private-signal also affecting the signal trading sensitivity. Solving for the equation (13), we can have the following closed from solution.

$$c_s^i = [1 + \Lambda_i \tilde{\sigma}_{s_p,i}^{-2} M_i]^{-1} \Lambda_i \sigma_{e,i}^{-2} \tag{19}$$

The investor's private signal trading incentive is positively related to the private signal accuracy $\sigma_{e,k}^{-2}$, and negatively related to the price signal accuracy, $\tilde{\sigma}_{s_p,i}^{-2}$. If the private signal is more precise than the price signal, the investor would put more weight on the private signal. Thus, he will response more to the private signal. If the price signal is more accurate, $\tilde{\sigma}_{s_p,i}^{-2}$, the investor will put less weight on private signal. Thus he will response less to the private signal.

The demand shrinkage Λ_i will makes the signal trading incentive small. To see this we rearrange the parameter as the following $c_s^i = [\Lambda_i^{-1} + \tilde{\sigma}_{s_p,i}^{-2} M_i]^{-1} \sigma_{e,i}^{-2}$. If Λ_i drops, the c_s^i will also reduced. When the investor has a large price impact, his trading will easy to reveal what they know. So he will have less incentive to trade on his signal. We conclude the finding using the following proposition.

Proposition 2. *(Signal trading incentive)*

- *The investor will trade intensively on its private signal s_i if the signal precision is high*

- *The investor will trade less intensively if the price can provide more information.*

- *The investor's price impact concerns will simultaneously reduce the above effects.*

3.3 Aggregate trading sensitivity and asset fragility

In the previous session, we examined the determinants of individual trading incentives. However, we care more about the aggregate incentive, as it is a determinant of asset fragility. We are particularly interested in how the distribution of investors' price impacts and how private information affects the aggregate trading sensitivities. In this session, we implement a partial equilibrium analysis to examine how changes in a single parameter will move the aggregate trading sensitivity.

Aggregate price sensitivity We first investigate aggregate price sensitivity, which appears in all fragility measurements. The aggregate price sensitivity measures how individuals would change their quantity demanded in response to a one-unit change in price. The aggregate price sensitivity is the sum of all investors' individual price sensitivity weighted by their size, $\hat{c}_p = \sum_i M_i c_p^i$. By solving the fixed point problem from individual price sensitivity, we can explicitly write out the aggregate price trading intensity as follows.

$$\hat{c}_p = \left[1 + \sum_i M_i \Lambda_i \tilde{\sigma}_{s_p,i}^{-2}\right]^{-1} \sum_i M_i \Lambda_i Var(v|s_i, p)^{-1} \tag{20}$$

We first notice that this expression tells us the aggregate price is determined by the weighted sum of the total information precision and the weighted sum of the price signal precision. The weight on $M_i\Lambda_i$ reflects the investor's influence on aggregate price, adjusted for demand shrinkage. Larger investors have a greater impact on price sensitivities, while significant demand shrinkage diminishes their influence.

To further determine which type of investor is the key player in determining this sensitivity, we express this weight as follows. $M_i\Lambda_i = 1/(\frac{1}{M_i} + Var(v|s_i, p)^{-1}\frac{1}{\sum_j M_j c_p^j})$. This expression tells us that, controlling everything else the same, (1) the weight drops when signal precision increases. (2) the weight increase, when the investor market size M_i increases. Therefore, the large, less informative investor would be the key player in determining the aggregate price sensitivity. Here, a less informative investor could include the uninformative investors. Even though the uninformed investor does not consider their price impact when making a decision, their order still moves the market.

To see the size effect on the price impact more clearly. We rewrite equation (20) as in the following form

$$\hat{c}_p = \left[\overline{\Lambda}^{-1} + \sum_i \frac{M_i \Lambda_i}{\overline{\Lambda}} \tilde{\sigma}_{s_p,i}^{-2}\right]^{-1} \sum_i \frac{M_i \Lambda_i}{\overline{\Lambda}} Var(v|s_i, p)^{-1} \tag{21}$$

Here $\overline{\Lambda} := \sum_i M_i \Lambda_i$ is the value weighted average of demand shrinkage. When the large investors have a large demand shrinkage, the $\overline{\Lambda}$ will be small. Also, since $M_i \Lambda_i = 1/\left(\frac{1}{M_i} + \frac{1}{\sum_j M_j c_p^j} Var(v|s_i, p)^{-1}\right)$ is convex increase on both its own size and on its opponent's size, it is Schur-convex. Therefore, conditional on the mean of M_i unchanged, if the distribution of M_i is more spread, $\overline{\Lambda}$ will be larger. This means an increase in $\hat{c}_p$. That is to say, even though the market becomes more concentrated, since the size effect still dominates, the aggregate price sensitivity remains increased.

