Estimating Investor Demand Elasticity with Endogenous Firm Responses

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Abstract

Estimates of investor demand elasticity are biased when firms endogenously respond to demand shocks by timing equity issuance, as observed price changes confound demand-driven price pressure with fundamental improvements. Empirically, firms experiencing mutual fund flow shocks exhibit both higher stock returns and increased equity issuance, supporting this channel. To address this identification problem, I develop a dynamic structural model capturing strategic interactions among firms, mutual funds, and residual investors. Estimating the model via indirect inference, I find a price elasticity of 2.4 for residual investors—higher than previous estimates that ignore firm responses. The higher elasticity, combined with endogenous firm-investor interactions that cause marginal price effects to diminish with shock size, implies more moderate capital misallocation effects.

Keywords: Demand Elasticity, Structural Estimation, Equity Issuance, Market Timing, Mutual Fund Flows, Capital Misallocation
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Introduction

The recent demand-based asset pricing literature (Koijen and Yogo, 2019) highlights that investor demand for stocks is inelastic, suggesting that demand shocks can drive substantial price fluctuations. Meanwhile, on the supply side of the equity market, firms actively time the market when issuing and repurchasing equity, suggesting they strategically respond to demand shocks (Bolton et al., 2013). When stock demand and supply are considered jointly, two questions naturally emerge. First, regarding identification on the demand side: how do endogenous supply variations affect the estimation of demand elasticity? Second, regarding real effects on the supply side: to what extent does inelastic demand, by allowing demand shocks to generate price fluctuations that distort firms' investment and financing decisions, lead to capital misallocation? This paper addresses both questions by developing and estimating a dynamic model of strategic firm-investor interactions.

Stock markets present a unique identification challenge where endogenous firm responses to demand shocks introduce intrinsic omitted variable bias. Consider a decomposition

$$d \log \tilde{P} = d \log \Lambda + d \log P, \tag{1}$$

where a firm's market value $\tilde{P}$ reflects both its *fundamental value* P (capacity to generate future cash flows) and a *price pressure* factor Λ driven by temporary demand shocks. When a positive demand shock raises a firm's stock price through Λ, the firm may respond by issuing equity to invest in capital or reduce debt, thereby enhancing the fundamental value P. Consequently, observed price increases reflect both demand-driven price pressure and fundamental improvement. When instrumenting observed price changes $d \log \tilde{P}$ with an exogenous demand shock, the estimated elasticity conflates the two effects as $d \log P$ and $d \log \Lambda$ are not separately observable. Because $\mathrm{Cov}(d \log \Lambda, d \log P) \neq 0$, the elasticity with respect to Λ—which is crucial for counterfactual analyses—cannot be recovered even with an exogenous instrument.

I directly model strategic firm-investor interactions in a dynamic setting, which allows me to estimate the demand elasticity by separating the price pressure from fundamental improvements and to evaluate the allocative efficiency implications of inelastic demand. By matching impulse responses from mutual fund flow shocks, I estimate an elasticity that is larger than in previous studies because this model attributes a smaller portion of price movements to price pressure. In counterfactual analyses, I find more moderate effects of demand shocks on capital misallocation, driven by two key mechanisms. First, the larger elasticity means smaller price pressures for a given demand shock, reducing firms' incentives to over-invest (under-invest) when price pressures are high (low) and thereby implying more efficient capital allocation. Moreover, as both firms and investors are incentivized to close the gap between market value and fundamental value, marginal price effects diminish rapidly with the size of demand shocks, mitigating price pressure, investment distortions, and misallocation.

Empirically, I estimate impulse response functions (IRFs) (Jordà, 2005) to mutual fund flow shocks (Dou et al., 2022; Chaudhary et al., 2022) to provide evidence on firms' reactions to demand shocks and establish targets for the structural model. A one-standard-deviation flow shock triggers an immediate 1.9% stock price increase with only modest subsequent reversal. Firms respond by issuing equity (0.2% of total assets), increasing cash reserves and capital investment, while reducing leverage, consistent with fundamental value improvements. Heterogeneity analyses point to potential frictions that generate market timing incentives: firms with higher mutual fund ownership, higher Tobin's Q, or greater financial constraints exhibit stronger responses to fund flow shocks.

To understand the interactions between investors and firms when estimating demand elasticity and conducting counterfactual exercises, I propose a dynamic model with three types of market participants, firms, mutual funds, and residual investors, to estimate the key parameters governing their interactions and to understand the mechanisms driving the empirical findings. While impulse responses alone cannot disentangle all the aforementioned forces, incorporating participants' optimization problems introduces additional relevant moments that help discipline the model and achieve identification. The model features a segmented stock market where market clearing determines each firm's *market value* relative to its *fundamental value*, with the gap defined as *price pressure*. Firms maximize their *fundamental value* through dynamic investment and borrowing decisions (Hayashi, 1982; Zhang, 2005; Belo et al., 2019), with the option to issue or repurchase equity at costs that depend on their *market value*. Mutual funds adjust their portfolios to balance risks and returns but face frictions, such as investment mandates or risk management requirements, that prevent them from adjusting holdings freely, making them unable to perfectly absorb the fund flow shocks.

Residual investors, collectively representing all other investors, act as fundamental investors with a downward-sloping demand curve with respect to *price pressure*. Their capacity constraints prevent them from perfectly absorbing mutual funds' position adjustments.

Using indirect inference, I estimate the demand elasticity of residual investors to be 2.4. This is higher than a back-of-the-envelope calculation based on price impacts in this setting, [1] underscoring the importance of a structural model. Intuitively, the simple calculation attributes all price movements to price pressure, whereas the structural model distinguishes these from fundamental improvements. At the estimated parameters, approximately 29% of the initial price response is driven by fundamental improvements. There is considerable heterogeneity across firms in the return decomposition. The fundamental improvement component is larger for smaller firms and firms with higher mutual fund ownership that are more likely to have higher marginal returns to investment.

The model naturally distinguishes between elasticity with respect to fundamental value and elasticity with respect to price pressure, with the latter being significantly larger. As argued in Koijen and Yogo (2019), the logit demand system captures that firm market value and other characteristics predict future returns, leading investors to reduce holdings in large firms, which offer lower expected returns due to lower risk. This relationship holds in my model for fundamental value variations. However, when comparing two firms with identical market values but different compositions of value—one with higher fundamental value, the other with higher price pressure—mutual funds reduce holdings more aggressively for the latter, anticipating larger corrections in expected returns.

To demonstrate these distinctions, I estimate instrumental variable (IV) specifications in the model-simulated economy. When instrumenting *observed price changes* with flow shocks, the IV approach estimates a demand elasticity of around 1.6, closer to the price impact calculation but significantly below the true elasticity of 2.4. This discrepancy occurs because this specification incorrectly attributes all price changes to exogenous demand shocks. In contrast, when instrumenting *price pressure changes* with flow

[1] Price impacts can be defined as changes in prices divided by changes in holdings following Gabaix and Koijen (2022). The price impact here is 1.36 and the implied elasticity is 1/1.36=0.73. Based on the calculation by Gabaix and Koijen (2022) using estimates from Lou (2010), in a similar setting, the price impact is 1.2 and the implied elasticity is 0.8.

shocks, the IV approach correctly recovers the demand elasticity of 2.4. To complete the picture, using productivity shocks to instrument fundamental value changes, I find mutual funds' elasticity with respect to *fundamental value* is 0.6, consistent with elasticity estimates surveyed in Gabaix and Koijen (2022).

Higher elasticity, combined with endogenously decreasing price impact of demand shocks, leads to a more efficient market with more moderate capital misallocation. Following Hsieh and Klenow (2009), Haltiwanger et al. (2018), and Baqaee and Farhi (2017), I calculate aggregate total factor productivity (TFP) as an indicator of allocative efficiency, where higher TFP reflects more efficient capital allocation. I also incorporate heterogeneous firm exposure to aggregate productivity shocks following David et al. (2022) and Choi et al. (2021). In a counterfactual scenario where fund flow shock volatility is reduced by half, aggregate TFP increases by 0.068% relative to the baseline. This improvement in allocative efficiency is comparable to the 0.050% TFP gain from cutting capital adjustment costs in half, though substantially smaller than previous estimates in the literature.

The moderate misallocation effects also reflect rapidly diminishing marginal price effects with the size of demand shocks. When firms face positive price pressure, they issue equity to improve fundamental values, thereby narrowing the gap between market value and fundamental value. Furthermore, potential losses from holding overvalued stocks become more pronounced as price pressure increases, prompting mutual funds to adjust their portfolios more aggressively. Consequently, even with fixed elasticity for residual investors with respect to price pressure, larger mutual fund flow shocks do not translate proportionally into larger price pressures due to strategic responses from both mutual funds and firms.

Related Literature

This paper contributes to several literatures. First, the recent demand-based asset pricing literature highlights the inelastic demand in stock markets. Following the estimation of low elasticity by Koijen and Yogo (2019), the literature has evolved to study interactions among market participants, with Haddad et al. (2021) finding weaker-than-expected strategic reactions among institutional investors. I contribute to this literature by further incorporating firms' supply-side responses to study the real effects of inelastic demand.

The paper most closely related to this one is Choi et al. (2021), who combine a dynamic firm model with the logit demand system estimated in Koijen and Yogo (2019), and find large economy-wide misallocation due to investor demand fluctuations. My approach differs in two key aspects. First, instead of taking the logit demand as given and abstracting away from participants' interactions, I explicitly model investors' optimization problems with equilibrium prices and estimate key parameters. This allows me to distinguish between elasticity with respect to a risk factor (market value) and elasticity with respect to mispricing, emphasizing the economic implications of the latter. Second, rather than attributing all unobserved heterogeneity to demand shocks, I Specifically focus on mutual fund flow shocks as the source of demand shifts, enabling cleaner identification and more precise quantitative assessment.

Fuchs et al. (2023), Davis et al. (2022), and Haddad et al. (2025) point out different theoretical and empirical challenges in identifying demand elasticities considering the interaction across different assets within a portfolio. This paper complements their work by tackling another dimension of interactions: the supply side.

Second, this paper connects to the literature on time-varying financing costs, which has primarily focused on firm-side responses while taking the variations as given. For example, Eisfeldt and Muir (2014) and Begenau and Salomao (2019) study aggregate financing patterns, while Belo et al. (2019) examine the asset pricing implications. Warusawitharana and Whited (2016) make a seminal contribution by using structural models to uncover hard-to-observe misvaluations and their implications on equity issuance. They emphasize misvaluation as a driver of financing cost variability. Empirically, Ma (2019) document how nonfinancial corporations act as cross-market arbitrageurs in their own securities. This paper contributes to this literature by incorporating the demand side of equity (or the supply side of capital), allowing for a detailed examination of the equilibrium forces at play.

Third, I extend empirical research on the price impacts of fund flows by introducing a dynamic equilibrium framework to examine the dynamic responses. Coval and Stafford (2007) and Lou (2010) both study the asset pricing implications of mutual fund flows. Khan et al. (2012), Edmans et al. (2012) and Lou and Wang (2018) empirically document the effects of flow-induced tradings on firm fundamentals. Chinco and Sammon (2024) and Sammon and Shim (2024) identify passive funds and find that firms' supply is key in clearing passive demand. A related literature examine sentiment-based explanations, some examples include Baker and Wurgler (2003), Frazzini and Lamont (2008), Polk and Sapienza (2009), and Chiu and Kini (2014). The mutual fund sector and their incentives to hedge against flow shocks in this paper are a direct extension of Dou et al. (2022).

Fourth, a recent literature featuring the combination of supply and demand in segmented bond markets (Vayanos and Vila, 2021), while I focus on the equity side. Some recent examples include Siani (2022) and Coppola (2025). The equity market features a unique direct feedback loop: firm issuance decisions directly influence transaction prices of new equity through their impact on fundamental value.

Finally, this paper contributes to the literature on how firm operations are influenced by investor ownership. While previous studies primarily emphasize the effects of ownership on governance, I examine the option value derived from opportunities to issue or repurchase equity at favorable prices due to mutual fund ownership. For example, Derrien et al. (2013) study the relationship between investor horizon and corporate policies, and Aghion et al. (2013) study how institutional ownership affects innovation. My analysis extends this literature by highlighting how mutual fund ownership can drive firm decisions through price dynamics and capital market timing.

The remainder of the paper is organized as follows. Section 1 introduces data, presents the empirical results, and conducts heterogeneity analyses to provide targets and initial guidance for the model. Section 2 presents a simple two-period model to illustrate the key mechanisms. Section 3 extends the model to a dynamic setting and defines the equilibrium. Section 4 discusses the calibration and estimation results. Section 5 analyzes the policy functions and key mechanisms. Section 6 conducts counterfactual experiments. Finally, Section 7 concludes the paper.

1 Data and Empirical Findings

This section presents empirical findings that both motivate and serve as estimation targets for the model. I document the impact of mutual fund flow shocks on stock prices and equity issuance. The impulse response analysis reveals demand-side frictions and highlights how firms endogenously respond to price movements, underscoring the importance of incorporating firm actions in demand elasticity estimation.

1.1 Data Sources

Mutual fund holdings data are from CRSP Survivor-Bias-Free US Mutual Fund Database. I focus on mutual funds with domestic equity holdings (CRSP style code starting with "ED" or "M"). Since holdings data are only available at quarterly frequency in earlier years and are more consistent at quarterly freqency in later years, I aggregate returns and total net assets (TNA) to quarterly level. Following Elton et al. (2001), I require the lagged TNA to be larger than \$15 million. The final sample is from 2003Q1 to 2021Q4. There are on average 3966 distinct mutual fund portfolios in each quarter and there is a growing number of mutual funds over time.

Firm characteristics are from CRSP/Compustat Merged Database. Section A.1 provides a detailed description of variable construction.

1.2 Mutual Fund Flow Shocks

Following Dou et al. (2022), for each mutual fund m in period t, flows are calculated by

$$\text{Flow}_{m,t} = \frac{\text{TNA}_{m,t} - \text{TNA}_{m,t-1} \times (1 + R_{m,t})}{\text{TNA}_{m,t-1}}$$

To extract flow shocks $\hat{\eta}_{m,t}$, for each T-quarter rolling window (here $T = 16$), I regress flows on fund and portfolio characteristics $\mathbf{X}_{m,t}$:

$$\begin{aligned}
\text{Flow}_{m,t} &= \mathbf{X}_{m,t}\boldsymbol{\beta}_\tau + \eta_{m,t} \quad \text{for } t = \tau + 1, \tau + 2, \ldots, \tau + T - 1, \\
\hat{\eta}_{m,\tau+T} &= \text{Flow}_{m,\tau+T} - \mathbf{X}_{m,\tau+T}\hat{\boldsymbol{\beta}}_\tau
\end{aligned}$$

The fund characteristics include lagged flow, fund excess return relative to the market return, and the portfolio characteristics are value-weighted characteristics in the Fama-French five-factor model (i.e. log market equity, book-to-market ratio, profitability, investment, and market beta) (Fama and French, 1993). The portfolio characteristics have significant predictive power and are time-varying as is shown in Figure A.1.

Then I calculate the idiosyncratic component of the flow shocks $f_{m,t}$ (with a slight abuse of notation) by regressing $\hat{\eta}_{m,t}$ on time and fund fixed effects to remove potential common factors

$$\hat{\eta}_{m,t} = \alpha_m + \delta_t + f_{m,t}. \tag{2}$$

Let $S_{i,m,t}$ denote the the number of shares of firm i held by fund m, firm-level shock $f_{i,t}$ is calculated by

$$f_{i,t} = \frac{\sum_m S_{i,m,t-1} f_{m,t}}{\sum_m S_{i,m,t-1}}. \tag{3}$$

After aggregating flow shocks to firm level, I standardize flow shocks for easier comparison.

1.3 Firm Responses

The mutual fund flow shocks are constructed using rolling window regressions with one-step ahead predictions, yielding the final sample period from 2007Q1 to 2021Q4. Following Eisfeldt and Muir (2014), Net Equity Issuance (NEI) is defined as Sale of Common and Preferred Stock net of Repurchase of Common and Preferred Stock and Dividends[2].

Table 1 presents the summary statistics of the firm panel. Mutual funds hold 24.6% of firm equity on average, with large variations across firms and time. Net equity issuance is positive on average (0.94% of total assets) and exhibits large heterogeneity, with firms engaging in substantial issuances and repurchases. As a validation check, I construct an alternative equity measure using book equity changes (total assets net of retained earnings and total liabilities), which exhibits patterns similar to the baseline cash flow-based NEI measure.

Table 1 Here

I estimate the following local projection in the spirit of Jordà (2005)

$$\Delta y_{i,t+h} = \alpha_i + \delta_t + \beta_h f_{i,t} + X_{i,t-1} + \varepsilon_{m,t+h} \text{ for } h = 0, 1, \ldots, 4, \tag{4}$$

where control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s^M_{i,t-1}$ and lagged firm characteristics: log market equity, log book-to-market ratio, cash scaled by asset, and investment. β_h can be interpreted as the $h-$quarter ahead impulse response from the mutual fund flow shocks. The coefficients are plotted in Figure 1. The shaded area indicates 90% pointwise confidence bands using standard errors clustered at firm level.

[2]Compustat item `sstk - prstkc - dv`

Figure 1 Here

In panel A, a one-standard deviation flow shock leads to a 1.9% stock price increase. This price impact suggests constraints on both mutual funds and other investors. When an unconstrained mutual fund receives unexpected inflows, it does not need to scale up its holdings, avoiding positive price pressure. Similarly, if other investors were unconstrained, they should be able to absorb the excess demand from unexpected mutual fund flow shocks. Instead of an immediate price correction, the price reversal in subsequent quarters are much smaller than the initial impact.

Panel B plots the impulse response of mutual fund holdings. On impact, mutual fund holding raises by 1.4%. Following Gabaix and Koijen (2022), the price impact, defined as change in prices divided by change in quantities, is 1.36, which in turn implies a pooled elasticity of 1/1.36=0.73. This number is broadly in line with the elasticity calculated by Gabaix and Koijen (2022) using estimates from Lou (2010). However, as is argued below in Section 3, this back-of-the-envelope calculation is a weighted average of several parameters and lacks clear economic interpretation for counterfactual analysis. In terms of dynamics, mutual funds gradually increase their holdings over the subsequent two quarters rather than making a one-time adjustment. This finding suggests that mutual funds aim to avoid price pressures and prefer a gradual adjustment.[3]

Panels C and D demonstrate that firms do react to these price impacts by issuing equity. The size of NEI (a cash flow measure) is 0.2% of total assets, which is corroborated by the growth of total assets (a balance sheet measure). This firm response highlights the identification challenge. Even if the initial flow shocks are plausibly exogenous, firms' optimal financing responses generate endogenous changes in fundamental value. Since equity issuance can fund investment or reduce leverage, thereby increasing future cash flows or reducing risks, part of the persistent price increase may reflect improved fundamentals rather than pure price pressure. This complicates the interpretation of demand elasticities.