Lemma 1. *The aggregate price sensitivity depends on the size of the investors and their information.*

1. *The large, less informative trader is the key player in determining the aggregate price sensitivity. If the markets are dominated by the larger investors, the aggregate trading sensitivity will be low.*

2. *If the weighted average total signal precision is high, the aggregate price sensitivity is high.*

3. *If the weighted average price signal precision is high, the aggregate price sensitivity is low.*

The asset fragility to liquidity shocks The asset price fragility to liquidity shocks is how price changes in response to one unit of total liquidity shock in the market. This fragility reflects how market resilience is to an uninformative move. The fragility of liquidity shocks reduces market efficiency, as they convey no information related to the true value while injecting pure noise into the price. Therefore, from a social welfare perspective, we aim to reduce this asset fragility.

From the previous analysis, we can measure this shock as $\partial rp/\partial z = 1/\hat{c}_p$. We can see that when the aggregate price sensitivity is large, the asset price fragility to liquidity shock is low. That is when the market is sufficiently liquid; it can easily absorb the liquidity shock. Then the asset price would be less fragile to liquidity shocks. Adapted from the results of the previous session, we can see that when the aggregate market total signal precision is high, this fragility is low. And when the market is dominated by large investors, the price fragility to the liquidity shock is low. Therefore, we can conclude the function of large investors and information to the asset price fragility to the liquidity shock as follows.

Proposition 3. *The signal quality and investor size have the following effects on the asset price fragility.*

1. *Large investors make the market more fragile to liquidity shocks.*
2. *The high signal quality encourages the investors to trade, which makes the market less fragile to liquidity shock.*

The aggregate information trading incentive Recall that the individual signals have two parts, $s_i = v + \epsilon_i$, the information part v, and pure noise parts, ϵ_i. Therefore, the trading of investors will both bring in information and noise. In this part, we are especially concerned about how the distribution of investors' size and their information will inject noise into the market through trading.

The price response to individual signal noise will be as $M_i c_s^i/\hat{c}_p \epsilon_i$. That is the total amount of noise of one investor injected into the market. If $\sigma_v^2/\sigma_{e,i}^2 < 1$, the informed investor's trading will inject more noise than signal to the market. This effect will be determined by the aggregate trading incentive. That is if an investor has a lower trading incentive when seeing a signal. The market will be less vulnerable to its signal noise.

Based on the previous analysis (Proposition 2), we can conclude that when investors are informed, they will be more active traders in response to price signals. The investor's trading behavior will have self-limiting behavior. That is, the less informed investor will reduce their trading, thus reducing the noise injected into the market. On the other hand, this pattern will stop when prices are more informative and investors pay less attention to their own information. On the other hand, (Proposition 2), the large investors will limit the trade due to their price impact concern. Therefore, their trading will limit the signal noise from entering the market.

The aggregate signal noise is given by $\sum_i M_i c_s^i \epsilon_i / \hat{c}_p$. The trading incentive when considering their size effect is given by

$$\begin{aligned} M_i c_s^i &= \frac{M_i \Lambda_i \sigma_{e,i}^{-2}}{1 + M_i \Lambda_i \tilde{\sigma}_{s_p,i}^{-2}} = \frac{\sigma_{e,i}^{-2}}{\frac{1}{M_i \Lambda_i} + \tilde{\sigma}_{s_p,i}^{-2}} \\ &= \frac{\sigma_{e,i}^{-2}}{\frac{1}{M_i} + \frac{1}{\sum_j M_j c_p^j} Var(v|s_i, p)^{-1} + \tilde{\sigma}_{s_p,i}^{-2}} \end{aligned} \tag{22}$$

Then, this signal trading effect, when considering the size effect, will increase when the investors' sizes increase. This means that the trading behavior of large investors will increase the price noise more than that of small investors when observing for the same precision of private signals and on the same market conditions. It means the large investors would be the noise makers if his information quality is low.