Table 2 presents the response on impact ($h = 0$ in equation (4)) on additional firm-level variables. Columns (1) and (2) provide further validation for the baseline results on equity issuance. In Column (1), book equity increases by about 0.1%. In Column (2),

[3]Note that this is not due to persistent $f_{i,t}$ since the AR(1) coefficient of $f_{i,t}$ estimated following Han and Phillips (2010) is only 0.017. Also, $f_{i,t-1}$ is always controlled for in the regressions.

when focusing on Sale of Common Stock and apply the 2% market equity filter following McKeon (2015), the estimate (0.16%) is slightly smaller than the baseline specification (0.2%) since the share repurchases are excluded. As expected from equity issuance, cash stock goes up in Column (3), while physical capital rises by 0.2% (Column (4)), indicating investment in productive assets. Column (5) shows that leverage decreases by 0.03 percentage points, reducing risks. Moreover, since the leverage decline is smaller than the asset increase, firms are increasing debt financing, possibly with the help of increased collateral capacity.

Table 2 Here

1.4 Heterogeneity Analysis

1.4.1 Positive and Negative Flow Shocks

While NEI is positive on average, Table 1 shows that there is a significant portion of observations with negative NEI, reflecting net repurchases. Do firms respond to flow shocks differently when faced with positive and negative price pressures? To test for such asymmetry, I interact $f_{i,t}$ with two dummy variables, each indicating whether flow shocks are positive or negative.

Table 3 shows the response on impact ($h = 0$ in equation (4)) for positive and negative flow shocks. Column (2) shows that the price impacts are roughly symmetric. However, share repurchases following negative flow shocks are weaker than share issuances following positive shocks. This is consistent with the fact that share repurchases, as a form of payout, are generally smaller than share issuances. Despite the asymmetry, the results demonstrate that firm managers actively respond to price pressures in both directions, exploiting both temporary overvaluations through issuance and undervaluations through repurchases.

Table 3 Here

1.4.2 Active and Passive Funds

Based on fund classification information from WRDS, I separately calculate flow shocks for active and passive funds, with detailed construction and properties described in Section A.1.1. On average, passive and active funds own 9% and 15% of firm equity, respectively. After removing time fixed effects, the correlation between the two shocks is only 0.07. This low correlation provides supporting evidence for the exogeneity of flow shocks, as it suggests that fund flows are not common reponses to firm fundamentals.

Figure 2 presents impulse response functions of firm returns to active and passive mutual fund flow shocks ($f_{i,t}^T$ for $T \in \{\text{Active}, \text{Passive}\}$). Despite similar standard deviations (0.362 versus 0.364), active and passive flow shocks generate different return responses. Passive fund flow shocks lead to a 2.0% contemporaneous return jump, nearly double the 1.1% response to active fund flow shocks. The subsequent reversals follow a similar pattern: passive fund flow shocks lead to a -0.5% reversal compared to a more moderate -0.25% reversal for active fund flow shocks.

Figure 2 Here

Passive funds typically operate under strict mandates, so unexpected AUM increases mechanically translate into heightened demand for constituent stocks. However, active funds should theoretically be able to avoid exerting positive price pressures on their holdings. Two factors likely explain why active funds still generate significant price pressures. First, active funds face portfolio constraints that limit their trading flexibility such as dividend reinvestment requirements (Schmickler and Tremacoldi-Rossi, 2022), benchmark tracking constraints (Kashyap et al., 2021), and client redemption pressures (Edmans et al., 2012). The weaker return responses relative to passive funds likely reflect these less stringent but still effective constraints. Second, as documented by Chinco and Sammon (2024), some nominally active funds are in fact index-tracking. Consequently, the impulse responses potentially reflect a mixture of truly active and passive investment strategies.

1.4.3 Firm Characteristics

To examine whether the baseline effects vary across firm types and provide suggestive evidence on mechanisms that are important for the model, I estimate the baseline specification (4) across subsamples based on key firm characteristics. Within each 2-digit SIC industry, I split the sample at the median of three lagged variables: mutual fund ownership, Tobin's Q, the size-age (SA) index (Hadlock and Pierce, 2010). Table 4 reports the return and NEI responses on impact ($h = 0$).

Table 4 Here

Panel A shows that firms with higher mutual fund ownership mechanically exhibit stronger responses in both returns and NEI. In Panel B, firms with higher growth potential (high Tobin's Q) demonstrate stronger responses across both dimensions. Return responses are twice as strong for the high-Q firms. Low-Q firms show minimal reaction to price pressures through equity issuance, consistent with their reduced need for external financing to fund expansion opportunities. While part of this pattern refrelcts the ownership channel as high-Q firms attract more mutual fund investment (28% versus 23%), this modest difference in ownership cannot fully account for the observed differences.

Panel C presents the results for subsamples partitioned by financial constraints. More financially constrained firms (high SA Index) have weaker return responses. This partly reflects mutual funds' tendency to avoid riskier, financially constrained firms, which is evident as high-SA firms average only 20% mutual fund ownership compared to 30% for their low-SA counterparts. Consistent with Panel A, the lower institutional ownership naturally reduces these firms' exposure to fund flow shocks. Despite the weaker return responses, high-SA firms react more aggresively through equity issuance. This apparent contradiction makes economic sense: when borrowing capacity is limited, equity markets become a critical channel for capital accumulation, making these firms particularly responsive to issuance opportunities (Frank and Sanati, 2021).

1.5 Additional Tests

Section A.2 presents several robustness checks. To address potential concerns about unobserved industry-driven flows and cross-industry substitution (Chaudhary et al., 2022), I include industry-by-time fixed effects and obtain qualitatively similar results. I also examine the sensitivity of the baseline results to alternative NEI definitions. First, excluding dividend payments from the baseline mesaure yields virtually identical findings. This is expected given that dividends are less volatile than stock issuances and repurchases. Second, I construct Gross Equity Issuance using the 2% market equity cutoff by McKeon (2015) and find similar results. While this definition offers certain advantages, I do not adopt this specification as the baseline because the cutoff cannot be applied to equity repurchases and that other forms of stock issuance also represent costly equity financing[4]. Finally, I explore how firm size influences both the magnitude of return and NEI responses, as well as the levels of issuance and repurchase activity.

Section A.3 report more properties of mutual fund flow shocks.

2 A Two-Period Model

To illustrate the mechanisms in a simple setting, I present a two-period model with minimal ingredients and near closed-form solutions. There are three types of agents: a firm making investment decisions, a mutual fund and a continuum of residual investors trading the firm's equity. Guided by empirical evidence, the model's core mechanism focuses on how exogenous fund flow shocks affect asset prices when financing constraints limit residual investors' arbitrage capacity. These price movements influence the firm's equity issuance costs, leading to changes in fundamental values that feed back into investor demand.

The model delivers three important properties. First, the comparative statics highlight the identification challenge: even with perfectly exogenous demand shocks, endogenous firm responses bias estimates of demand elasticities. Second, efforts by both investors and the firm to trade against price pressure attenuate price responses, limiting the real effects of demand shocks. Finally, the notion of demand elasticity depends on the source of price changes, as different sources have different implications for expected returns.

2.1 Model Setup

There is a firm, a mutual fund, and a continuum of residual investors. The timeline is as follows. In the first period, the firm first chooses investment, then the mutual fund decides its portfolio allocation, and finally the residual investors trade to clear the market. Absent frictions, residual investors would trade to ensure the firm is priced at its fundamental value P. However, when the mutual fund experiences a demand shock, the residual investors' limited trading capacity prevents full price correction, causing the market value $\tilde{P}$ to deviate from P. The ratio $\Lambda = \tilde{P}/P$ measures the price pressure

[4] For more discussions, see Huddart (1994), Fama and French (2005), Belo et al. (2019), and Sammon and Shim (2024), among others.

and determines the issuance cost for the firm and returns for the mutual fund. In the second period, the firm produces output and distributes all profits.

The firm. The firm has initial capital K and therefore production K^α, where $\alpha \in (0,1)$. With full depreciation, investment I becomes next-period capital K' as in (6). Net income E equals production minus investment, given by (7). When $E < 0$, the firm issues equity to cover the shortfall, incurring cost Ψ in (8). The cost decreases in price pressure Λ, as higher prices allow the firm to raise the same funds by issuing fewer shares. The firm maximizes its value V in (5), the sum of current and discounted future payouts. Payout in the first period equals net income minus any issuance cost. The present value of future payout is the expected value of next-period production $A'K'^\alpha$ discounted by the stochastic discount factor (SDF) M', where A' is a productivity shock with $\log A' \sim \mathcal{N}(0, \sigma_a^2)$.

$$\max_I \quad V = E - \mathbb{1}_{\{E<0\}}\Psi + \mathbb{E}[M'A'K'^\alpha] \tag{5}$$

$$\text{s.t.} \quad K' = I \tag{6}$$

$$E = K^\alpha - I \tag{7}$$

$$\Psi = \frac{c_h}{2}\left(\frac{E}{\Lambda K}\right)^2 K \tag{8}$$

This setup yields some convenient simplifications. The ex-dividend price

$$P = \mathbb{E}[M'A'I^\alpha] = \beta I^\alpha \tag{9}$$

depends only on $\beta \equiv \mathbb{E}[M'A']$, not on the SDF or productivity shock separately. Combined with full profit distribution and no trading in the second period, this simplifies the return calculation:

$$R = \frac{V'}{\tilde{P}} = \frac{A'I^\alpha}{\Lambda\beta I^\alpha} = \frac{A'}{\beta\Lambda} \implies \log R = \log A' - \log\beta - \log\Lambda. \tag{10}$$

Consequently, expected log return $\mu = \mathbb{E}[\log R]$ is independent of investment I, and the log return variance $\sigma^2 = \mathrm{Var}(\log R) = \sigma_a^2$ is independent of both investment I and price pressure Λ.

The mutual fund. The mutual fund chooses its portfolio weight ϕ to maximize its mean-variance preferences over log returns, as in (11), where γ is the risk aversion parameter and r_f is the risk-free rate. The fund also faces a quadratic adjustment cost with parameter c_ϕ, capturing benchmarking incentives tied to a target portfolio weight $\bar{\phi}$.

$$\max_{\phi} \quad \phi(\mu - r_f) - \frac{\gamma}{2}\phi^2\sigma^2 - \frac{c_\phi}{2}(\phi - \bar{\phi})^2 \tag{11}$$

Let Ω denote the fund's size, the share of the firm held by the fund is caculated as $s^{M'} = \phi\Omega/\tilde{P}$.

Residual investors. There is a continuum of one-period living residual investors representing all other shareholders. These investors price firms using the exogenously specified stochastic discount factor and trade accordingly, consistent with the firms' inherited preferences. Absent financing costs, they would trade to ensure that each firm's market value equals its fundamental value. However, financing constraints limit their arbitrage capacity. When mutual funds increase (decrease) their holdings, possibly due to positive (negative) flow shocks, residual investors cannot adjust their positions sufficiently, creating temporary overvaluation (undervaluation).

Residual investors begin with shares s^R and choose new shares $s^{R'}$. Recognizing the firm's fundamental value P and given the market price $\tilde{P}$, they act as fundamental investors aiming to trade toward fundamental value. Their limited trading capacity is captured by a quadratic adjustment cost with parameter c_r. They solve:

$$\max_{s^{R'}} \quad s^{R'}(P - \tilde{P}) - \frac{c_r}{2}\left(s^{R'} - s^R\right)^2 \tilde{P} \tag{12}$$

Market Clearing. Market clearing requires that the total demand for shares equals the total supply,

$$s^{M'} + s^{R'} = 1. \tag{13}$$

Equilibrium. An equilibrium consists of investment I^*, mutual fund portfolio weight ϕ^*, residual investor shares $s^{R'*}$, and market price pressure Λ^*, such that

1. Given optimal responses of the mutual fund and residual investors, the firm's investment I^* solves its optimization problem (5)–(8).

2. Given firm investment I^* and optimal responses of residual investors, the mutual fund's portfolio weight ϕ^* maximizes its objective (11).

3. Given firm investment I^* and fund portfolio weight ϕ^*, the residual investors'

shares $s^{R'*}$ solve their optimization problem (12).

4. Market clearing (13) holds.

2.2 Optimality Conditions

Following backward induction, I start with the optimality conditions of the residual investors, then the mutual fund, and finally the firm.

Residual investors. The residual investor optimality condition is

$$s^{R'} = s^R + \frac{P - \tilde{P}}{c_r \tilde{P}}. \tag{14}$$

Substituting into the market clearing condition (13) yields price pressure as a function of the mutual fund's portfolio adjustment:

$$\tilde{P} = \frac{1}{1 + c_r(s^M - s^{M'})} P \equiv \Lambda P. \tag{15}$$

When $c_r \to 0$, residual investors have unlimited trading capacity. If the firm is overvalued ($\tilde{P} > P$) residual investors short the firm to eliminate price pressure, driving $\tilde{P}$ toward P. The same mechanism applies when the firm is undervalued.

When mutual fund ownership does not change, $s^{M'} = s^M$, no forces push prices away from fundamental values. Even with positive financing costs, there is no price pressure, $\tilde{P} = P$. In contrast, a positive mutual fund flow shock (larger Ω) increases mutual fund ownership to $s^{M'} > s^M$, as portfolio adjustment costs prevent mutual funds from swiftly adjusting their portfolio weights. With finite trading capacity ($c_r > 0$), residual investors cannot fully trade away this price pressure, causing $\tilde{P} > P$.

The mutual fund. Internalizing how its actions affect price pressure, the mutual fund's optimality condition is

$$\phi = \frac{\mu - r_f + c_\phi \bar{\phi}}{\gamma\sigma^2 + c_\phi + \frac{d \log \Lambda}{d\phi}}. \tag{16}$$

The first two terms in the numerator and the first term in the denominator represent the standard risk-return trade-off. The third term in the numerator and the second term in the denominator capture the effects of portfolio mandates. The mutual fund chooses a weighted average of the mean-variance optimal portfolio and the target portfolio $\bar{\phi}$.

The final term in the denominator reflects the strategic interaction with residual investors. Since $\log \Lambda$ enters return via (10), and Λ depends on the mutual fund's choice via (15), the mutual fund internalizes this feedback. The derivative $d \log \Lambda / d\phi > 0$ (proven in Section B.1) implies that increasing portfolio weight ϕ raises the firm's current valuation, which in turn reduces the marginal benefit of further increasing ϕ.

The firm. The firm's optimality condition is

$$\beta \alpha I^{\alpha-1} = 1 + \mathbb{1}_{\{E<0\}} \frac{c_h}{K_0} \left[\frac{-E}{\Lambda^2} - \frac{\Lambda \frac{d\Lambda}{dI}}{\Lambda^4} E^2 \right], \tag{17}$$

where the left-hand side is the standard marginal benefit of investment and the right-hand side is the marginal cost. When $E \geq 0$, the marginal cost is 1 as there is no capital adjustment cost. When $E < 0$, the firm raises equity and incurs issuance costs. As with the mutual fund, the final term reflects that the firm internalizes how investment affects price pressure and issuance costs. The derivative $d\Lambda/dI < 0$ (proven in Section B.1) because higher investment requires supplying more shares, which reduces price pressure by absorbing some of the excess demand, and thereby raising issuance costs.

2.3 Model Properties

To make sure that equity issuance is relevant, I focus on parameter values such that the firm issues equity in equilibrium. The comparative statics in Property 1 and Property 2 are derived under the regularity condition that higher-order feedback effects through $\frac{d\Lambda}{dI} E^2$ are small relative to the first-order effects through E. All proofs and the regularity conditions are in Section B.1.

Property 1 (Source of Bias)**.** *Both equilibrium price pressure Λ^* and fundamental value P^* increase in mutual fund size Ω.*

Property 2 (Mitigating Forces)**.** *When fund size Ω increases, the mutual fund optimally reduces its portfolio weight ϕ^*, and the firm optimally increases investment I^*, both partially offsetting the increase in price pressure Λ^*. Formally,*

$$\underbrace{\frac{d\Lambda^*}{d\Omega}}_{>0} = \underbrace{\frac{\partial \Lambda^*}{\partial \Omega}}_{>0} + \underbrace{\frac{\partial \Lambda^*}{\partial \phi^*}}_{>0} \cdot \underbrace{\frac{d\phi^*}{d\Omega}}_{<0} + \underbrace{\frac{\partial \Lambda^*}{\partial I^*}}_{<0} \cdot \underbrace{\frac{dI^*}{d\Omega}}_{>0}.$$

Proof for Property 1 and Property 2 (Sketch). The equilibrium is a system of two unknowns (I, ϕ) and two equations: the firm optimality condition (17) and the mutual fund optimality condition (16), with Λ given by (15). The comparative statics follow from the implicit function theorem. □

Property 1 illustrates the identification challenge. When price pressure rises due to mutual fund inflows, equity issuance costs fall, encouraging higher investment and improving fundamental value. Consequently, the observed price response reflects both exogenous demand pressure and endogenous fundamental improvements.

Property 2 shows the strategic interactions that attenuate price responses. Higher price pressure reduces expected returns for the mutual fund, leading it to reduce its portfolio weight. At the same time, lower issuance costs incentivize the firm to invest more. Both actions absorb part of the excess demand, thereby reducing price pressure.

This property also has important implications for understanding the real effects of demand shocks. With inelastic demand for residual investors, issuance costs for the firm and benchmarking constraints for the mutual fund allow deviations of market prices from fundamental values for small shocks. However, as demand shocks grow larger, the mitigating forces also become stronger, potentially limiting the magnitude of price pressure and consequent real effects.

Property 3 (Context-Dependent Elasticities)**.** *For the residual investors, the elasticity with respect to price pressure Λ is negative, while the elasticity with respect to fundamental value P is zero. For the mutual fund, the elasticity with respect to price pressure Λ is negative, while the elasticity with respect to fundamental value P is positive.*

Proof (Sketch). The elasticities for residual investors follow directly from their optimality condition (14). For the mutual fund, the elasticity with respect to fundamental value P follows from the optimality condition (16). The elasticity with respect to price pressure Λ is derived by considering an exogenous change in $\log \Lambda$. □

Property 3 highlights that the notion of demand elasticity depends on the nature of price changes. The distinction for residual investors is by construction, as they only trade to correct deviations from fundamental value. However, the distinction naturally arises for the mutual fund as well. When the mutual fund expects a sharp correction in price pressure—a significant reduction in returns—it reduces its portfolio weight. In contrast, a rise in fundamental value does not necessarily reduce returns. In particular, higher fundamental value driven by more supply of equity can absorb some of the price pressure, increasing returns. In more general settings where fundamental value changes for other reasons, which then have different implications for expected returns, the elasticity with respect to fundamental value can be positive or negative[5].

3 Dynamic Model

This section extends the two-period model to a dynamic setting. The main limitation of the two-period model is that the firm side is highly simplified and cannot quantitatively capture the firm's investment, financing, and return dynamics. Therefore, it is difficult to assess the quantitative importance of fundamental value changes versus price pressure in driving empirical price responses, and the resulting implications for demand elasticity and capital misallocation. The dynamic equilibrium framework provides an environment to identify key parameters that would be difficult to estimate from reduced-form impulse responses alone and to evaluate the quantitative importance of the mechanisms.

3.1 Firms

Firms maximize their fundamental value, defined as the infinite sum of discounted payouts, through optimal investment and financing decisions. The costs of equity issuance and buyback depend on the firm's market valuation. When market value exceeds fundamental value, firms face lower equity issuance costs; conversely, undervaluation makes share buybacks less costly.