The asset price fragility to fundamental shock Another aspect of the signal is its informativeness. Each time an investors trade on his signal, he will also provide information to the market. This trading amount is given by $M_i c_s^i / \hat{c}_p$. From the previous analysis, we can see that large investors will have a greater price impact on the market, conditional on the market liquidity conditions. Therefore, the large investor's trade will convey more information to the market.

We can measure the aggregate price fragility to fundamental shock as $\partial rp / \partial v = \hat{c}_s / \hat{c}_p$.

Here $\hat{c}_s = \sum_i [1 + \tilde{\sigma}_{s_p,i}^{-2} M_i \Lambda_i]^{-1} M_i \Lambda_i \sigma_{e,i}^{-2}$ is the aggregate signal trading sensitivity. We can see the relationship between investors' size M_i and demand shrinkage Λ_i by rewriting it as follows

$$\hat{c}_s = \sum_i [(\Lambda_i M_i)^{-1} + \tilde{\sigma}_{s_p,i}^{-2}]^{-1} \sigma_{e,i}^{-2}. \tag{23}$$

Then, when the market is dominated by large investors, the market prices will move more when the fundamentals change by one unit, conditional on the same market conditions. Then we can view large investors as the information provider if their signal is precise. We conclude this result using the following lemma.

Lemma 2. *The market aggregate information trading intensity depends on the size of the investor and their information.*

1. *If the investor is large but informative, the aggregate information trading will be large, making the market more informative on fundamental shocks and more fragile to signal noise.*
2. *If the investor is large and uninformative, their aggregated information trading will be low, making the market less informative on fundamental shocks and less fragile to the signal noise.*

The asset price fragility to a fundamental shock would be determined by the aggregate private signal trading incentive and aggregate price sensitivities. We further express this relationship as follows.

$$\frac{\hat{c}_s}{\hat{c}_p} = \frac{\sum_i [1 + M_i \Lambda_i \tilde{\sigma}_{s_p,i}^{-2}]^{-1} \Lambda_i \sigma_{e,i}^{-2}}{\left[1 + \sum_i M_i \Lambda_i \tilde{\sigma}_{s_p,i}^{-2}\right]^{-1} \sum_i M_i \Lambda_i Var(v|s_i, p)^{-1}} \tag{24}$$

Therefore, if the aggregate price trading incentive is greater than the aggregate price trading sensitivities, the price is fragile to the fundamental shock. This means the total signal-induced trading cannot be fully absorbed by the trade counter-parties. Therefore, the price will respond more to attract more trading orders to balance the market.

The role of large investors in the market We conclude our partial equilibrium analysis with the effect of the large investor and their information advantage on the asset market. The function of the large investors in the asset market is a two-edged sword. On the one hand, large investors inject information into the market, but this can make the market more fragile to its noise. On the other hand, it makes the market more illiquid and more fragile to a liquidity shock. If the large investor has superior information, that is, his information has a high signal-to-noise ratio, the asset market is relatively more efficient. If the large investor has superior information, that is, his signal is noisy, the asset market is relatively less efficient. We formalized the finding using the following lemma

Lemma 3. *The large investor and their information advantage will affect the market in the following aspects*

1. *The large investor will simultaneously improve the market by making it more efficient to convey information, and making it more vulnerable to the liquidity shock*

2. *The large investor will make the market convey less information if they are uninformative.*

This analysis suggests that we face a trade-off between liquidity shocks and price informativeness. We advocate for splitting the large investor if they do not have superior information. We advocate for keeping the large investor large if they have superior information.

4 Simulation and Comparative Statics

In previous analyses, we controlled for all factors and conducted a partial equilibrium analysis. This session examines how changes in the market size of informed and uninformed investors, as well as information concentration, impact outcomes. We test our mechanism prediction and the recent trend in the wealth management industry—the rise in passive fund market share—as implications.

4.1 Simulation algorithm

Table 1 lists the exogenous and endogenous parameters for our model simulation. We begin by generating the distributions of investors' sizes and private signals. We are sourcing real fund size data from the CRSP Survivor-Bias-Free US Mutual Fund Database, focusing on fixed-income corporate bond funds from Q1 2010 to Q1 2024, as these mutual funds are key players in the corporate bond market. We define uninformed investors as those who invest in index funds or ETFs. We measure the concentration of the mutual fund industry using the Herfindahl-Hirschman Index (HHI). Figure 3 illustrates the trend in their market share and the HHI for the total market. The data show that the market share of uninformed investors grew from nearly 20% in 2010:Q1 to nearly 65% in 2024:Q1, indicating increased market concentration in the mutual fund industry. We then randomly draw investor sizes from a log-normal distribution, matching the mean and variance to the informed investor distribution during this period, and calculate the HHI for informed investors. Since we keep the mean the same, our sample generates the mean-preserving variance of the informed investors.

Table 1: Parameters and interpretation

Parameter	Symbol	Value	Data source
Mean payoff prior belief	$\bar{v}$	10	Kacperczyk et al. (2024)
Risk-free rate	r	2.5%	Kacperczyk et al. (2024)
Risk aversion	ρ	2.32	Kacperczyk et al. (2024)
Volatility of liquidity shock	σ_z^2	1	Normalized (Exogenous)
Volatility of payoff prior belief	σ_v^2	1	Normalized (Exogenous)
Volatility of individual price signal	$\sigma_{s_p,i}^2$		Endogenous
Volatility of individual private signal	$\sigma_{e,i}^2$		Simulated (Exogenous)
Investor size	M_i		Simulated (Exogenous)
Individual price impact	λ_i		Endogenous
Individual demand shrinkage	Λ_i		Endogenous
Individual prior trading intensity	c_0^i		Endogenous
Individual signal trading intensity	c_s^i		Endogenous
Individual price trading sensitivity	c_p^i		Endogenous

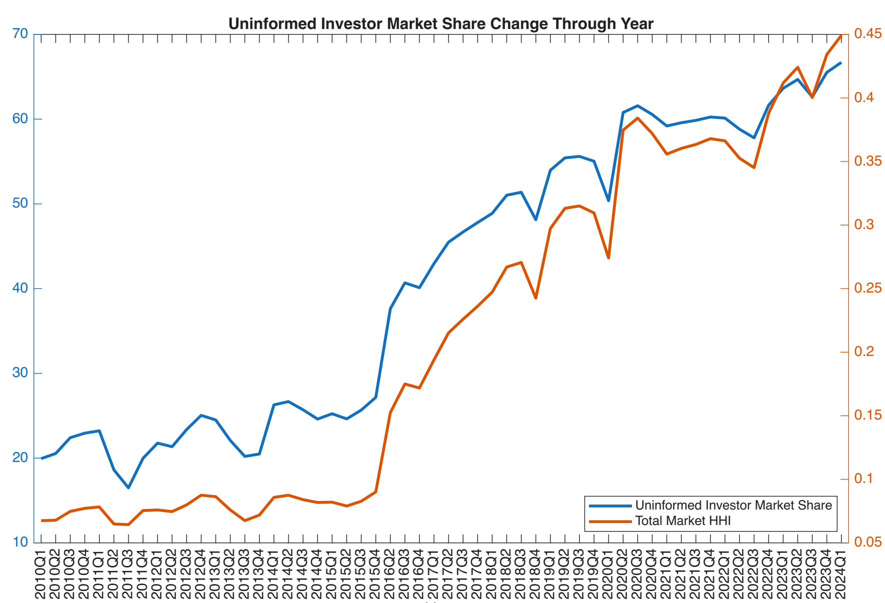


Figure 3: US corporate fixed income fund market concentration and the uninformed investors' market share

To simulate the private signal an investor observed, we randomly draw a private signal for each informed investor from the log-normal distribution with $E(\epsilon) = \overline{v}$, and $Var(\epsilon_i) = 0.1$. We calculate the signal concentration using the size-weighted Theil-T index of private signal accuracy level. Recall that the uninformed investors have no private information. We define the Theil-T index on informed investors. The Theil-T is the entropy-based inequality measurement. It is commonly used in labor economics to measure income inequality. See the discussion by Cowell (2000) and Foster (1983). Here, the Theil-T for private information accuracy is the following.