3.1.1 Technology

Firm i uses physical capital $K_{i,t}$ to produce $Y_{i,t}$:

$$Y_{i,t} = A_t X_{i,t} K_{i,t}^{\alpha}, \tag{18}$$

[5] In the full model in Section 3 below, larger firms have lower expected returns due to lower risk, implying a negative elasticity with respect to fundamental value.

where A_t is the aggregate productivity and $X_{i,t}$ is the idiosyncratic productivity. The logarithm of aggregate productivity $a_t = \log A_t$ follows an AR(1) process,

$$a_{t+1} = (1 - \rho_a)\bar{a} + \rho_a a_t + \epsilon_{a,t+1},\ \ \epsilon_{a,t+1} \sim \mathcal{N}(0, \sigma_a^2), \tag{19}$$

where ρ_a, $\bar{a}$, and σ_a are the persistence, mean, and conditional volatility of the AR(1) process.

Define $x_{i,t} = \log X_{i,t}$ as the logarithm of idiosyncratic productivity, which follows an AR(1) process:

$$x_{i,t+1} = (1 - \rho_x)\bar{x} + \rho_x x_{i,t} + \epsilon_{x,i,t+1}, \tag{20}$$

where ρ_x and $\bar{x}$ are the persistence and mean of the AR(1) process. $\epsilon_{x,i,t+1}$ is an i.i.d. normal shock that follows $\epsilon_{x,i,t+1} \sim \mathcal{N}(0, \sigma_x^2)$, where σ_x is the conditional volatility.

Capital accumulation follows

$$K_{i,t+1} = (1 - \delta)K_{i,t} + I_{i,t}, \tag{21}$$

where δ is the depretiation rate, $I_{i,t}$ denotes investment, and $e^{\eta_{i,t+1}}$ is an i.i.d. capital quality shock.

Convex investment adjustment costs $G_{i,t}$ are given by

$$G_{i,t} = \frac{c_k}{2}\left(\frac{I_{i,t}}{K_{i,t}}\right)^2 K_{i,t}, \tag{22}$$

where cost parameter c_k determines the speed of adjustment.

3.1.2 Debt Financing

Each period, firms issue one-period debt L_t, which is to be repaid at $t+1$ at interest rate r_f. Following Hennessy and Whited (2005), collateral constraint is given by

$$L_{i,t+1} \leq \varphi K_{i,t+1}, \tag{23}$$

where $\varphi \in (0, 1)$ denotes the borrowing capacity. When $L_t < 0$, the firm saves with interest rate $r_s = r_f - \kappa$, where $\kappa \in (0, r_f)$ denotes the wedge between borrowing and saving rate. Finally, $r_l = r_f \mathbb{1}_{\{L_t>0\}} + r_s \mathbb{1}_{\{L_t \leq 0\}}$ denotes the applicable interest rate.

3.1.3 Issuance, Repurchase, and Payout

With corporate taxes τ, the operating profit can be expressed as after-tax sales plus depreciation tax shield, net of investment, investment adjustment costs, and changes in debt financing:

$$E_{i,t} = (1-\tau)Y_{i,t} + \tau\delta K_{i,t} + \tau r_f L_t \mathbb{1}_{\{L_t>0\}} - I_{i,t} - G_{i,t} + L_{i,t+1} - (1+r_l)L_{i,t}. \quad (24)$$

If total operating costs exceed total profits, $E_{i,t} < 0$, firms can raise external equity,

$$H_{i,t} = \max\{0, -E_{i,t}\}, \quad (25)$$

which incurs costs

$$\Psi_{i,t} = c_{h0}\frac{K_{i,t}}{\Lambda_{i,t}} + \frac{c_{h1}}{2}\left(\frac{H_{i,t}}{\Lambda_{i,t}K_{i,t}}\right)^2 K_{i,t}, \quad (26)$$

where c_{h0} and c_{h1} are the fixed and variable issuance cost parameters and $\Lambda_{i,t}$ is the price pressure factor that fluctuates around 1 (an equilibrium outcome defined in Section 3.4). When a firm is overvalued ($\Lambda_{i,t} > 1$), the issuance size $H_{i,t}$ becomes relatively smaller compared to the firm's total market value, making issuance less costly. I adopt a reduced-form specification to capture the empirical relationship in Section 1.4.3, consistent with micro foundations in Baker and Wurgler (2002); Kim and Weisbach (2008); Bolton et al. (2013).

If the operating profit is positive, $E_{i,t} > 0$, following Warusawitharana and Whited (2016), the firm can pay out to shareholders by choosing any combination of dividend $D_{i,t}$ and share repurchase $B_{i,t}$ such that

$$D_{i,t} + B_{i,t} \leq E_{i,t}. \quad (27)$$

Dividend is subject to dividend tax τ_D, and buyback $B_{i,t}$ incurs costs

$$\Phi_{i,t} = \frac{c_b}{2}\left(\frac{\Lambda_{i,t}B_{i,t}}{E_{i,t}}\right)^2 E_{i,t}, \quad (28)$$

where c_b is the repurchase cost parameter. Similar to the argument about issuance costs Ψ, when investor demand is weak and the firm is undervalued ($\Lambda_{i,t} < 1$), firms are more incentivized to repurchase stocks at a lower price.

Finally, the payout $O_{i,t}$ is operating profit minus issuance costs when operating profit is negative, or the combination of after-dividend tax dividend and repurchase net of repurchase costs when operating profit is possitive:

$$O_{i,t} = \begin{cases} E_{i,t} - \Psi_{i,t} & \text{if } E_{i,t} \leq 0, \\ (1-\tau_D)D_{i,t} + B_{i,t} - \Phi_{i,t} & \text{if } E_{i,t} > 0. \end{cases} \tag{29}$$

Following Zhang (2005) I specify the stochastic discount factor (SDF) as

$$\log(M_{t+1}) = \log \beta - \gamma_t(a_{t+1} - a_t) \tag{30}$$

$$\gamma_t = \gamma_0 + \gamma_1(a_t - \bar{a}), \tag{31}$$

where $\bar{a}$ is the long-run mean of aggregate productivity. Constant β determines the level of risk-free rate. Constants $\gamma_0 > 0, \gamma_1 < 0$ captures countercyclical price of risk.

Finally, the firm maximizes its continuation value

$$V_{i,t} = \max_{I_{i,t}, K_{i,t+1}} O_{i,t} + \mathbb{E}_t\left[M_{t+1}V_{i,t+1}\right] \equiv O_{i,t} + P_{i,t}, \tag{32}$$

subject to constraints (18) through (31).

3.2 Mutual Funds

There is one one-period living mutual fund for each firm, holding equity positions and earning a fixed fee based on their AUM. Fund AUM is influenced by returns from equity holdings and exogenous fund flow shocks. Idiosyncratic fund flow shocks introduce cross-sectional heterogeneity in fund sizes, providing the variation needed for identification. Position adjustment costs prevent funds from achieving the optimal portfolio allocations.

A mutual fund i manages its inherited AUM $Q_{i,t}$ by allocating its portfolio weights ϕ_{t+1} in firm i and a risk-free asset to gain portfolio returns $R^M_{i,t+1}(\phi_{t+1}) = R_f + \phi_{i,t+1}(R_{i,t+1} - R_f)$.

Let lower case letters denote the logarithm of their upper case counterparts, the size of the mutual fund evolves following

$$\tilde{q}_{i,t+1} = q_{i,t} + r^M_{i,t+1}.$$

The mutual fund manager will then calculate the fixed fee based on $\tilde{q}_{i,t+1}$.

Following the same setup as the SDF [6], up to a constant scaling factor (e.g. a fixed 2% management fee), the fund manager's discounted payoff is then

$$\frac{\beta}{1-\gamma_m}\mathbb{E}_t\left[\tilde{Q}^{1-\gamma_m}_{i,t+1}\right] = \frac{\beta}{1-\gamma_m}\mathbb{E}_t\left[e^{(1-\gamma_m)\tilde{q}_{i,t+1}}\right]. \tag{33}$$

For tractability, I assume that after the returns are realized and the fund managers collect their fees, mutual fund clients will withdraw the returns from the funds and rebalance their portfolios across mutual funds, so that the AUM for each mutual fund available for investment is the sum of an aggregate component and an idiosyncratic component:

$$q_{i,t+1} = \bar{q} + \omega_{i,t+1}, \tag{34}$$

where $\bar{q}$ is the average size of the mutual fund industry and $\omega_{i,t+1}$ is specific to mutual fund i, denoting its deviation from average size.

The idiosyncratic size deviation $\omega_{i,t+1}$ follows an AR(1) process that captures the persistence of each fund's size

$$\omega_{i,t+1} = (1-\rho_\omega)\bar{\omega} + \rho_\omega\omega_t + \epsilon_{\omega,i,t+1}, \tag{35}$$

where $\bar{\omega}$ and ρ_ω are the long run mean and persistence of idiosyncratic fund size. Idiosyncratic fund size shock $\epsilon_{\omega,i,t+1}$ is drawn from an i.i.d. normal distribution with conditional volatility σ_ω.

The amount of proceeds invested to firm i is the portfolio weight for next period $\phi_{i,t+1}$ multiplied by fund size today $Q_{i,t}$. Divide it by the total market value $\mathcal{V}_{i,t}$, we get the mutual fund ownership for next period:

$$s^M_{i,t+1} = \frac{Q_{i,t}\phi_{i,t+1}}{\mathcal{V}_{i,t}}. \tag{36}$$

[6]With a CRRA preference, the manager's disconted utility is $\beta\tilde{Q}^{1-\gamma_m}_{i,t+1}/(1-\gamma_m)$. Taking the first order derivative with respect to $\tilde{Q}_{i,t+1}$ gives us the marginal utility $\beta\tilde{Q}^{-\gamma_m}_{i,t+1}$. The log marginal utility is therefore $\log\beta - \gamma_m\tilde{q}_{i,t+1}$, consistent with (31).

A standard Taylor approximation yields $r^M_{i,t+1} \approx r_f + \phi_{i,t+1}(r_{i,t+1} - r_f) + \frac{1}{2}\phi_{i,t+1}(1 - \phi_{i,t+1})\sigma^2_{i,t}$, where $\sigma^2_{i,t} = \text{Var}_t(r_{i,t+1})$ is the conditional variance of returns. Given normally distributed returns and dropping the constant terms, the fund manager's discounted payoff can be rewritten as

$$u^M = \phi_{i,t+1}(\mu_{i,t} - r_f) + \frac{1}{2}\phi_{i,t+1}(1 - \phi_{i,t+1})\sigma^2_{i,t} + \frac{1}{2}(1 - \gamma_m)\phi^2_{i,t+1}\sigma^2_{i,t}, \tag{37}$$

where $\mu_{i,t} = \mathbb{E}_t[r_{i,t+1}]$ is the conditional expected return.

Fund managers face two portfolio adjustment constraints. First, managers avoid deviating too far away from targeted positions $\bar{\phi}$ due to investment mandates, risk management requirements, and index benchmarking. This constraint is captured by the portfolio adjustment cost $\frac{c_\phi}{2}(\phi_{i,t+1} - \bar{\phi})^2$, where c_ϕ controls the size of the cost. Second, executing trades is costly, leading managers to spread trades over time (Kyle, 1985). Since the model features one-period living funds, I capture this smoothing incentive by an ownership adjustment cost $\frac{c_s}{2}(s^M_{i,t+1} - s^M_{i,t})^2$, where c_s controls the cost of deviating from previous period's ownership.

Finally, the maximization problem can be written as

$$\max_{\phi_{i,t+1}} \; u^M(\phi_{i,t+1}) - \frac{c_\phi}{2}(\phi_{i,t+1} - \bar{\phi})^2 - \frac{c_s}{2}(s^M_{i,t+1}(\phi_{i,t+1}) - s^M_{i,t})^2 \tag{38}$$

subject to constraints (34) through (37). Importantly, as is analyzed in detail in Section 3.4, conditional returns and volatilities that affect payoff u^M are all functions of the choice variable $\phi_{i,t+1}$.

3.3 Residual Investors

Each firm is paired with a continuum of one-period living residual investor representing all other shareholders. Following Section 2, they solve

$$\max_{s^R_{i,t+1}} \; s^R_{i,t+1}(P_{i,t} - \tilde{P}_{i,t}) - \frac{c_r}{2}\left(s^R_{i,t+1} - s^R_{i,t}\right)^2 \tilde{P}_{i,t}, \tag{39}$$

where constant c_r controls the financing cost magnitude.

The first-order condition gives optimal share holding

$$s^R_{i,t+1} = s^R_{i,t} + \frac{P_{i,t} - \tilde{P}_{i,t}}{c_r \tilde{P}_{i,t}} \tag{40}$$

Rearranging (40),

$$\frac{s^R_{i,t+1} - s^R_{i,t}}{s^R_{i,t}} = \frac{1}{c_r s^R_{i,t}} \frac{P_{i,t} - \tilde{P}_{i,t}}{\tilde{P}_{i,t}}. \tag{41}$$

In other words, $1/(c_r s^R_{i,t})$ is the elasticity with respect to price pressure for residual investors.

3.4 Market Clearing and Price Pressure

By substituting $s^R_{i,t+1}$ and $s^M_{i,t+1}$ into the equity market clearing condition,

$$s^R_{i,t+1} + s^M_{i,t+1} = 1, \tag{42}$$

we get

$$\tilde{P}_{i,t} = \frac{1}{1 + c_r \left(s^M_{i,t} - s^M_{i,t+1}\right)} P_{i,t} \equiv \Lambda_{i,t} P_{i,t}, \tag{43}$$

where $\Lambda_{i,t}$, fluctuating around 1, denotes the degree of price pressure.

3.5 Equilibrium

Let S denote the vector of state variables $(A_t, X_{i,t}, \Omega_{i,t}, L_{i,t}, K_{i,t}, s^R_{i,t})$. With some abuse of notation, the recursive equilibrium is defined as

1. a cum-dividend fundamental value function for firms $V(S)$ (and hence ex-dividend value $P(S)$);
2. a set of policy functions for firms $K'(S), L'(S)$;
3. portfolio holding decisions for mutual funds $\phi'(K', L', S)$;
4. price pressure function for firms $\Xi(S)$;

such that in each period

1. Taking $\phi'(K', L', S)$ as given, the firm chooses $K'(S)$ and $L'(S)$ to maximize $V(S)$

2. Observing K', L', taking $\Xi(S)$ and $V(S)$ as given, mutual funds calculate expected returns and variances and choose portfolio weights $\phi'(K', L', S)$.

3. Given K', L' and $s^{M'}$, residual investors choose $s^{R'}$.

4. Markets clear for each state. Realized price pressures are consistent with $\Xi(S)$,

$$\frac{1}{1 + c_r \left[(1 - s^R) - \frac{\bar{Q}\Omega\phi'\left(K'(S), L'(S), S\right)}{\Xi(S)V(S)} \right]} = \Xi(S) \tag{44}$$

The timing of events within each period is as follows:

1. All shocks are realized and assets are reshuffled among newly established mutual funds.

2. Firms make investment and financing decisions.

3. Mutual funds choose portfolio weights.

4. Residual investors determine their positions.

5. Transactions are executed, markets clear, and prices are realized.

Details of the computation algorithm are provided in Appendix C. Several key features help make this system numerically tractable. First, the sequential nature means early movers only need to form beliefs about late movers' decisions rather than solving the optimization for all potential strategy combinations. Second, firms' investment and borrowing decisions determine both next-period state variables and current-period issuance and buyback decisions. This approach prevents the state space for investors, whose decisions depend on the firm's actions, from becoming unmanageable. Third, given firm and mutual fund actions, residual investors' optimal decisions have closed-form solutions that, combined with market clearing, directly yield the price pressure rule.

Mutual funds calculate the return of firm i by

$$R_{i,t+1} = \frac{\tilde{P}_{i,t+1} + O_{i,t+1}}{\tilde{P}_{i,t}}. \tag{45}$$

While at the optimum, it is still true that

$$V_{i,t} = O_{i,t} + \mathbb{E}_t[M_{t,t+1}V_{i,t+1}] \implies 1 = \mathbb{E}\left[M_{t,t+1}\frac{V_{i,t+1}}{V_{i,t} - O_{i,t}}\right] \tag{46}$$

$\mathbb{E}_t[M_{t,t+1}R_{i,t+1}] \neq 1$ due to the price pressure terms.

The equilibrium return differs from traditional dynamic firm models (e.g., Zhang, 2005), due to stock market segmentation, where each mutual fund and residual investor can only invest in their assigned firm. This segmentation is similar to the preferred-habitat literature on the term structure of interest rates (e.g., Vayanos and Vila, 2021). While residual investors follow the market-wide SDF (31), their trading is constrained by financing costs. Consequently, firm pricing reflects the baseline market-wide marginal utility adjusted by a factor measuring residual investor's marginal financing costs.

4 Calibration and Estimation

This section presents the calibration and estimation of model parameters by targeting data moments. I also employ instrumental variable estimation within the model-simulated economy to illustrate the source and magnitude of the bias from ignoring endogenous firm actions.

To maintain consistency with the empirical analysis, the model is solved at a quarterly frequency. I calculate the model-implied moments by simulating 10 samples and reporting the cross-sample average. Each sample contains 3,000 firms simulated over 1,000 quarters. To mitigate the effects of initial conditions, I discard the first 400 quarters and treat the remaining simulated data as drawn from the economy's stationary distribution.

4.1 Calibration

Table 5 reports the calibrated parameters in the baseline model. To avoid complicating the estimation with an excess of parameters, I calibrate the parameters that do not directly affect the demand and supply dynamics by first estimating them outside of the dynamic model. If a direct estimation is not possible, the parameters are set by matching some selected moments or using values reported in previous studies.

Table 5 Here

Aggregate parameters. The long-run mean of mutual fund size $\bar{q}$ is calibrated such that the average mutual fund AUM is one-third of average firm market value. The inverse of risk-free rate β is set to be 0.99 at quarterly frequency. The risk aversion parameters γ_0 and γ_1 are set to match an average aggregate stock market return of 3% per quarter and an annual Sharpe ratio of 0.35.

Mutual Funds. The persistence and volatility of idiosyncratic flow shocks are directly estimated from data. On average, mutual funds own 20% of a firm. The firm's market value is three times the size of the fund. This implies that targeted position $\bar{\phi} = \bar{s} \times (\bar{V}/\bar{Q}) = 0.2 \times 3 = 0.6$. The risk aversion coefficient γ^M is set to 2.0, close to the median value of 2.5 estimated by Koijen (2014), and also roughly consistent with the targeted position $\bar{\phi}$[7].

Firms. Following Zhang (2005) and Belo et al. (2019), the persistence ρ_x and the volatility σ_x of productivity shocks are set to 0.97^3 and 0.16, respectively. The curvature of the production function α, quarterly depreciation rate δ, corporate tax rate τ are standard parameters, set at 0.65, 0.03, and 0.3, respectively. Following Warusawitharana and Whited (2016), dividend tax rate τ_D is 0.15. The collateral constraint $\phi = 0.8$ and the quarterly saving-borrowing wedge $\kappa = 0.005/4$ follow Livdan et al. (2009); Belo et al. (2019); Choi et al. (2021).

4.2 Estimation

I estimate the seven key parameters that directly affect supply and demand dynamics using indirect inference.