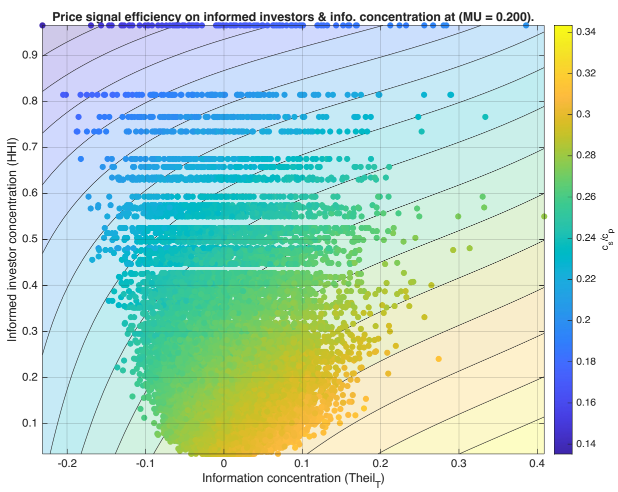
$$T_T = \sum_i M_i \frac{\sigma_{e,i}^{-2}}{\overline{\sigma}_e^{-2}} \ln\left(\frac{\sigma_{e,i}^{-2}}{\overline{\sigma}_e^{-2}}\right) \tag{25}$$

where $\overline{\sigma}_e^{-2} = \frac{1}{I}\sum_i \sigma_{e,i}^{-2}$ is the average price signal precision, and M_i is the investor's market share. This Theil-T measure can be highly negative if a small investor has a strong signal while others are mostly uninformative. Conversely, it can be extremely positive if a large investor holds a great signal under the same conditions. While this measure depends on market size structure, it reveals whether information is concentrated with large or small investors.

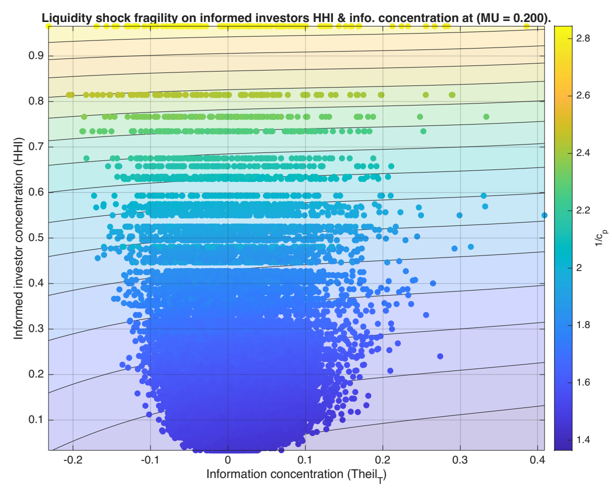
Next, we calculate the individual demand function parameter based on equations (12) and (14) using the fixed point algorithm. We first guess the aggregate trading sensitivity $\hat{c}_p$, individual signal trading sensitivity c_s^i, and individual prior trading sensitivity c_0^i. Then we calculate the individual price signal precision $\sigma_{s_p,i}^{-2}$, individual ex-post variance $Var(v \mid s_i, s_p)$, individual price impact λ_i and demand shrinkage λ_i. Then we calculate the individual demand function parameter, c_0^i,c_s^i, and c_p^i. After that, we aggregate the individual demand function into the aggregate parameters as defined in (6). Finally, we calculate the difference between the new calculated parameters and the initial guess and repeat the previous steps until the difference is small enough.

4.2 The market concentration and the signal concentration to the price fragility

Our first focus in comparative statics is to examine how investor concentration affects the fragility of asset prices. Previously, we found that large investors enhance market efficiency in conveying information but increase vulnerability to liquidity shocks. To illustrate this, we begin with Q1 2010, where uninformed investors held a 20% market share. We then change the size distribution of informed investors while keeping the concentration of information constant. Our goal is to examine how asset prices are vulnerable to liquidity shocks and how the price informativeness of fundamentals changes with varying concentrations of informed investors.