On the firm side, the issuance cost parameters c_{h0} and c_{h1} and the repurchase cost parameter c_b directly determine both the average level of net equity issuance and the reaction of equity issuance to cost changes caused by price pressure. The investment adjustment cost parameter c_k governs the intertemporal Euler equation and implicitly determines both issuance and repurchase decisions.

[7]Absent the position adjustment costs and price impacts, the optimal position of a mutual fund with CRRA utility is $\phi = (\mu - r_f)/(\gamma\sigma^2)$, where $\mu - r_f$ is the risk premium and σ^2 is the variance of returns. With an annual risk premium of 6% and a volatility of 20%, the optimal position is 0.75 when $\gamma = 2$.

For mutual funds, the position adjustment cost parameter c_s determines the size of initial price responses: higher adjustment costs constrain mutual funds from significantly raising their ownership, resulting in smaller price jumps as outlined by (43). This parameter also helps generate the gradual adjustment dynamics in Panel B of Figure 1. Without position adjustment costs, one-period living mutual funds do not take future generations of mutual funds into consideration, leading to sharper position adjustments. Different from the position adjustment cost c_s, the portfolio deviation cost c_ϕ depends on portfolio levels rather than past ownership. This parameter roughly works in the opposite direction of position adjustment costs. In the limit where c_ϕ approaches infinity, mutual fund portfolio ϕ stays constant, and all changes in s^M are driven solely by the fluctuation in their size.

Finally, for given changes in mutual fund holdings, the residual investor financing cost c_r directly controls the size of price pressure in (43). As derived in Section 3.3, the inverse of c_r represents the semielasticity with respect to price pressure.

I use ten target moments for the indirect inference estimation.

The first five moments capture the dynamic interaction between mutual funds, residual investors, and firms. First, I target the IRF of returns at $h = 0$ and $h = 1$[8]. The initial response ($h = 0$) is directly related to the cost parameters. The return response at $h = 1$ captures dynamic adjustments. Stronger return reversals occur when initial reactions are primarily driven by price pressure or when mutual funds pay less effort to smooth their position changes. I focus on the first two periods because the model lacks mechanisms for significant long-term responses, and empirical evidence suggests that longer-term responses are not significantly different from zero. Second, I use the IRF of NEI at $h = 0$. High firm issuance and repurchase costs reduce firms' responsiveness to price pressure. Third, I target the variance of changes in mutual fund ownership share (Δs^M), which governs the extent of active portfolio rebalancing and determines the magnitude of return responses. Fourth, I target the variance of returns. Given the volatility of productivity shocks and fund flow shocks, it reveals market participants' capacity to absorb shocks.

The next five moments discipline parameters related to firm technology and financing.

[8]In the model the IRF of returns is defined as the change in log market value $\Delta \log \mathcal{V}$ for easier comparison and decomposition in Section 4.4. Empirically the IRFs of $\Delta \log \mathcal{V}$ and $\mathcal{R}$ are similar. This is because $\Delta \log \mathcal{V} = \log \left(1 + \frac{\mathcal{V}_{t+1} - \mathcal{V}_t}{\mathcal{V}_t}\right) \approx \frac{\mathcal{V}_{t+1} - \mathcal{V}_t}{\mathcal{V}_t} = (\mathcal{R}_{t+1} - 1)\left(1 - \frac{O_t}{\mathcal{V}_t}\right)$, and that total payout is usually small relative to the market value.

To match the level of NEI, I calculate average NEI conditional on being non-negative, and average NEI conditional on being non-positive.[9]. I also target the regression coefficient of $SALE/K$ on I/K. A large coefficient indicates investment dynamics driven primarily by productivity shocks, while a small coefficient suggests a more important role for fund flow shocks, which affect issuance costs. Finally, I target the mean leverage L/K and the variance of investment rate. Both moments closely reflect financing and investment costs.

Since this model is overidentified, I construct the weighting matrix for the objective function using the influence function approach in Erickson and Whited (2002). Let x denote the data, b denote the vector of parameters, g denote the difference between data and simulated moments, and $\hat{W}$ denote the weighting matrix. The indirect inference estimator of b is then defined as the solution to the minimization of

$$\hat{b} = \arg\min_{b} g(x,b)'\hat{W}g(x,b).$$

Computational details are provided in Appendix C. Table 6 presents the estimation results.

Table 6 Here

Panel A of Table 6 reports the estimated parameters. The key parameter of interest is the financing cost for residual investors, c_r. Since residual investors on average hold 80% of a firm's shares, their elasticity with respect to price pressure can be naively calculated as $\frac{1}{c_r \bar{s}^R} \approx 1.6$, where $\bar{s}^R$ is the average residual investor holding. However, accounting for the full distribution of s^R yields a higher average elasticity, as shown in Section 4.4 below[10]. This is consistent with the empirical evidence provided by Schmickler and Tremacoldi-Rossi (2022).

Panel B of Table 6 compares the moments calculated from the model with those from the data. Despite overidentification, the model fits the data well overall. The

[9]Zero-NEI observations contribute to both averages. Since many observations are small but non-zero, this approach captures NEI levels without imposing arbitrary thresholds for "active" versus "inactive" NEI, which could introduce biases to the extensive margin of NEI. Since the firm side is overidentified, other moments help indirectly identify relevant parameters.

[10]Formally, let $f(s)$ denote the distribution of residual investor holdings, the average elasticity is calculated as $\int \frac{1}{c_r s} f(s) ds$. With a symmetric distribution, Jensen's inequality implies that the average elasticity is greater than $\frac{1}{c_r \bar{s}^R}$.

return reversal at $h = 1$ is stronger than in the data, which is expected given that one-period-living investors generate more immediate and pronounced reactions. The discrepancy is weaker in the longer horizon. For example, the cumulative return from $h = 1$ to $h = 3$ is -0.81 in the data and -1.66 in the model. In Figure 3, the blue solid line plots the model-implied return IRF.

Figure 3 Here

While the standard errors provide initial evidence on local identification, I further investigate the sources of identification by computing the sensitivity matrix of $\hat{b}$ to $\hat{g}(b)$ using $-(G'WG)^{-1}G'W$, where G is the Jacobian, following Andrews et al. (2017). As the raw sensitivity measures are not scale invariant, I standardize the sensitivity matrix by scaling each element with the square root of the ratio of moment variance to parameter variance to facilitate interpretation. Table 7 presents the local elasticities of parameter estimates with respect to the targeted moments, calculated at estimated parameters.

Table 7 Here

Most moments work as expected. For example, stronger return responses imply lower demand elasticity. However, the many non-zero elements in the sensitivity matrix highlight the interdependence of parameters, underscoring both the importance of a structural model and the difficulty of fitting the moments. Several moments react strongly to multiple parameters: the IRF of NEI, the size of issuance, and the variance of returns all respond to changes across most parameters. Similarly, average leverage not only helps identify firm financing parameters, but also strongly affects the residual investor financing cost c_r.

4.3 Return Response Decomposition

Following (43),

$$d\log \tilde{P} = d\log \Lambda + d\log P. \tag{47}$$

The red dashed line in Figure 3 plots the IRF of $\log \Lambda$. The price pressure response (1.33%) is weaker than the return response (1.88%) at $h = 0$ due to improved fundamental value following NEI responses. At longer horizons the two lines closely track each other as firm actions no longer affect fundamental value, and return responses are primarily driven by price pressure. The gap between the observable return response and the unobservable price pressure response is the source of bias in the demand elasticity estimate.

In Table 8, I decompose return responses into changes in price pressure and changes in fundamental value. To explore the heterogeneity across firms, I first sort firms into three equal-sized portfolios based on beginning-of-period capital levels. Within each size portfolio, firms are further divided into two groups based on the median of beginning-of-period mutual fund ownership.

Table 8 Here

In the full sample, 29% of the initial return response is driven improvements in fundamental value, while the remaining 71% is attributed to price pressure. There is substantial heterogeneity across firms. Consistent with the empirical findings in Table 4, firms with high mutual fund ownership exhibit stronger return responses. Looking at the components of the return responses, firms with high mutual fund ownership still experience stronger price pressure responses, but the differences within each size category are smaller. The differences in fundamental value responses are more pronounced. This suggests that mutual funds select to hold firms with higher growth potential that benefit more from reduced issuance costs.

Along the size dimension, small firms experience stronger return responses, again mainly driven by fundamental value improvements. Small firms benefit most from reduced issuance costs while actively expanding. In contrast, for the largest firms with lower marginal returns to investment, rising price pressure only has limited effects on their investment decisions. Price pressure may even increase repurchase costs, potentially lowering fundamental value.

4.4 An Instrumental Variable Estimation

In this section, I estimate the demand elasticity for residual investors and mutual funds using an instrumental variable approach using the model-simulated economy.

To estimate the demand elasticity for residual investors, I need a residual supply shock that is orthogonal to the residual investor demand (40). In the model, fund flow shocks are demand shocks independent of residual investor demand by construction, seemingly satisfying the traditional exclusion restriction. However, as shown in Section 4.3, this approach still yields biased results in our context because we cannot disentangle changes in firm value driven by price pressure Λ from those driven by fundamental value P, introducing inevitable omitted variable bias.

To illustrate this potential bias, I conduct instrumental variable estimation using the model-simulated economy, as reported in Panel A of Table 9. I regress changes in log ownership by residual investors against different measures of price changes, using fund flows as instruments.

Table 9 Here

In columns 1 and 2, the independent variable is changes in log market value $d\log\tilde{P}$. Without instrumenting, the estimate is positive, illustrating the traditional omitted variable bias. When firm fundamentals change, mutual funds endogenously rebalance their portfolios to achieve the optimal return-variance trade-off., so the estimate represents a weighted average of optimization responses by firms, mutual funds, and residual investors. In Column 2, using fund flow shocks as instruments yields a demand elasticity estimate of approximately 1.7.

Columns 3 and 4 use changes in log price pressure $d\log\Lambda$ as the independent variable, which is unobservable in actual data but can correctly remove the endogenous fundamental value changes. Without instruments (column 3), the estimate is already -0.9, reflecting that residual investors reduce holdings in response to positive price pressure to mitigate value deviation. With proper instrumenting, Column 4 estimates the true demand elasticity of 2.4, 40% higher than the estimate in Column 2.

The specification in columns 3-4 remain slightly misspecified. Following (40), the correct specification should use deviations from fundamental value $(P_{i,t} - \tilde{P}_{i,t})/\tilde{P}_{i,t}$ instead of changes in price pressure. Columns 5 and 6 present the estimates using this specification. Both with or without instruments yield similar estimates. This is because fundamental value P cancels out in the numerator and denominator, leaving only price pressure Λ, which does not suffer from the omitted variable bias. The numbers are also close to the estimates in column 4, indicating that the bias from using changes in price pressure is small.

I estimate demand elasticity for mutual funds in Panel B of Table 9. Following Koijen and Yogo (2019), the demand curve is downward sloping with respect to firm market value (rather than price pressure) because larger firms on average have lower expected returns. The demand elasticity estimate thus shows how the size premium is reflected in mutual funds' portfolio choices, which is not directly related to the price pressure. In this case, productivity shocks help firms grow but do not directly affect mutual fund demand, satisfying the exclusion restriction.

Columns 1 to 3 provide the reduced form, first stage, and IV estimates using changes in log market value. The first stage in Column 1 is biased upward. While mutual funds do cut holdings when firms grow bigger, they also increase holdings due to positive fund flow shocks, which rasies the market value through price pressure. With proper instrumenting, the IV estimate in Column 3 is -0.6, close to elasticity estimates surveyed in Gabaix and Koijen (2022). This estimate is still biased because when mutual funds adjust their holdings following productivity shocks, they also create price pressure.

Columns 4 to 6 use changes in log fundamental value, which is unobservable in actual data but can correctly remove the endogenous price pressure changes. Comparing Columns 4 and 6, the bias in the first stage is now small because biases introduced by price pressure are already removed. The elasticity estimate in Column 6 is smaller in magnitude than the estimate in Column 3, suggesting that mutual funds are more sensitive to price pressure increases than to fundamental value increases. This makes sense because the reduction in expected returns from price pressure should be sharper than that from fundamental value increases. Without additional instruments in the model, we cannot separately identify their demand elasticity with respect to price pressure as they are the ones introducing price pressure in the first place.

5 Mechanism

5.1 Firm Optimality Conditions

Let q and μ be the Lagrange multipliers for the capital accumulation (21) and borrowing constraint (23). The first-order conditions with respect to I, K', and L' are

$$-\frac{\partial O}{\partial I} = q \tag{48}$$

$$q = \mathbb{E}\left\{M'\left[\frac{\partial V'}{\partial K'}\right]\right\} + \mu\varphi + \frac{\partial O}{\partial \Xi}\frac{\partial \Xi}{\partial \phi'}\frac{\partial \phi'}{\partial K'} \tag{49}$$

$$\mu - \mathbb{E}\left\{M'\left[\frac{\partial V'}{\partial L'}\right]\right\} = \frac{\partial O}{\partial E}\frac{\partial E}{\partial L'} + \frac{\partial O}{\partial \Xi}\frac{\partial \Xi}{\partial \phi'}\frac{\partial \phi'}{\partial L'}. \tag{50}$$

The left-hand side of (48) represents the marginal cost of investment: investing more reduces current payout. The first two terms on the right-hand side are standard marginal benefits of capital accumulation. More capital increases future production capacity and relaxes the borrowing constraint. The last term reflects the novel firm-investor interaction: firms recognize that their investment decisions affect mutual fund trading through $\frac{\partial \phi'}{\partial K'}$, which in turn influences their cost of capital and payout $\frac{\partial O}{\partial \Xi}\frac{\partial \Xi}{\partial \phi'}$.

Similarly, the left-hand side of (50) represents the marginal cost of borrowing: potentially binding borrowing constraints and future debt repayment. The marginal benefit on the right-hand side includes higher current cash flows, and the effect of borrowing on mutual fund trading and thus payout costs through $\frac{\partial \phi'}{\partial L'}$.

5.2 Policy Functions

In this section, I examine the numerical policy functions to understand the mechanisms driving the quantitative performance of the model.

To understand how mutual fund flow shocks increase fundamental value, Figure 4 plots policy functions over fund size for two sample firms. As the mutual fund's size increases (positive flow shock), it reduces its portfolio weight ϕ' to prevent excessive market value increases that would lower future returns. However, mutual fund ownership $s^{M'}$ still rises due to the adjustment costs, increasing price pressure Λ.

Figure 4 Here

The top panel shows a smaller firm with ample savings. With higher marginal returns to investment and lower equity financing costs from elevated market values, the firm increases both NEI and investment while drawing down cash reserves. Fundamental value rises as productive capital is added for future growth.

The bottom panel shows a larger firm with limited savings. While the mutual fund behaves similarly, the firm is not seeking expansion ($I/K < 0$). Instead, it exploits lower equity issuance costs to raise capital and accumulate savings. Fundamental value rises through increased savings.

Figure 5 plots policy functions over mutual fund ownership for two sample firms. In both panels, without position adjustment costs, optimal mutual fund ownership $s^{M\prime}$ would be independent from current ownership (appearing as a flatline). With position adjustment costs, however, mutual funds avoiding deviating too far from their current ownership s^M. As a result, the ownership policy lies between the flat line and the 45-degree line, creating "mean reversion" where next-period ownership is lower when current ownership is high, and vice versa. This pattern implies that price pressure decreases as current mutual fund ownership rises.

Figure 5 Here

The firm responses differ by type. For the smaller, expanding firm (top panel), higher ownership makes capital more expensive, causing reduced issuance and greater reliance on borrowing, which decreases fundamental value. Conversely, the larger firm seeking to reduce capital benefits from lower price pressure through lower repurchase costs, allowing cheaper share buybacks that increase fundamental value. Also, since lower valuation could benefit repurchasing firms, the average effects of fund ownership (and fund shocks) on fundamental value, and also the implications of demand elasticity estimation, vary significantly across firm groups, as is shown in Table 8.

Finally, Figure 6 illustrates the equilibrium price formation process for a firm seeking to increase investment. Following backward induction[11], the top panel shows equilibrium expected returns and volatility as functions of mutual fund portfolio weights, given optimal firm decisions. When mutual funds increase weights, current price pressure rises, reducing the expected returns. For this firm, conditional volatility also decreases, creating a trade-off between lower returns and lower volatility for mutual funds. However,

[11]The last step where residual investors form their portfolios follows (40).

since the volatility variation is relatively muted, the trade-off between returns and adjustment costs in (38) likely dominates.

Figure 6 Here

Moving backward in the analysis, firm decisions directly affect conditional expected returns and volatility by changing both current and future fundamental values. These changes influence mutual funds trade-offs, which affect price pressure, and feed back into expected returns and volatility. The middle panel shows how returns and volatility depend on firm investment decisions, taking mutual fund portfolio responses as given. The dashed black line indicates current capital level, while the dotted red line shows equilibrium optimal capital for next period. Compared to mutual funds, firm actions have smaller impact on expected returns but larger impact on volatility.

Considering both steps, the bottom panel plots equilibrium price pressure and mutual fund portfolio weights as functions of firm investment decisions. As shown in (43), price pressure closely tracks mutual fund holdings. However, higher price pressure does not automatically translate into lower expected returns. For example, to the left of the peak of returns in the middle panel, increasing capital generates both higher returns and higher price pressure. Higher investment is associated with higher price pressure and cheaper issuance, suggesting the firm invests more than it would if issuance costs were not affected by market valuation. The importance of fundamental value variations is also evident in that, at equilibrium, the firm is 4.3% overvalued yet expected returns remain around 0.7% rather than approximately -4.3%.

6 Counterfactuals

This section presents counterfactual analyses to evaluate how demand shocks affect firm fundamentals and capital allocation. I examine three scenarios: (1) reduced volatility in mutual fund flows, (2) higher residual investor demand elasticity, and (3) lower capital adjustment costs.

6.1 MPK and Capital Misallocation

Following Hsieh and Klenow (2009), Haltiwanger et al. (2018), and Baqaee and Farhi (2017) I measure capital misallocation using aggregate TFP, calculated as $\text{TFP}_{agg} =$

Y_{agg}/K_{agg}^{α}, where Y_{agg} and K_{agg} denote aggregate output and capital, respectively. Higher aggregate measured TFP indicates more efficient capital allocation across firms. In this exercise, I specify the firm-level production function as $Y_{i,t} = A_t^{b_i} X_{i,t} K_{i,t}^{\alpha}$, following David et al. (2022) and Choi et al. (2021), where $b_i \sim \mathcal{N}(1, 0.2)$ captures heterogeneous firm exposure to aggregate productivity shocks. Table 10 presents the percentage changes of aggregate TFP in counterfactual specifications from the baseline.

Table 10 Here

With less friction, firms over-invest (under-invest) less heavily experiencing high (low) price pressures from mutual fund flow shocks. As a result, aggregate TFP improves. In a counterfactual where mutual fund flow shock volatility reduces from 0.21 to 0.09, aggregate TFP increases by 0.068%. When the semi-elasticity of residual investors increases from 1/0.8 to 1/0.7, residual investors respond more actively to price changes, and lower price variation results in a 0.060% TFP gain. Reducing investment adjustment costs from 0.50 to 0.25 yields a 0.050% TFP gain. These results suggest that the productivity gains from mitigating financial market frictions are economically meaningful and comparable in magnitude to those from reducing real investment frictions.

Since one key source of capital misallocation in this model is the NEI responses that promote over- and under-investment, one might conjecture that stronger NEI responses to flow shocks would lead to larger investment dispersion and thus higher capital misallocation. However, this conjecture overlooks two important factors. First, stronger responses can arise from either more financing frictions or fewer real frictions. With the same flow shock volatility, when investment adjustment costs decrease, firms adjust capital more flexibly toward desired levels. This makes NEI responses more pronounced but actually reduces misallocation. Second, the relationship between response strength and misallocation is nonlinear. In the first counterfactual in Table 10, shock volatility falls by more than half (from 0.21 to 0.09), yet the IRF of NEI/K *per standard deviation* of shocks declines less (by 49%). This implies that the *per-unit* response actually increases by 19% ($(({-0.49}+1) \times \frac{0.21}{0.09} - 1 = 19\%)$). Despite stronger per-unit responses, overall misallocation decreases because these amplified responses apply only to smaller shocks, where mutual funds and firms have weaker incentives to counteract the resulting price pressures, limiting the magnitude of the distortions.

6.2 Discussion

In a similar setting, Choi et al. (2021) conduct a similar counterfactual analysis and find much stronger capital misallocation gains when reducing the magnitude of non-fundamental flows volatility by half.

Three mechanical differences that drive this discrepancy. First, the elasticity estimate is higher when accounting for endogenous firm reactions. Higher elasticities implies smaller price impacts. Second, Choi et al. (2021) attribute all investor demand not explained by a linear Fama and French (1993) five-factor system as non-fundamental excess noisy demand. This paper allows more flexibility on the way mutual funds form their portfolios without restricting the demand structure focusing only on plausibly exogenous flow shocks. Third, firms in Choi et al. (2021) are assumed to have more dispersed exposure to aggregate productivity shocks, and are therefore ex-ante more heterogeneous in their MPK. While this paper does not impose such ex-ante heterogeneity, the dispersion in returns, investment rates, changes in mutual fund holdings, and even standard deviation of the level of mutual fund holdings (non-targeted, 22% in model versus 17% in data) closely match the data.

More importantly, as shown in Section 5, strategic interactions in this model cause marginal price effects to diminish rapidly with the size of demand shocks.

First, the model distinguishes between elasticity with respect to fundamental value and elasticity with respect to price pressure, with the latter being significantly larger, as shown in Table 9. Following Koijen and Yogo (2019), the logit demand system captures that firm market value and other characteristics predict future returns, leading investors to reduce holdings in large firms due to their lower expected returns from lower risk. This relationship holds in my model for fundamental value variations. However, when comparing firms with identical market values but different compositions—one with higher fundamental value, the other with higher price pressure—mutual funds reduce holdings more aggressively for the latter, anticipating larger corrections in expected returns.

Second, when firms face positive price pressure, they issue equity to improve fundamental values, narrowing the gap between market value and fundamental value. Consequently, even with a fixed elasticity for residual investors with respect to price pressure, larger mutual fund flow shocks do not translate proportionally into larger price fluctuations due to strategic responses from both mutual funds and firms.

Figure 7 illustrates this mechanism by plotting the initial impulse responses of market value, price pressure, and NEI under different mutual fund flow shock sizes. Panel A shows the IRFs to a one-standard-deviation shock for varying shock sizes. As the volatility of shocks increases, market value responses (blue solid line) also increase, but the marginal increase diminishes very fast. When volatility increases from 0.09 to 0.15, the market value response increases by 54% (0.98% to 1.52%); when volatility increases from 0.15 to 0.21, the market value response only increases by 24% (1.52% to 1.87%). Increasing NEI responses (green dotted line on the right axis) exhibit a similar pattern, suggesting that market value response increases are driven by fundamental value responses due to larger equity issuances. Therefore, the equilibrium price pressure response (red dashed line) increases more mildly, and even decreases slightly when the shock volatility increases beyond 0.24. Panel B shows the corresponding per-unit responses normalized to the baseline shock size ($\sigma_{\omega i} = 0.21$). Consistent with Panel A, the price pressure response (red dashed line) decreases rapidly as mutual funds and firms counteract larger shocks more aggressively.

Figure 7 Here

7 Conclusion

This paper examines the impact of temporary stock price fluctuations on capital allocation among firms by estimating a dynamic structural model using variations from mutual fund flow shocks. Empirically, using cross-sectional idiosyncratic fund flow shocks, I document that these shocks cause an initial jump in stock price with limited reversal, accompanied by a positive response in net equity issuance and a gradual increase in mutual fund ownership. I then propose a dynamic structural model that captures interactions among firms, mutual funds, and residual investors. In the model, trading and financing frictions constrain mutual funds and residual investors. Thus, when mutual funds adjust positions in response to flow shocks, residual investors cannot perfectly absorb these changes, and market clearing implies deviations between market and fundamental values. For firms, higher misvaluation lowers issuance costs, while lower misvaluation reduces repurchase costs. Consequently, shifts in market values feed back into firm operations, further affecting fundamental values.

Using indirect inference that targets the impulse responses, I estimate a high elasticity with respect to misvaluation for residual investors. The results suggest that return responses can be decomposed into fundamental improvements and misvaluation changes. Counterfactual analyses show that high-ownership firms benefit from mutual funds' hedging motives and a larger inelastic mutual fund sector by expanding their capital, while low-ownership firms tend to contract.

This paper focuses on the dynamics following mutual fund flow shocks, estimating a context-specific elasticity that underscores the distinctive role of prices in stock markets. Specifically, it suggests that demand elasticities may vary depending on the drivers of price changes. Future research could follow a similar equilibrium framework to further clarify these elasticities. Additionally, this paper illustrates how equilibrium prices can feedback into the real economy, influencing capital allocation. While the current analysis centers on mutual funds, future research could examine diverse investor types by incorporating broader data on investor holdings. Finally, this paper models individual firms in isolated markets for tractability, but exploring aggregate quantities and prices could reveal meaningful macroeconomic implications.

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Figures

Figure 1: Firm Responses

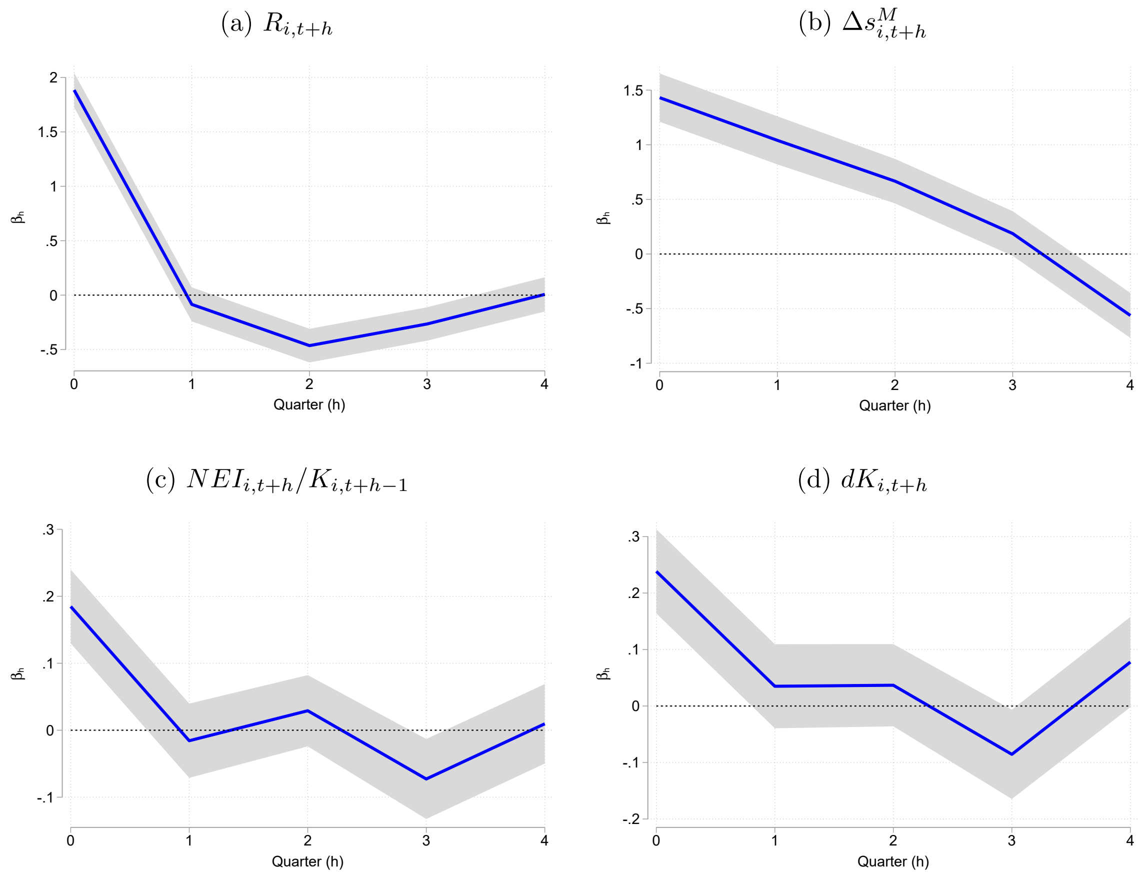
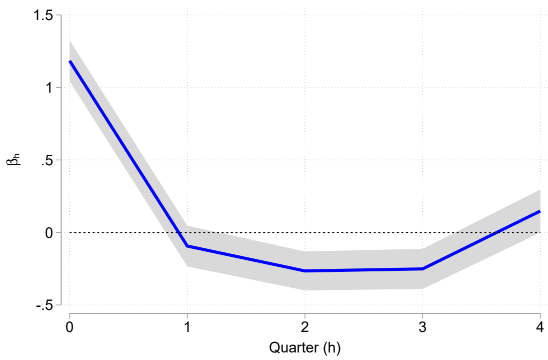


Figure 1 presents impulse response functions of returns, mutual fund holdings, net equity issuance, and investment. The blue solid line plots coefficients β_h from estimating the local projection following Jordà (2005): $\Delta y_{i,t+h} = \alpha_i + \delta_t + \beta_h f_{i,t} + X_{i,t-1} + \varepsilon_{m,t+h}$ for $h = 0, 1, \ldots, 4$. The shaded area indicates 90% pointwise confidence bands using standard errors clustered at firm level. control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s^M_{i,t-1}$ and lagged firm characteristics (log market equity, log book-to-market ratio, cash scaled by asset, and investment). The sample is from 2007Q1 to 2021Q4.

Figure 2: Firm Return Responses to Active and Passive Fund Flow Shocks

(a) Active



(b) Passive

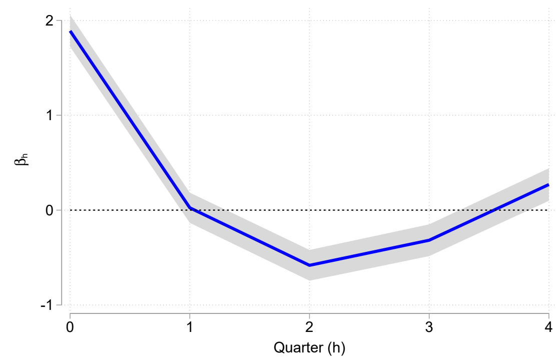


Figure 2 presents impulse response functions of firm returns to active and passive mutual fund flow shocks ($f_{i,t}^T$ for $T \in \{\text{Active}, \text{Passive}\}$). The blue solid line plots coefficients β_h from estimating the local projection following Jordà (2005): $\Delta y_{i,t+h} = \alpha_i + \delta_t + \beta_h f_{i,t}^T + X_{i,t-1} + \varepsilon_{m,t+h}$ for $h = 0, 1, \ldots, 4$. The shaded area indicates 90% pointwise confidence bands using standard errors clustered at firm level. control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s_{i,t-1}^M$ and lagged firm characteristics (log market equity, log book-to-market ratio, cash scaled by asset, and investment). The sample is from 2007Q1 to 2021Q4.

Figure 3: Simulated Return Responses

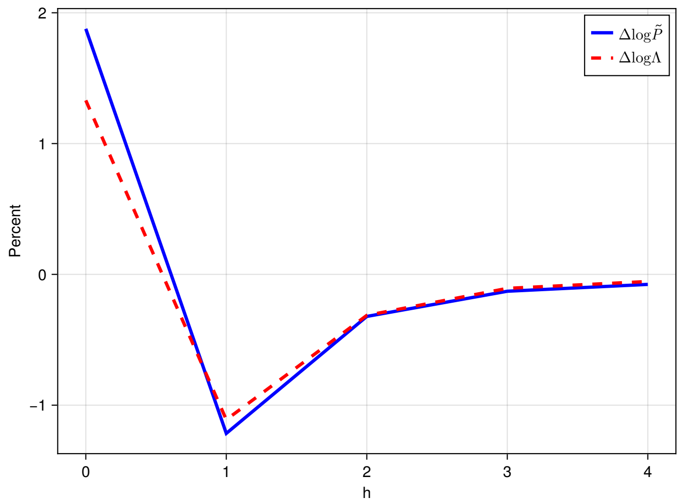


Figure 3 presents return impulse responses simulated in the model. The blue solid line shows the first difference of log market value, while the red dashed line shows the first difference of log price pressure. The responses are averages across 10 simulated panels, where each panel contains 3,000 firms over 1,000 quarters, with the first 400 quarters discarded.

Figure 4: Policy Function Over Fund Size

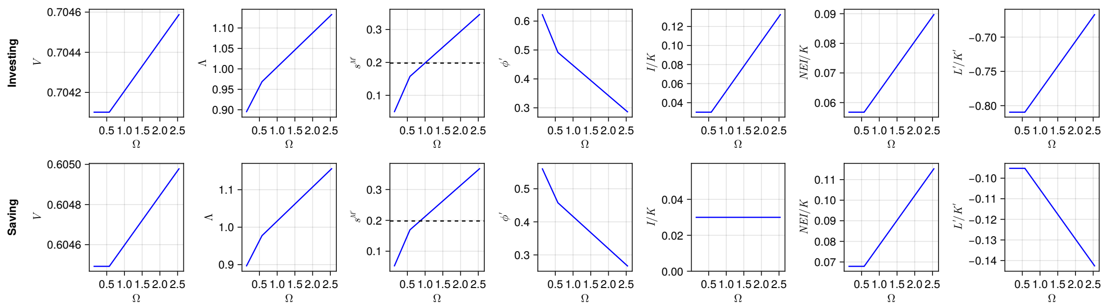


Figure 4 shows how fund flows affect firm policies by plotting policy functions against idiosyncratic fund size from the baseline model at two states. The top (bottom) panel presents a firm using equity issuance to raise investment (accumulate savings). The seven columns are fundamental value V, price pressure Λ, next-period mutual fund ownership $s^{M\prime}$, next-period mutual fund portfolio weight ϕ', investment rate I/K, net equity issuance scaled by capital NEI/K, and next-period leverage L'. The black dashed line in $s^{M\prime}$ shows current mutual fund ownership s^M.

Figure 5: Policy Function Over Mutual Fund Ownership

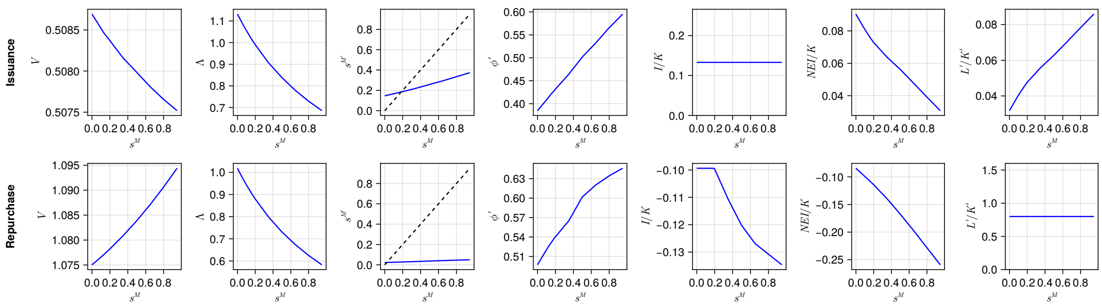


Figure 5 shows how mutual fund ownership affects firm fundamental value by plotting the policy functions against mutual fund ownership from the baseline model at two states. The top (bottom) panel presents a firm issuing (repurchasing) equity. The seven columns are fundamental value V, price pressure Λ, next-period mutual fund ownership $s^{M'}$, next-period mutual fund portfolio weight ϕ', investment rate I/K, net equity issuance scaled by capital NEI/K, and next-period leverage L'. The black dashed line in $s^{M'}$ shows current mutual fund ownership s^M.

Figure 6: Equilibrium Price Formation

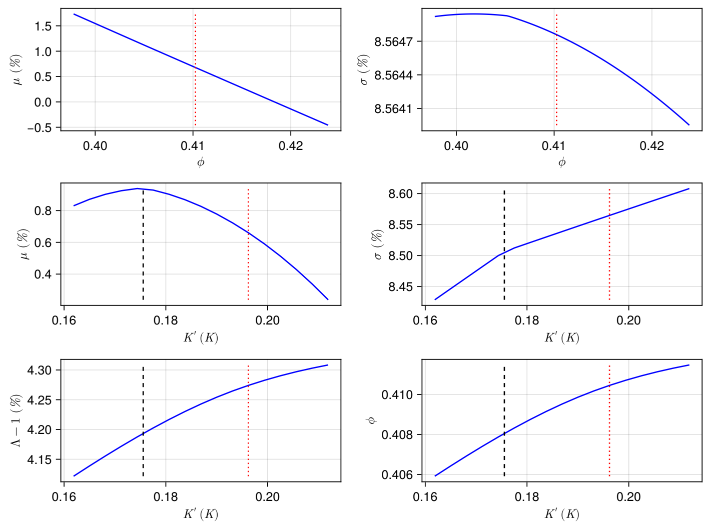


Figure 6 illustrates the equilibrium price formation process for a firm seeking to increase investment. The top panel plots equilibrium expected returns and volatility as functions of mutual fund portfolio weights, given optimal firm decisions. The middle panel plots equilibrium expected return and volatility as functions of the firm's investment decisions, taking optimal mutual fund responses as given. The bottom panel plots equilibrium price pressure and mutual fund holding rules as functions of the firm investment decisions. The dotted red line indicates the mutual fund's optimal portfolio weight in the top panels, and the firm's equilibrium optimal capital for the next period in the middle and bottom panels. The dashed black line indicates the firm's current level of capital.