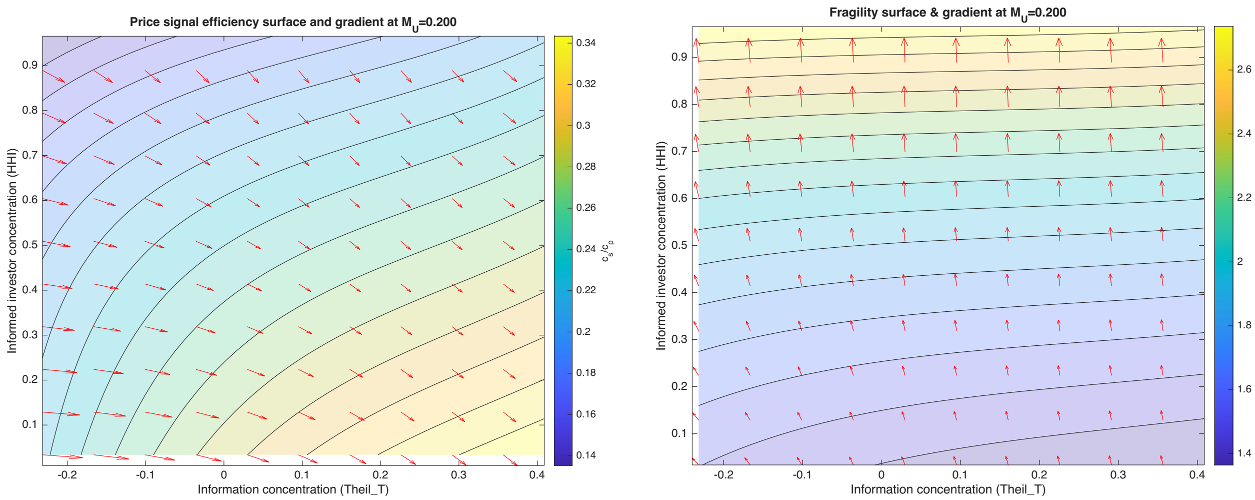


(a) Price signal efficiency: $\hat{c}_s/\hat{c}_p$



(b) Liquidity shock fragility: $1/\hat{c}_p$

Figure 4: Price signal efficiency $\hat{c}_s/\hat{c}_p$ and liquidity shock fragility $1/\hat{c}_p$ on informed investors HHI and information concentration Theil-T at $M_U = 20\%$



(a) Price signal efficiency gradient: $\hat{c}_s/\hat{c}_p$ (b) Liquidity shock fragility gradient: $1/\hat{c}_p$

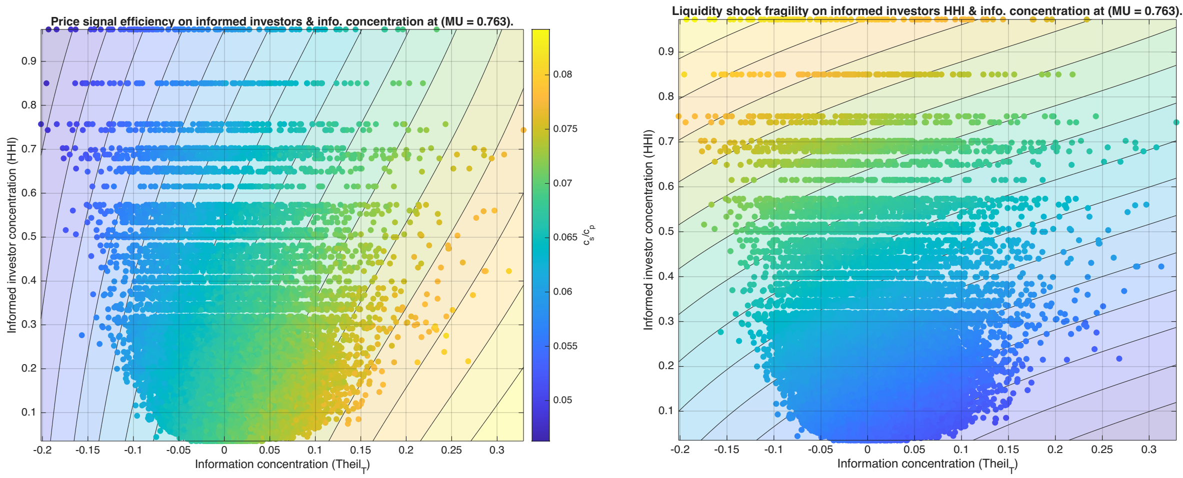
Figure 5: Gradient of Price signal efficiency $\hat{c}_s/\hat{c}_p$ and liquidity shock fragility $1/\hat{c}_p$ gradient on informed investors HHI and information concentration Theil-T at $M_U = 20\%$