Figure 7: Responses Under Different Shock Sizes

(a) IRF to One-Standard-Deviation Shocks (b) Per-Unit IRF Normalized to Baseline

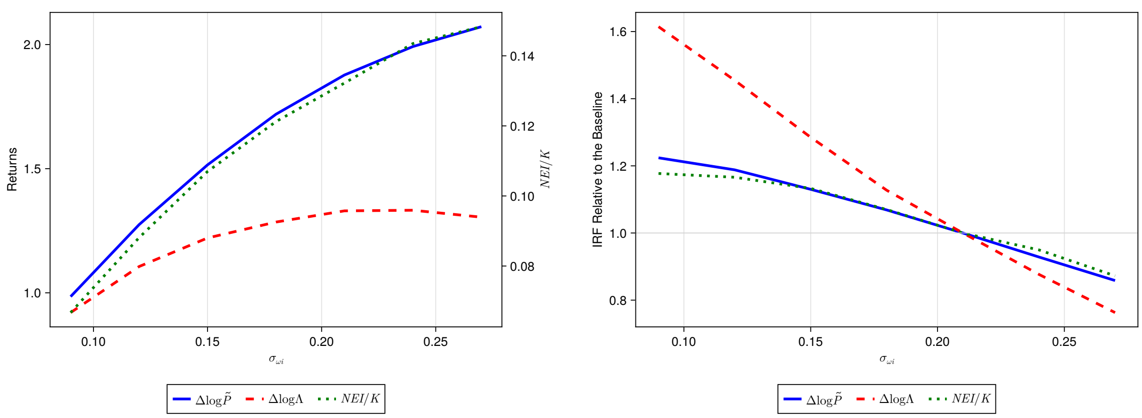


Figure 7 illustrates the initial impulse responses of market value, price pressure, and NEI under different mutual fund flow shock sizes. Panel A presents the IRFs to one-standard-deviation shocks of different sizes. Panel B presents the per-unit IRFs normalized to those under the baseline shock size. For each $\sigma_{\omega i}$, the plotted value is $\frac{\text{IRF}(\sigma_{\omega i})}{\text{IRF}(0.21)} \frac{0.21}{\sigma_{\omega i}}$. The blue solid line shows the market value response, the red dashed line shows the price pressure response, and the green dotted line shows the net equity issuance response (on the right axis in Panel A). The responses are averages across 10 simulated panels, where each panel contains 3,000 firms over 1,000 quarters, with the first 400 quarters discarded.

Tables

Table 1: Summary Statistics

	count	mean	sd	min	max
$f_{i,t}$	172,584	0.00	1.00	-2.97	3.04
$R_{i,t}$ (%)	172,584	2.51	25.28	-66.42	89.99
$NEI_{i,t}/K_{i,t-1}$ (%)	172,584	0.94	8.45	-9.35	62.89
$s^M_{i,t}$ (%)	172,568	24.57	16.71	0.07	60.32
$dK_{i,t}$ (%, AT)	172,584	1.57	11.22	-28.45	58.70
$dK_{i,t}$ (%, PPENT)	169,147	2.20	12.61	-29.64	72.31
$dBE_{i,t}$ (%)	171,054	1.92	13.58	-57.85	81.17

Table 1 presents the summary statistics of the merged panel. $f_{i,t}$ is holding-weighted and standardized idiosyncratic mutual fund flow shocks. $R_{i,t}$ is quarterly stock return from CRSP. $NEI_{i,t}$ is Sale of Common and Preferred Stock net of Repurchase of Common and Preferred Stock and Dividends. In robustness checks, I alternatively define this variable without subtracting dividends or apply a 2% market equity filter following McKeon (2015). In the baseline, to be consistent with the model, $K_{i,t-1}$ is lagged total assets. $s^M_{i,t}$ is mutual fund holding defined as total number of shares held by mutual funds divided by total number of shares outstanding. Investment $dK_{i,t}$ is the DHS growth rate (Davis et al., 1996) of total asset. Book equity is Total Assets net of Retained Earnings and Total Liabilities. $dBE_{i,t}$ is the DHS growth rate of book equity. The sample is from 2007Q1 to 2021Q4.

Table 2: Other Firm Fundamental Responses

	$dBE_{i,t}$ (%)	$GEI_{i,t}/K_{i,t-1}$ (%)	$dCash_{i,t}$ (%)	$dK_{i,t}$ (%, PPENT)	$\Delta\text{Leverage}_{i,t}$ (%)
	(1)	(2)	(3)	(4)	(5)
$f_{i,t}$	0.132***	0.157***	0.450***	0.209***	-0.034***
	(3.15)	(4.70)	(2.88)	(4.26)	(-2.60)
Observations	157092	158593	158270	155387	156590
R-Squared	0.064	0.263	0.120	0.208	0.078
Time	Yes	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Clustered By	Firm	Firm	Firm	Firm	Firm

Table 2 presents regression coefficients from $\Delta y_{i,t} = \alpha_i + \delta_t + \beta f_{i,t} + X_{i,t-1} + \varepsilon_{m,t}$. Dependent variables include the DHS growth rate of book equity, cash, physical capital, and leverage. Gross equity issuance is defined as Sale of Common and Preferred Stock when it is larger than 2% of lagged market equity following McKeon (2015), and zero otherwise. Control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s^M_{i,t-1}$ and lagged firm characteristics (log market equity, log book-to-market ratio, cash scaled by asset, and investment). Standard errors are clustered at firm level. The sample is from 2007Q1 to 2021Q4.

Table 3: Initial Return and Issuance Response, Positive and Negative Shocks

	$R_{i,t}$ (%)		$NEI_{i,t}/K_{i,t-1}$ (%)	
	(1)	(2)	(3)	(4)
$f_{i,t} \times 1\{f \geq 0\}$	2.111***	1.949***	0.219***	0.221***
	(13.03)	(11.82)	(3.67)	(3.68)
$f_{i,t} \times 1\{f < 0\}$	1.442***	1.821***	0.108**	0.149***
	(10.53)	(12.54)	(2.13)	(2.91)
Observations	216248	158605	216248	158605
R-Squared	0.249	0.307	0.249	0.298
Time	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Clustered By	Firm	Firm	Firm	Firm

Table 3 presents regression coefficients from $\Delta y_{i,t} = \alpha_i + \delta_t + \beta f_{i,t} + X_{i,t-1} + \varepsilon_{m,t}$. $\mathbb{1}\{f \geq 0\}$ ($\mathbb{1}\{f \geq 0\}$) is a dummy variable that equals one when the flow shock is greater than or eqaul to (smaller than) 0. Control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s^M_{i,t-1}$ and lagged firm characteristics (log market equity, log book-to-market ratio, cash scaled by asset, and investment). Standard errors are clustered at firm level. The sample is from 2007Q1 to 2021Q4.

Table 4: Initial Return and Issuance Response, Subsamples

	(1) $R_{i,t}$ (%)	(2) $NEI_{i,t}/K_{i,t-1}$ (%)	(3) $R_{i,t}$ (%)	(4) $NEI_{i,t}/K_{i,t-1}$ (%)
Panel A: By Mutual Fund Ownership				
	High $s^M_{i,t-1}$		Low $s^M_{i,t-1}$	
$f_{i,t}$	3.389***	0.212***	1.244***	0.144***
	(21.58)	(4.41)	(10.09)	(3.24)
Observations	79561	79561	70994	70994
R-Squared	0.374	0.266	0.291	0.341
Mean s^M	0.377	0.377	0.115	0.115
Panel B: By Q				
	High Q		Low Q	
$f_{i,t}$	2.242***	0.338***	1.316***	0.001
	(15.42)	(5.06)	(9.64)	(0.04)
Observations	75031	75031	70126	70126
R-Squared	0.312	0.359	0.373	0.305
Mean s^M	0.277	0.277	0.232	0.232
Panel C: By SA Index				
	High SA Index		Low SA Index	
$f_{i,t}$	1.274***	0.191***	2.753***	0.127***
	(9.90)	(3.88)	(18.68)	(3.92)
Observations	73252	73252	82408	82408
R-Squared	0.308	0.336	0.347	0.276
Mean s^M	0.199	0.199	0.304	0.304
Time	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Clustered By	Firm	Firm	Firm	Firm

Table 4 presents regression coefficients from $\Delta y_{i,t} = \alpha_i + \delta_t + \beta f_{i,t} + X_{i,t-1} + \varepsilon_{m,t}$. I sort firms by lagged mutual fund ownership, Tobin's Q, or SA Index (Hadlock and Pierce, 2010) into two equal-sized groups within each 2-digit SIC industry. Control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s^M_{i,t-1}$ and lagged firm characteristics (log market equity, log book-to-market ratio, cash scaled by asset, and investment). Standard errors are clustered at firm level. The sample is from 2007Q1 to 2021Q4.

Table 5: Calibrated Parameters

Panel A: Aggregate		
Long-run mean of fund size	$\exp(\bar{q})$	0.38
Persistence of aggregate productivity shocks	ρ_a	0.95
Volatility of aggregate productivity shocks	σ_a	0.006
Inverse of risk-free rate	β	0.99
Risk aversion, constant component	γ_0	36
Risk aversion, time-varying component	γ_1	-2000
Panel B: Mutual Funds		
Persistence of idiosyncratic flow shocks	ρ_ω	0.98
Volatility of idiosyncratic flow shocks	σ_ω	0.21
Risk aversion	γ^M	2.0
Targeted portfolio position	$\bar{\phi}$	0.60
Panel C: Firm		
Persistence of idiosyncratic productivity shock	ρ_x	0.97^3
Volatility of idiosyncratic productivity shock	σ_x	0.16
Long-run mean of idiosyncratic productivity shock	$\bar{x}$	-3.08
Decreasing returns to scale	α	0.65
Depreciation rate	δ	0.03
Corporate tax rate	τ	0.3
Dividend tax rate	τ_D	0.15
Collateral constraint	φ	0.8
Saving-borrowing rate wedge	κ	0.005/4

Table 5 presents the calibrated parameters for the baseline model.

Table 6: Identified Parameters

Panel A: Parameter Estimates		
Parameter	Symbol	Value
Capital adjustment costs	c_k	0.507
		(0.005)
Fixed issuance costs ($\times$100)	c_{h0}	0.285
		(0.046)
Variable issuance costs	c_{h1}	0.956
		(0.040)
Variable buyback costs	c_b	0.902
		(0.011)
Mutual funds position adjustment costs	c_s	0.904
		(0.425)
Mutual funds target deviation costs	c_ϕ	1.576
		(0.161)
Residual investor position adjustment costs	c_r	0.795
		(0.041)

Panel B: Targeted Moments		
Moment	Data	Model
Return IRF, $h = 0$ (%)	1.81	1.87
Return IRF, $h = 1$ (%)	0.11	-1.21
NEI IRF, $h = 0$ (%)	0.27	0.13
Var(Δs^M) ($\times 10^4$)	11.55	16.46
$\mathbb{E}[NEI_t/K_{t-1}\|NEI_t \geq 0]$ (%)	3.57	4.71
$\mathbb{E}[NEI_t/K_{t-1}\|NEI_t \leq 0]$ (%)	-0.82	-1.14
$\beta(SALE/K,\, I/K)$	0.15	0.16
$\mathbb{E}[L/K]$	0.23	0.27
Var(R) ($\times 10^4$)	569.58	326.63
Var(I/K) ($\times 10^4$)	54.52	41.84

Table 6 presents estimated parameters and compares the moments from the simulated economy with data. Standard errors are in parentheses. The moments are calculated as the average across 10 simulated panels. Each simulated panel is composed of 3,000 firms over 1,000 quarters. The first 400 quarters are discarded. Data moments are from 2007Q1 to 2021Q4.

Table 7: Sensitivity of Parameters With Respect to Moments

	c_k	c_{h0}	c_{h1}	c_b	c_s	c_ϕ	c_r
Return IRF, $h = 0$	0.007	-0.186	0.190	0.141	-0.004	0.061	0.581
Return IRF, $h = 1$	-0.112	-0.066	-0.036	0.042	0.462	0.415	-0.065
NEI IRF, $h = 0$	-0.067	0.349	-0.348	-0.322	-0.181	-0.185	-0.079
Var(Δs^M)	-0.001	0.001	0.001	-0.003	-0.037	0.009	-0.123
$\mathbb{E}[NEI_t/K_{t-1} \| NEI_t \geq 0]$	-0.014	0.833	-0.797	-0.721	-0.574	-0.603	-0.510
$\mathbb{E}[NEI_t/K_{t-1} \| NEI_t \leq 0]$	0.006	-0.010	-0.020	0.420	0.003	0.003	0.004
$\beta(SALE/K,\, I/K)$	0.127	-0.014	0.033	0.014	-0.003	-0.001	-0.003
$\mathbb{E}[L/K]$	0.010	0.195	-0.078	-0.222	-0.138	-0.143	-0.130
Var(R)	0.143	-0.125	0.279	0.190	-0.558	-0.559	-0.514
Var(I/K)	-0.925	0.032	-0.171	-0.038	0.050	0.038	0.067

Table 7 presents local elasticity of parameters (columns) with respect to moments (rows) at the estimated parameter values. The matrix is calculated following Andrews et al. (2017). Each element is scaled by the square root of the ratio of the moment variance to the parameter variance. Elasticities are calculated using central finite difference with a step size equal to 0.01 of the estimated parameter value. The moments are calculated as the average across 10 simulated panels. Each simulated panel is composed of 3,000 firms over 1,000 quarters. The first 400 quarters are discarded.

Table 8: Decomposition of Return Impulse Responses

	Full Sample	Small		Medium		Large	
		Low	High	Low	High	Low	High
Return	1.88	1.62	2.44	1.46	2.38	1.23	2.19
Price Pressure	1.33	1.39	1.36	1.31	1.40	1.17	1.38
Share (%)	*71*	*86*	*56*	*90*	*59*	*96*	*63*
Fundamental Value	0.55	0.23	1.08	0.15	0.98	0.05	0.81
Share (%)	*29*	*14*	*44*	*10*	*41*	*4*	*37*

Table 8 presents the decomposition of return impulse responses estimated from the baseline model. The moments are calculated as the average across 10 simulated panels. Each simulated panel is composed of 3,000 firms over 1,000 quarters. The first 400 quarters are discarded. Each sample is sorted into three equal-sized portfolios based on beginning-of-period capital levels. Within each size portfolio, firms are further divided into two groups based on the median of beginning-of-period mutual fund ownership.

Table 9: Instrumental Variable Estimation

Panel A: Residual Investor Elasticity						
	$d\log s^R$					
	(1)	(2)	(3)	(4)	(5)	(6)
$d\log \tilde{P}$	0.098	-1.671				
	(0.001)	(0.006)				
$d\log \Lambda$			-0.916	-2.359		
			(0.003)	(0.005)		
$(P_{i,t} - \tilde{P}_{i,t})/\tilde{P}_{i,t}$					-2.670	-2.270
					(0.005)	(0.004)
Estimator	OLS	IV	OLS	IV	OLS	IV

Panel B: Mutual Fund Elasticity						
	$d\log s^M$	$d\log \tilde{P}$	$d\log s^M$	$d\log s^M$	$d\log P$	$d\log s^M$
	(1)	(2)	(3)	(4)	(5)	(6)
$d\log \tilde{P}$	-0.298		-0.598			
	(0.003)		(0.003)			
$d\log X$		0.350			0.388	
		(0.000)			(0.000)	
$d\log P$				-0.514		-0.540
				(0.002)		(0.002)
Estimator	OLS	OLS	IV	OLS	OLS	IV

Table 9 presents instrumental variable estimations for the demand elasticity in simulated samples. Standard errors are clustered at firm level. The coefficients from the simulated sample are calculated as the average across 10 simulated panels. Each simulated panel is composed of 3,000 firms over 1,000 quarters. The first 400 quarters are discarded. Standard errors are in parentheses.

Table 10: Capital Misallocation: Percentage Change from Baseline

	Agg TFP	Mean NEI/K	IRF NEI/K
$\sigma_{\omega i} = 0.09$	0.068	-2.000	-49.109
$c_r = 0.70$	0.060	0.449	-7.639
$c_k = 0.25$	0.050	22.713	2.926

Table 10 presents the percentage changes of some moments from the baseline model. The moments are calculated as the average across 10 simulated panels. Each simulated panel is composed of 3,000 firms over 1,000 quarters. The first 400 quarters are discarded.

A Empirical Appendix

A.1 Variable Definition

Variables from CRSP/Compustat Merged Database

I retrieve monthly returns `ret` from CRSP, adjust for delisting returns following Bali et al. (2017), and subtract the risk-free rate. I then aggregate the excess returns to quarterly level. Number of shares outstanding is the last observation of `shrout` for each quarter. Market capitalization is calculated as the absolute value of the product of `shrout` and `altprc`.

In the baseline results, following the convention in literature, NEI is defined as `sstk - prstkcy - dvy`. For robustness, I alternatively define NEI as `sstk - prstkcy` to exclude effects of dividends.

I include some other firm outcome variables. dBE is the DHS growth rate of `at - re - lt`. GEI/K is `sstk` divided by lagged `at` when `sstk` is larger than 2% of the market capitalization. $dCash$ is the DHS growth rate of `che`. $dK(PPENT)$ is the DHS growth rate of `ppent`. ΔLeverage is the first difference of leverage, which is defined as `dltt` + `dlc` scaled by `at`. Tobin's Q is defined as (market capitalization + `at` - texttttceq) / `at`.

I include portfolio-level characteristics to predict mutual fund flows. Profitability is defined as (`sale - cogs - xsga - xint`)/Book Equity, where Book Equity is `seq` + `ceq` + `pstk` + `at - lt` + `txditc - pstk`. Log book-to-market ratio is the logarithm of Book Equity divided by market capitalization. Log market size is the logarithm of market capitalization. Log asset growth is the log difference of `at`. Market beta is calculated from rolling window regressions estimated using monthly return data. For each firm, I regress excess returns on excess market returns. The window size is 60 months and the firm must have at least 48 quarters of observations. Risk-free rate and market return is from Kenneth French's Data Library.

CRSP Survivor-Bias-Free US Mutual Fund Database

Mutual fund excess return is calculated at monthly level by subtracting market return from `mret` and then aggregated to quarterly level. Mutual fund size is `mtna`. I use `percent_tna` as weights to aggregate firm characteristics to portfolio level. I use lagged `nbr_shares` as weights to aggregate mutual fund flow shocks to firm level. In rare cases where the last observation of `nbr_shares` is missing, I use information up to two quarters to fill the missing values. Mutual fund ownership s^M is the sum of `nbr_shares` across mutual funds divided by `shrout` from CRSP.

Figure A.1 plots the coefficients estimated from the rolling window regressions. Consistent with the literature, lagged flows and excess returns have significant predictive power. However, the coefficients are time-varying. The coefficients on portfolio characteristics are also significant and time varying.

Figure A.1: Coefficients of Rolling Window Regressions

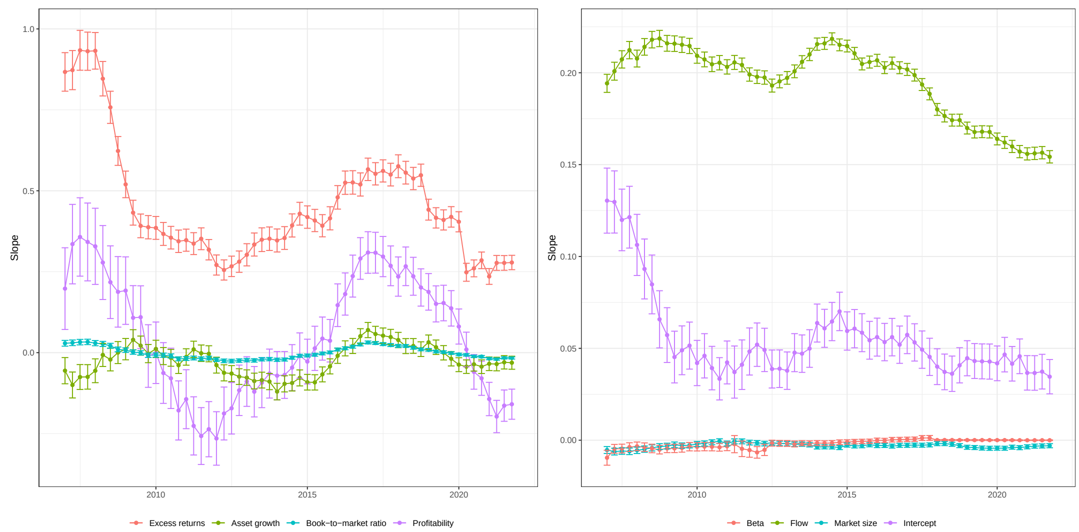


Figure A.1 presents coefficients estimated from regressing fund flows on lagged flow, fund excess returns, and lagged portfolio characteristics, including log market equity, book-to-market ratio, profitability, investment, and market beta. Each regression is performed on a panel with 16 quarters. All regressors are winsorized at 1% level.

A.1.1 Active and Passive Funds

In CRSP mutual fund database, the variable `index_fund_flag` identifies if a fund is an index fund. If a fund is a pure index fund (`index_fund_flag==D`), an index-based fund (`index_fund_flag==B`), or an index fund enhanced (`index_fund_flag==E`), I classify it as passive. Further, following Appel et al. (2016), I classify a fund as passively managed if its name includes a string that identifies it as an index fund. The strings include *"Index"*, *"Idx"*, *"Indx"*, *"Ind "*, *"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"*, *"5000"*.

A.2 Robustness

A.2.1 Industry-by-Time Fixed Effects

Although firm characteristics are controlled for when constructing fund flow shocks and estimating the baseline specification (4), concerns about the endogeneity of flow shocks may remain. In particular, if investors correctly anticipate superior performance in certain industries, their buying activity could reflect expected fundamentals rather than an exogenous shock. To mitigate this concern, I replace time fixed effects with industry-by-time fixed effects, where industries are defined by 2-digit SIC codes. This approach ensures that impulse responses are identified by comparing firms within the same industry, helping to isolate variation unrelated to broader industry trends.

Figure A.2 presents impulse response functions of returns, mutual fund holdings, net equity issuance, and investment. The results remain qualitatively similar to the baseline findings.

A.2.2 Alternative Definition of NEI

Figure A.3 presents the impulse response from estimating (4). The dependent variable is defined as `sstk - prstkcy`. The result is very similar to the baseline results in Figure 1. It is to be expected since the variation of dividend in the short term is small.

A.2.3 Size

Since higher mutual fund ownership firms experience larger price fluctuations, they should be better positioned to exploit these opportunities to issue and buyback at advantageous prices. Therefore, I compare the issuance and buyback decisions for firms with high and low mutual fund ownership conditional on size.

Because now we are interested in the level instead of only the variation in NEI. For this analysis, I exclude dividend which is not affected by price fluctuations and therefore define NEI as Sale of Stock net of Share Repurchase. I first sort firms by lagged asset into ten equal-sized portfolios. Within each size portfolio, I further split the firms into the high- and low-ownership group by median mutual fund holdings. I then calculate the mean of non-negative NEI (issuance) and non-positive NEI (buyback) for each group, weighted by lagged asset. These measures combine the extensive margin and the intensive margin. The overlap between the two measures consists of observations with NEI (excluding dividends)

Figure A.2: Firm Responses

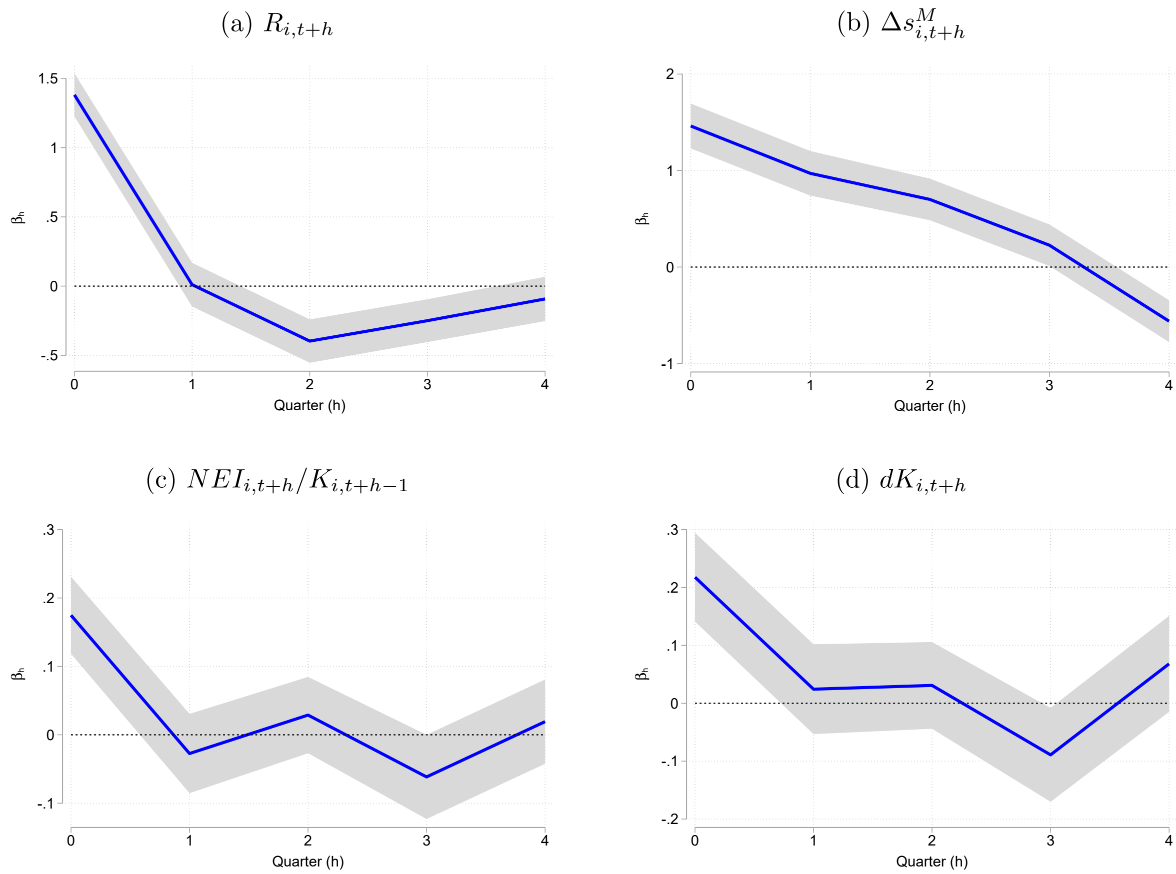


Figure A.2 presents impulse response functions of returns, mutual fund holdings, net equity issuance, and investment. The blue solid line plots coefficients β_h from estimating the local projection following Jordà (2005): $\Delta y_{i,t+h} = \alpha_i + \delta_{j,t} + \beta_h f_{i,t} + X_{i,t-1} + \varepsilon_{m,t+h}$ for $h = 0, 1, \ldots, 4$. $\delta_{j,t}$ is industry-by-time fixed effects. The shaded area indicates 90% pointwise confidence bands using standard errors clustered at firm level. control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s^M_{i,t-1}$ and lagged firm characteristics (log market equity, log book-to-market ratio, cash scaled by asset, and investment). The sample is from 2007Q1 to 2021Q4.

equal to zero [12]. This approach is designed to avoid an excessive number of parameters in the model and to maintain consistency between the calculation of moments in the simulated data and the real data. I discuss this choice in detail in Section 4.

Figure A.4 presents average stock issuance and buyback by mutual fund holding and firm size. Consistent with the previous analysis, equity issuance decreases monotonically with firm size, while share buybacks are higher in the middle of the size distribution. Most importantly, in almost all size deciles, firms with higher mutual fund ownership both issue and buy back more stock. Combined with the previously observed heterogeneity in impulse

[12] In the dataset, about 20% observations have NEI (excluding dividends) equal to zero.

Figure A.3: Firm NEI (Excl. Dividends) Response

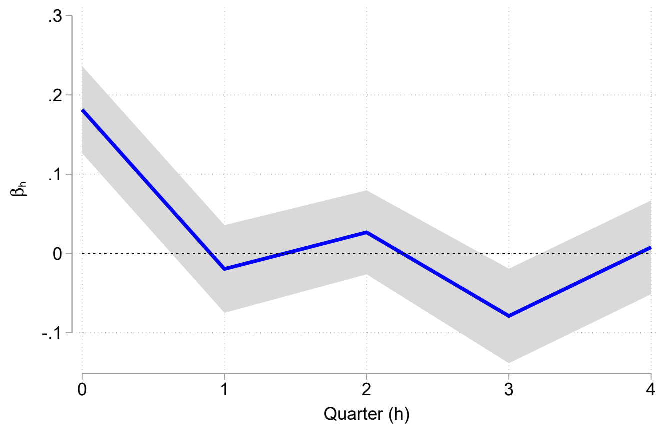


Figure A.3 presents impulse response functions of net equity issuance (excluding dividends), The blue solid line plots coefficients β_h from estimating the local projection following Jordà (2005): $\Delta y_{i,t+h} = \alpha_i + \delta_t + \beta_h f_{i,t} + X_{i,t-1} + \varepsilon_{m,t+h}$ for $h = 0, 1, \ldots, 4$. The shaded area indicates 90% pointwise confidence bands using standard errors clustered at firm level. control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s^M_{i,t-1}$ and lagged firm characteristics (log market equity, log book-to-market ratio, cash scaled by asset, and investment). The sample is from 2007Q1 to 2021Q4.

Table A.1: Initial Return and Issuance Response, Subsamples

	Large		Small	
	$R_{i,t}$ (%)	$NEI_{i,t}/K_{i,t-1}$ (%)	$R_{i,t}$ (%)	$NEI_{i,t}/K_{i,t-1}$ (%)
$f_{i,t}$	3.502***	0.115***	0.985***	0.164***
	(23.00)	(4.15)	(7.93)	(3.46)
Observations	80668	80668	74383	74383
R-Squared	0.382	0.251	0.280	0.338
Mean s^M	0.327	0.327	0.171	0.171
Time	Yes	Yes	Yes	Yes
Firm	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Clustered By	Firm	Firm	Firm	Firm

Table A.1 presents regression coefficients from $\Delta y_{i,t} = \alpha_i + \delta_t + \beta f_{i,t} + X_{i,t-1} + \varepsilon_{m,t}$. I sort firms by lagged total assets into two equal-sized groups within each 2-digit SIC industry. Control variables $X_{i,t-1}$ include $\Delta y_{i,t-1}$, $f_{i,t-1}$, $s^M_{i,t-1}$ and lagged firm characteristics (log market equity, log book-to-market ratio, cash scaled by asset, and investment). Standard errors are clustered at firm level. The sample is from 2007Q1 to 2021Q4.

responses, these results suggest that mutual fund ownership is correlated with more active issuance and buyback in the stock market.

Figure A.4: Issuance and Repurchase by Mutual Fund Holding and Size

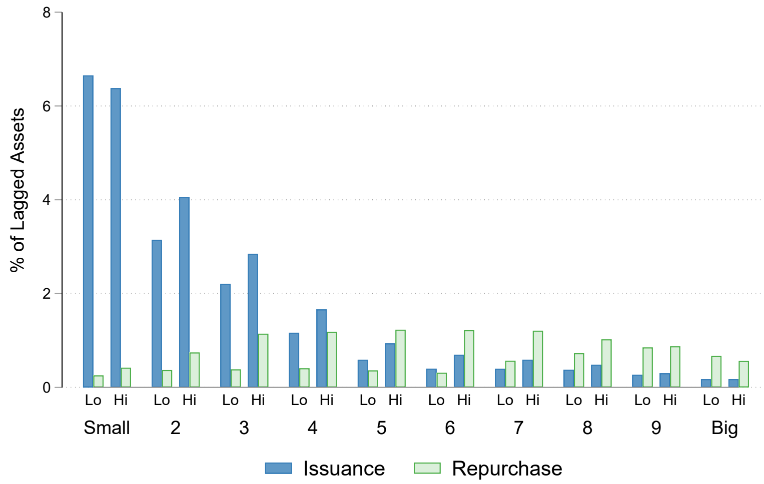


Figure A.4 shows the average share issuance and buyback by mutual fund ownership and firm size. Issuance is calculated as the mean of non-negative net issuance, and buyback is calculated as the mean of non-positive net buyback. Both measures are scaled and then weighted by lagged assets. Firms are first sorted into ten equal-sized size groups by lagged asset. Within each size decile, firms are then sorted into high and low mutual fund ownership groups by median mutual fund ownership. The dark blue bar to the left is issuance and the light green bar to the right is buyback.

A.3 Fund Flow Shocks

A.3.1 Fund Portfolio Responses

As an additional check to the results presented in Figure 1, I check whether mutual funds scale up their positions on firms they are currently holding. To that end, let $\phi_{i,m,t}$ denote the portfolio weight of mutual fund m in firm i, and $I_{m,t}$ denote the set of firms held by mutual fund m, I calculate the value-weighted increase in their current portfolio $\Delta \log S_{m,t}$ by

$$\Delta \log S_{m,t} = \sum_{i \in I_{m,t} \cap I_{m,t-1}} \phi_{i,m,t-1} (\log S_{i,m,t} - \log S_{i,m,t-1}) \tag{A.1}$$

I estimate the following local projection regression:

$$\Delta \log S_{m,t+h} = \alpha_m + \delta_t + \beta_h f_{m,t} + X_{i,t-1} + \varepsilon_{m,t+h} \text{ for } h = 0, 1, \ldots, 4, \tag{A.2}$$

where α_m and δ_t are mutual fund and time fixed effects, and control variables $X_{i,t-1}$ include lagged portfolio weight change and flow shocks. β_h can be interpreted as the $h-$quarter ahead impulse response from the mutual fund flow shocks. The coefficients are plotted in

Figure A.5. A one percent unexpected increase in size leads funds to increase holdings in their current portfolio by 0.5 percent on impact. Consistent with the results on Δs^M at firm level, mutual funds keep gradually raising positions on firms they currently own until several quarters after the shock.

Figure A.5: Portfolio Increases

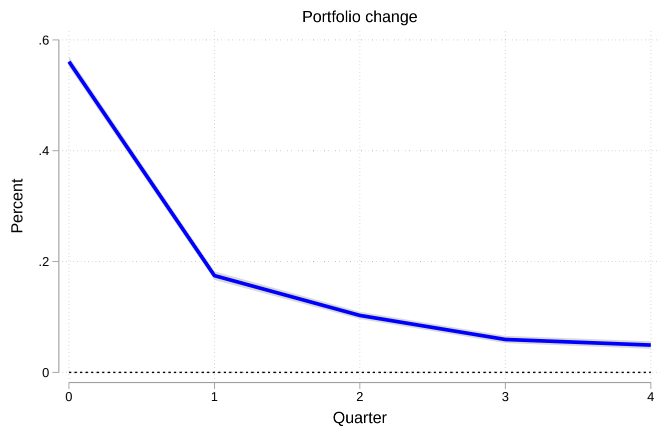


Figure A.5 presents impulse responses β_h estimated from

$$\Delta \log S_{m,t+h} = \alpha_m + \delta_t + \beta_h f_{m,t} + X_{i,t-1} + \varepsilon_{m,t+h} \text{ for } h = 0, 1, \dots, 4$$

where the dependent variable is value-weighted increase in mutual fund's current portfolio. α_m and δ_t are mutual fund and time fixed effects, and control variables $X_{i,t-1}$ include lagged portfolio weight change and flow shocks. β_h can be interpreted as the $h-$quarter ahead impulse response from the mutual fund flow shocks. The sample is from 2007Q1 to 2021Q4.

A.3.2 Aggregate Flow Shocks

Figure A.6 plots the detrended aggregate flow shock δ_t together with aggregate profitability shock. The correlation between aggregate flow shock and aggregate profitability shock is 0.44. Intuitively, when fund clients are wealthier, they tend to delegate more money to mutual funds. However, aggregate profitability shock is not the sole driver of the flow shock fluctuations. For example, Dou et al. (2022) documents that heightened uncertainty drives aggregate outflow. [13]

[13] I do not explicitly model the delegation problem in this paper. Dou et al. (2022) provides a more comprehensive view on the drivers of aggregate flows.

Figure A.6: Aggregate Fund Flow Shocks and Aggregate Profitability Shocks

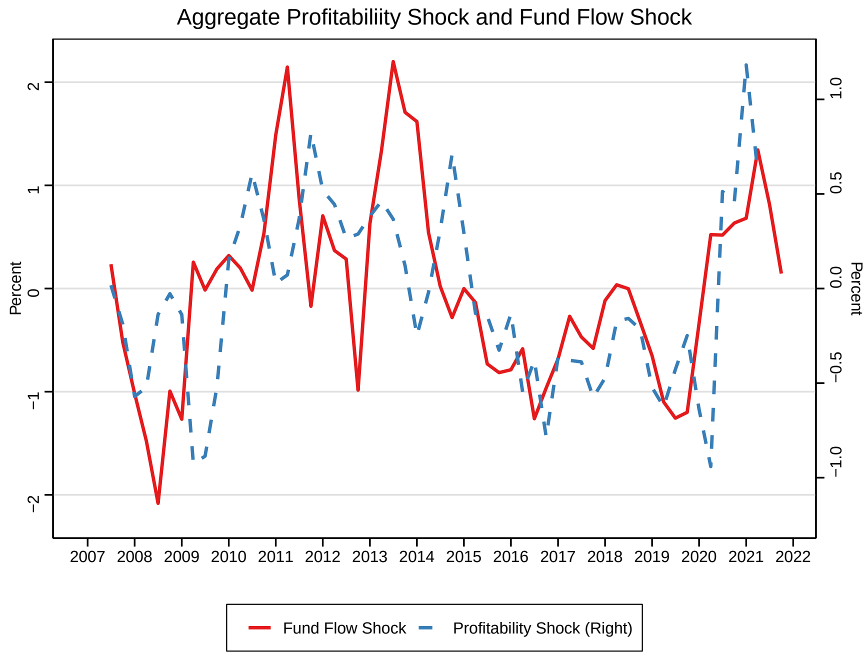


Figure A.6 presents the relationship between aggregate fund flow shock and aggregate profitability shock. Aggregate fund flow shocks are detrended time fixed effects δ_t in equation (2). To get aggregate profitability shocks, I first detrend profit per unit of real gross value added of nonfinancial corporate business from FRED, and estimate an AR(1) model extract the residuals. The correlation between the two shocks is 0.44, but profitability shocks are not the only driver of fund flow shocks.