Figure 4 shows the result of price signal efficiency $\hat{c}_s/\hat{c}_p$ (figure 4a) and price fragility on liquidity shock $1/\hat{c}_p$ (figure 4b) on informed investor concentration HHI and information concentration Theil-T. The dots in this figure are the simulation points, and the counter plot is 3rd third-order polynomial fitted surface of the simulation points. The horizontal axis represents the Theil-T measurement of the information concentration. The zero point of this Theil-T represents that every investor has the same private signal accuracy. The negative Theil-T statistic indicates that large investors have an information disadvantage, while the positive Theil-T statistic represents that large investors have an information advantage. Fixing on an information concentration distribution, we can see that as the market size concentration increases, the price signal efficiency drops, and the liquidity shock fragility increases. This echoes our previous analysis that the price impact of an investor, and thus their market power, will reduce investors' incentive to trade and respond to their signal. And this will make the market less efficient in revealing the fundamental value and be less liquid.

The ownership of information will also play an important role. Also, on Figure 4, if we control for an informed investor's concentration, as large investors have an information advantage, a large positive Theil-T value will improve the price signal efficiency. If the small investors have an information advantage, the larger the information advantage they have, the more the price efficiency will drop. On the other hand, if we fixed the concentration of informed investors, when large investors have an information advantage, the price fragility to liquidity shock will decrease. And when the small informed investors have an information advantage and the large investors have an information disadvantage, the price fragility will increase. This also echoes our previous proposition that better information will facilitate investor trade. And since large investors are more like the price maker, improving their signal accuracy level will help improve the price informativeness and improve the liquidity.

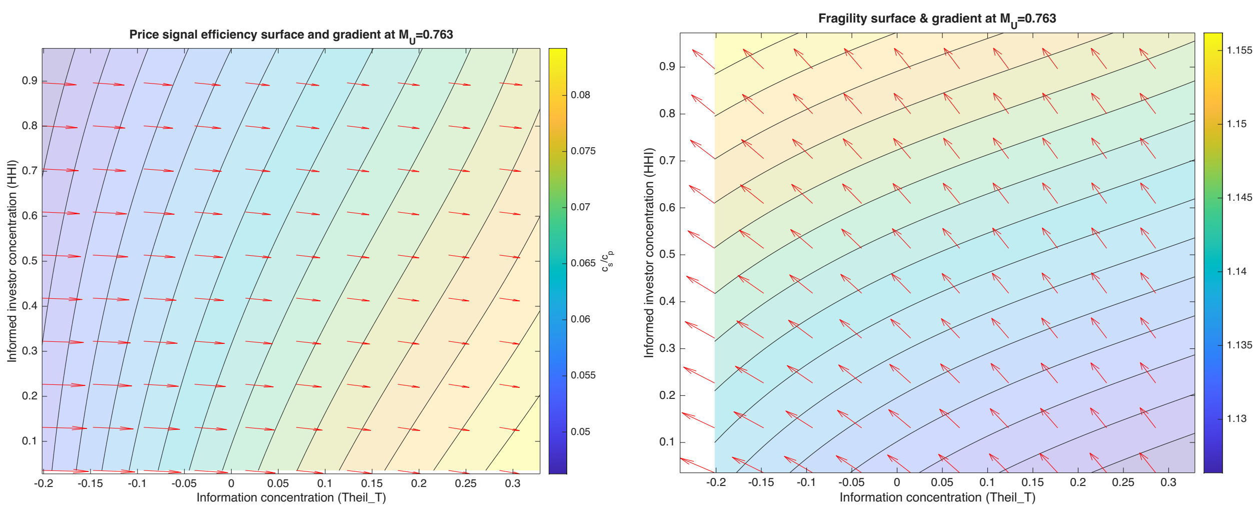
4.3 The price fragility when uninformed investors' size increases

The recent trend in the asset management industry is the increase in ETFs and index funds. In this session, we increase the size of the uninformative investors to examine how this trend affects the price fragility to fundamental and liquidity shocks. In this session, we want to see how the size concentration effect and the information concentration effect play different role when uninformed investors' size changes. In the previous session, we set the uninformed investor's size as 20% to match the Q1 2010 data. In this session, we increase this percentage to match the uninformed investor's market share as in Q1 2024.



(a) Price signal efficiency: $\hat{c}_s/\hat{c}_p$ (b) Liquidity shock fragility: $1/\hat{c}_p$

Figure 6: Price signal efficiency $\hat{c}_s/\hat{c}_p$ and liquidity shock fragility $1/\hat{c}_p$ gradient on informed investors HHI and information concentration Theil-T at $M_U = 75\%$



(a) Price signal efficiency gradient: $\hat{c}_s/\hat{c}_p$ (b) Liquidity shock fragility gradient: $1/\hat{c}_p$

Figure 7: Price signal efficiency $\hat{c}_s/\hat{c}_p$ and liquidity shock fragility $1/\hat{c}_p$ on informed investors HHI and information concentration Theil-T at $M_U = 75\%$

Figure 6 shows the result after we increase the uninformed investor's market share. Comparing the color bar range with Figure 4, we can see that the price signal efficiency is systematically lower than in the cases of low-informative investors. The liquidity shock is also lower than in the low-informative investor market share cases. This means that the increase in the share of uninformative investors would greatly improve the market liquidity condition, but would decrease the price efficiency in revealing fundamentals.

The size concentration effect The effect of investor size concentration echoes our previous analysis. Holding information concentration constant, higher size concentration among informed investors reduces price signal efficiency and increases asset price fragility to liquidity shocks. Comparing figures 5a and 7a, we observe that when uninformed investors are significant, the impact of informed investor size concentration diminishes, as informed investors play a minor role in such markets. Regarding liquidity shock fragility, Figures 5b and 7b show that informed investor concentration dominates when uninformed investors are small. Conversely, when uninformed investors are large, market size concentration takes a back seat, and informational effects prevail. This shift occurs because dominant informed investors are primarily concerned with their price impact, driven by their size. As their influence wanes, market information encourages broader trading, amplifying information's role in price dynamics.

The information concentration effect When we change our focus to the information concentration, we want to see how the change of information concentration would help improve the price signal efficiency. Comparing figures 5a and 7a, we can see that making the large investors observe high quality of information is more important when the size of uninformative investors is large. When an uninformative investor's size is small, improving the informative is not dominantly important, as facilitating competition could also effectively improve the price informativeness. To reduce liquidity shock fragility, when the uninformative investors are large, it would be meaningful to improve the large investors' private information. But when the size of uninformed investors is small, it is not helpful to improve the large investors' private information.

5 Conclusion

In this paper, we answer the question of how investors' price impact and information quality distribution shape the asset price and create fragility. We adopt the rational expectation theoretical framework, modeling mutual funds explicitly as strategic price makers who internalize their price impacts, a departure from traditional microstructure literature that typically assumes passive investor behavior.

Our findings indicate that increased market power among large institutional investors significantly reduces market elasticity, leading to diminished liquidity, elevated price fragility, and impaired price efficiency. Conversely, high-quality information concentrated among large investors can partially mitigate these adverse effects by encouraging investors to trade, enhancing market elasticity, decreasing fragility, and improving informational efficiency. But this gives the large investor a larger market power. These theoretical predictions are validated by our comparative statics analyses and simulation results, which illustrate how changes in investor size and information precision concentration will distinctly affect market outcomes.

Our simulation results, using U.S. corporate bond mutual fund data (2010–2024), confirm these theoretical predictions. Conditional on an information distribution, increases in informed-investor concentration reduced price efficiency and magnified fragility. In contrast, when large investors become significantly more informed, they can offset the fragility that comes from size concentration. Further, performance comparison suggests different policy levers are appropriate depending on passive ownership share: reducing informed-investor size concentration works best in low-passive environments; whereas enhancing informational advantages of large active players is more effective when passive ownership dominates.

Our model adds to finance literature by highlighting how strategic trading and informational endowment collectively drive market fragility and inelasticity. These insights point to two distinct policy recommendations: regulators should monitor both ownership concentration and signal quality of large institutional participants—promoting transparency, supporting active managers, and mitigating information dilution as passive investing expands. Ultimately, this research speaks to a central question: in increasingly concentrated and passive markets, how can we preserve price efficiency and stability?

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