B Model Appendix

B.1 Two-Period Model

B.1.1 $d\log\Lambda/d\phi > 0$

Plugging in the fund position $s^{M'}$ to (15), we get

$$\Lambda = \frac{1 + \frac{c_r Q\phi}{\beta^i I^\alpha}}{1 + c_r s_0^M}$$

$$\frac{d\log\Lambda}{d\phi} = \frac{c_r Q}{\beta^i I^\alpha (1 + c_r s_0^M)\Lambda}$$

$$= \frac{c_r Q}{\beta^i I^\alpha + c_r Q\phi} > 0$$

B.1.2 $d\Lambda/dI < 0$

Define $D = \gamma\sigma^2 + c_\phi$. Let $G(\phi, I)$ denote the first order condition of the mutual fund's problem (16), by the implicit function theorem,

$$\frac{d\phi}{dI} = -\frac{\partial G/\partial I}{\partial G/\partial \phi} = \frac{\alpha c_r \Omega\phi(2\beta^i I^\alpha + c_r\Omega\phi)}{I\left(D(\beta^i I^\alpha + c_r\Omega\phi)^2 + c_r\Omega(2\beta^i I^\alpha + c_r\Omega\phi)\right)}.$$

Using the definition of Λ in (15),

$$\begin{aligned}\frac{d\Lambda}{dI} &= \frac{\partial\Lambda}{\partial I} + \frac{\partial\Lambda}{\partial\phi}\frac{d\phi}{dI} \\ &= \Lambda\frac{-\alpha c_r\Omega\phi D(\beta^i I^\alpha + c_r\Omega\phi)}{I\left(D(\beta^i I^\alpha + c_r\Omega\phi)^2 + c_r\Omega(2\beta^i I^\alpha + c_r\Omega\phi)\right)} < 0\end{aligned}$$

B.1.3 Proof of Model Properties

Proof of Property 2. Let $C = \mathbb{E}\log A - \log\beta - r_f + c_\phi\bar{\phi}$, Λ_I^ϕ denote the derivative of Λ with respect to I along the optimality path of ϕ, and $\lambda_I^\phi = \Lambda_I^\phi/\Lambda$. Using the two derivatives above, the two first order equations can be written as

$$\begin{aligned}F(\phi, I; \Omega) &= \beta^i\alpha I^{\alpha-1} - 1 + c_h\frac{(K_0^\alpha - I) + (K_0^\alpha - I)^2\lambda_I^\phi(\phi, I, \Omega)}{K_0\Lambda(\phi, I, \Omega)^2} = 0 \\ G(\phi, I; \Omega) &= D\phi + \frac{c_r\Omega\phi}{\beta^i I^\alpha + c_r\Omega\phi} - C + \log\left(1 + \frac{c_r\Omega\phi}{\beta^i I^\alpha}\right) - \log(1 + c_r s_0^M) = 0\end{aligned}$$

where

$$\begin{aligned}\Lambda(\phi, I; \Omega) &= \frac{1 + \frac{c_r\Omega\phi}{\beta^i I^\alpha}}{1 + c_r s_0^M} \\ \lambda_I^\phi(\phi, I; \Omega) &= \frac{-\alpha c_r\Omega\phi D(\beta^i I^\alpha + c_r\Omega\phi)}{I\left(D(\beta^i I^\alpha + c_r\Omega\phi)^2 + c_r\Omega(2\beta^i I^\alpha + c_r\Omega\phi)\right)}.\end{aligned}$$

Using the implicit function theorem,

$$\begin{aligned}\frac{dI}{d\Omega} &= -\frac{F_\Omega G_\phi - F_\phi G_\Omega}{F_I G_\phi - F_\phi G_I}, \\ \frac{d\phi}{d\Omega} &= -\frac{F_I G_\Omega - F_\Omega G_I}{F_I G_\phi - F_\phi G_I},\end{aligned}$$

It is straightforward to show that

$$
\begin{aligned}
F_I G_\phi - F_\phi G_I &= \frac{\beta^i \alpha(\alpha-1) I^{\alpha-2} M}{(P+B)^2} - \frac{c_h}{K_0 \Xi^2} \frac{M}{(P+B)^2} + \frac{\alpha B D c_h}{K_0 \Xi^2 I (P+B)} \left(4E + \frac{C_1}{I(P+B)M^2} E^2 \right) \\
F_\Omega G_I - F_I G_\Omega &= \frac{c_h B D}{K_0 \Xi^2 (P+B)^2 \Omega} \left(-2(P+B)E + \frac{\alpha}{IM^2} C_2 E^2 \right) \\
F_I G_\Omega - F_\Omega G_I &= \frac{c_r \phi (2P+B) \beta^i \alpha(\alpha-1) I^{\alpha-2}}{(P+B)^2} \\
&\quad + \frac{c_h}{K_0 \Xi^2 (P+B)} \left(-\frac{c_r \phi (2P+B)}{(P+B)} + \frac{2 c_r \alpha \phi D B}{IM} E + \frac{\alpha D B^2 (2P+B)}{I^2 M \Omega} E^2 \right)
\end{aligned}
$$

where $B = c_r \Omega \phi$, $M = D(P+B)^2 + c_r Q(2P+B)$. When the terms associated with E^2 (and therefore λ_I^ϕ, as the two terms only appear together in $F(\phi, I; \Omega)$) are small enough, $F_I G_\phi - F_\phi G_I < 0, F_\Omega G_I - F_I G_\Omega < 0, F_I G_\Omega - F_\Omega G_I < 0$. Therefore, $dI/d\Omega > 0$ and $d\phi/d\Omega < 0$. □

Proof of Property 1. First, note that

$$
\frac{dP^*}{d\Omega} = \frac{\partial P^*}{\partial I} \frac{dI}{d\Omega} > 0
$$

Second, from the definition of Λ^*,

$$
\frac{d\Lambda^*}{d\Omega} = \frac{\partial \Lambda^*}{\partial \Omega} + \frac{\partial \Lambda^*}{\partial I} \frac{dI}{d\Omega} + \frac{\partial \Lambda^*}{\partial \phi} \frac{d\phi}{d\Omega}
$$

Plugging in the derivatives derived above and rearranging terms, this derivative can be written as

$$
\beta^i \alpha(1-\alpha) I^{\alpha-2} D\phi + \frac{c_h D \phi}{K_0 \Xi^2} - \frac{2\alpha B D c_h \phi}{K_0 \Xi^2 I (P+B)} \left(1 - \frac{c_r Q}{M} \right) E > 0
$$

as all three terms are positive. □

Proof of Property 3. The elasticities $ds^{R'}/dP$, $ds^{R'}/d\Lambda$ directly follow from the first order condition of residual investors' problem (14).

To derive the mutual fund's elasticities with respect to fundamental value and price pressure, we need to modify the system slightly so that there is an extra source of exogenous variation that shifts price pressure Λ but not from mutual fund flows. Consider a revised system that is summarized as

$$D\phi + \frac{d\log\Lambda}{d\phi}\phi = C - \log\Lambda$$
$$\Lambda = \Theta\frac{1+\frac{c_r Q\phi}{\beta^i I^\alpha}}{1+c_r s_0^M},$$

where Θ is an exogenous variable that shifts price pressure.

Note that $d\log\Lambda/d\phi$ is the same as before. The counterpart of mutual fund optimality $G(\cdot)$ can be rewritten as

$$D\phi + \frac{c_r Q}{P+c_r Q\phi}\phi = C - \log\Theta - \log\left(1+\frac{c_r Q\phi}{P}\right) + \log(1+c_r s_0^M)$$

Using the implicit function theorem, we get

$$\frac{d\phi}{d\log\Theta} = -\frac{1}{D+\frac{c_r Q}{P+c_r Q\phi}+\frac{c_r QP}{(P+c_r Q\phi)^2}} < 0$$
$$\frac{d\phi}{d\log P} = \frac{c_r Q\phi(2P+c_r Q\phi)}{(P+c_r Q\phi)^2\left(D+\frac{c_r Q}{P+c_r Q\phi}+\frac{c_r QP}{(P+c_r Q\phi)^2}\right)} > 0$$

□

B.2 Mutual Fund Utility

$$\begin{aligned}
&\frac{\beta}{1-\gamma_t}\mathbb{E}_t\left[e^{(1-\gamma_t)\tilde{q}_{i,t+1}}\right] \\
=&\frac{\beta}{1-\gamma_t}\mathbb{E}_t\left[e^{(1-\gamma_t)(q_{i,t}+r^M_{i,t+1})}\right] \\
=&\frac{\beta Q_t^{1-\gamma_t}}{1-\gamma_t}\mathbb{E}_t\left[e^{(1-\gamma_t)(r^M_{i,t+1})}\right] \\
=&\frac{\beta Q_t^{1-\gamma_t}}{1-\gamma_t}\mathbb{E}_t\left[\exp\left((1-\gamma_t)(r_f+\phi_{i,t+1}(r_{i,t+1}-r_f)+\frac{1}{2}\phi_{i,t+1}(1-\phi_{i,t+1})\sigma^2_{i,t})\right)\right] \\
=&\frac{\beta Q_t^{1-\gamma_t}R_f^{1-\gamma_t}1}{1-\gamma_t}\mathbb{E}_t\left[\exp\left((1-\gamma_t)\left(\phi_{i,t+1}(r_{i,t+1}-r_f)+\frac{1}{2}\phi_{i,t+1}(1-\phi_{i,t+1})\sigma^2_{i,t}\right)\right)\right] \\
=&\frac{\beta Q_t^{1-\gamma_t}R_f^{1-\gamma_t}}{1-\gamma_t}\exp\left[(1-\gamma_t)\left(\phi_{i,t+1}(\mu_{i,t}-r_f)+\frac{1}{2}\phi_{i,t+1}(1-\phi_{i,t+1})\sigma^2_{i,t}+\frac{1}{2}(1-\gamma_t)\phi^2_{i,t+1}\sigma^2_{i,t}\right)\right] \\
\equiv&\frac{\beta Q_t^{1-\gamma_t}R_f^{1-\gamma_t}}{1-\gamma_t}\exp\left[(1-\gamma_t)u^M\right]
\end{aligned}$$

Therefore,

$$u^M = \frac{1}{1-\gamma_t} \log \mathbb{E}_t \left[R^{1-\gamma}\right] - r_f$$

Alternatively, if we assume $\tilde{q}_{i,t+1} = \bar{q} + r^M_{i,t+1} + \omega_{i,t+1}$, there will be an extra hedging motive to avoid firms that will be strongly affected by flow shocks.

B.3 Hedging Motives and Biased Holdings

Following Dou et al. (2022) and motivated by Figure A.6, to incorporate the aggregate component of fund flow shocks, suppose that the size of mutual fund i evolves following

$$\tilde{q}_{i,t+1} = q_{i,t} + r^M_{i,t+1} + \epsilon_{q,t+1},$$

where $\epsilon_{q,t+1}$ is the aggregate fund flow shock.

Using the same reshuffling assumption, the AUM available for investment is now time varying. Replace $\bar{q}$ with q_{t+1} in (34),

$$q_{i,t+1} = q_{t+1} + \omega_{i,t+1}, \tag{A.3}$$

where q_{t+1} is the average size of the mutual fund industry.

The aggregate average mutual fund size q_{t+1} and the aggregate profitability a_{t+1} follow a VAR(1) process:

$$\begin{bmatrix} q_{t+1} \\ a_{t+1} \end{bmatrix} = \begin{bmatrix} (1-\rho_q)\bar{q} \\ (1-\rho_a)\bar{a} \end{bmatrix} + \begin{bmatrix} \rho_q & 0 \\ 0 & \rho_a \end{bmatrix} \begin{bmatrix} q_t \\ a_t \end{bmatrix} + \begin{bmatrix} \epsilon_{q,t+1} \\ \epsilon_{a,t+1} \end{bmatrix}, \quad \begin{bmatrix} \epsilon_{q,t+1} \\ \epsilon_{a,t+1} \end{bmatrix} \sim n\left(0, \begin{bmatrix} \sigma_q^2 & \rho_{q,a}\sigma_q\sigma_a \\ \rho_{q,a}\sigma_q\sigma_a & \sigma_a^2 \end{bmatrix}\right), \tag{A.4}$$

where $\bar{q}$ is the long-run mean of the log size of the mutual fund sector, ρ_q and ρ_a are the persistence parameters, and shocks $\epsilon_{q,t+1}$ and $\epsilon_{a,t+1}$ are jointly normal. σ_q and σ_a are their respective conditional volatility. $\rho_{q,a}$ is the correlation between the two shocks. Motivated by Figure A.6, $\rho_{q,a} > 0$ captures the occurrence of large inflow shocks during good times in a reduced-form manner.

Using the same Taylor approximation, tha manager's discounted payoff can be written as

$$\begin{aligned} u^M \approx & \frac{1}{1-\gamma_t} \mathbb{E}_t \left[\exp\left((1-\gamma_t) \left(\phi_{i,t+1}(r_{i,t+1} - r_f) + \frac{1}{2}\phi_{i,t+1}(1-\phi_{i,t+1})\sigma^2_{i,t} + \epsilon_{q,t+1} \right) \right) \right] \\ = & \phi_{i,t+1}(\mu_{i,t} - r_f) + \frac{1}{2}\phi_{i,t+1}(1-\phi_{i,t+1})\sigma^2_{i,t} + \frac{1}{2}(1-\gamma_t)\left(\phi^2_{i,t+1}\sigma^2_{i,t} + 2\phi_{i,t+1}C_{i,t}\right), \end{aligned} \tag{A.5}$$

where $C_{i,t} = \text{Cov}_t[r_{i,t+1}, \epsilon_{q,t+1}]$ is the conditional covariance between the return of firm i and aggregate flow shock $\epsilon_{q,t+1}$. The covariance term exists because positive aggregate profitability shocks drive up both firm production and returns, and these shocks typically coincide with positive mutual fund flow shocks ($\rho_{q,a} > 0$), Since $1 - \gamma_t < 0$, higher covariance between returns and aggregate flow shocks reduces the fund manager's payoff. Therefore, fund managers are incentivized to underweight (overweight) firms that are more (less) cyclical to hedge against aggregate flow shocks.

Since ϵ_q and ϵ_a are jointly normal, we can write $\epsilon_q = \mathbb{E}[\epsilon_q|\epsilon_a] + \varepsilon_{qa} = \frac{\rho_{q,a}\sigma_q\sigma_a}{\sigma_a^2}\epsilon_a + \varepsilon_{qa}$, where $\text{Cov}(\epsilon_a, \varepsilon_{qa}) = 0$. Therefore, $C_i = \text{Cov}\left(\mathbb{E}[\epsilon_q|\epsilon_a], r_i\right) + \text{Cov}(\varepsilon_{qa}, r_i) = \tilde{C}_i + \text{Cov}(\varepsilon_{qa}, r_i)$. To capture the hedging incentive without materially changing the model structure, I use $\tilde{C}_{i,t} = \text{Cov}_t\left[r_{i,t+1}, \frac{\rho_{q,a}\sigma_q}{\sigma_a}\epsilon_{a,t+1}\right]$ to proxy for $C_{i,t}$. Since positive aggregate flow shocks likely raise stock prices, $\text{Cov}(\varepsilon_{qa}, r_i) > 0$, the proxy underestimates the hedging motives. To gauge the size of the error term, the variance of the residual is $\mathbb{V}(\varepsilon_{qa}) = \sigma_q^2(1 - \rho_{q,a}^2)$. Using the Cauchy-Schwarz inequality, $|\text{Cov}(\varepsilon_{qa}, r_i)| \leq \sqrt{\mathbb{V}(\varepsilon_{qa})\mathbb{V}(r_i)} = \sigma_r\sigma_q\sqrt{1 - \rho_{qa}^2}$.

B.4 Extension on Ownership Dynamics

It is natural to extend the model to include the changes in ownership and discuss its implication for misvaluation.

Given the issuance $H_{i,t}$ at market value $\tilde{P}_{i,t}$, current stockholders only hold $(\tilde{P}_{i,t} - H_{i,t})/\tilde{P}_{i,t}$ fraction of the firm. In other words, current stock holdings are shrunk to

$$s_{i,t}^{M,post} = \frac{\tilde{P}_{i,t} - H_{i,t}}{\tilde{P}_{i,t}} s_{i,t}^M \text{ and } s_{i,t}^{R,post} = \frac{\tilde{P}_{i,t} - H_{i,t}}{\tilde{P}_{i,t}} s_{i,t}^R \tag{A.6}$$

And the portion of new issuance equals $H_{i,t}/\tilde{P}_{i,t}$. Therefore, the new share holdings for residual investors should be written as

$$s_{i,t+1}^R = s_{i,t}^R \frac{\tilde{P}_{i,t} - H_{i,t}}{\tilde{P}_{i,t}} + \frac{V_{i,t} - \tilde{P}_{i,t}}{c_r \tilde{P}_{i,t}} \tag{A.7}$$

Note that we already calculated the targeted ownership share for investors, so we can calculate the change in their positions and calculate how costly it is to get them to purchase the new issuance, since newly issued shares are entirely purchased by the mutual funds and residual investors.

To get a simple analytical solution that is qualitatively similar, assume mutual fund adjustments are not affected by this effect. We can then calculate the incremental holding for residual investors:

$$s^R_{i,t+1} - s^R_{i,t} = \left(1 - \frac{\tilde{P}_{i,t} - H_{i,t}}{\tilde{P}_{i,t}}\right) s^R_{i,t} - \frac{V_{i,t} - \tilde{P}_{i,t}}{c_r \tilde{P}_{i,t}} = \frac{H_{i,t}}{\tilde{P}_{i,t}} s^R_{i,t} - \frac{V_{i,t} - \tilde{P}_{i,t}}{c_r \tilde{P}_{i,t}} \tag{A.8}$$

The more you issue, the less residual investors want to increase their holdings. So it is easier to get mutual funds to buy the new issuance.

In real life, it could be easier to get mutual funds to pay for the new issuance because they are bulk long-term investors whose postitions are relatively stable. Negotiating with the hedge funds and retailer investors (what residual investors really represent in this model) could be harder.

When we consider how shares are diluted, residual investor shares will shrink following (A.7). Now that we have an additional term $h_{j,t} = H_{j,t}/P_{j,t}$ (and $\tilde{h}_{j,t} = H_{j,t}/\tilde{P}_{j,t}$), it becomes

$$\tilde{P}_{j,t} = \frac{1}{1 + c_h \left(s^M_{j,t} - s_{j,t+1} + \tilde{h}_{j,t} s^H_{j,t}\right)} P_{j,t} \tag{A.9}$$

$$= \frac{1 - c_h s^H_{j,t} h_{j,t}}{1 + c_h \left(s^M_{j,t} - s^M_{j,t+1}\right)} P_{j,t} \tag{A.10}$$

Under normal parameterization, when $H_{j,t}$ goes up, market value goes down. Note that this intuition is not entirely complete because of $s^M_{j,t+1}(\tilde{P}_{j,t})$ and $\tilde{h}_{j,t}(\tilde{P}_{j,t})$ are both functions of $\tilde{P}$.

B.5 First order conditions

The firm problem is

$$V_{i,t} = \max_{I_{i,t}, K_{i,t+1}, L_{i,t+1}} O_{i,t} + \mathbb{E}_t\left[M_{t,t+1} V_{i,t+1}\right],$$

where

$$
\begin{aligned}
O_{i,t} &= \begin{cases} E_{i,t} - \Psi_{i,t} \equiv O^{+}(E_{i,t}, K_{i,t}, \Lambda_{i,t}(\phi_{i,t+1}(K_{i,t+1}, L_{i,t+1}))) & \text{if } E_{i,t} \leq 0, \\ (1-\tau_D)(E_{i,t} - B_{i,t}) + B_{i,t} - \Phi_{i,t} \equiv O^{-}(E_{i,t}, \Lambda_{i,t}(\phi_{i,t+1}(K_{i,t+1}, L_{i,t+1}))) & \text{if } E_{i,t} > 0. \end{cases} \\
E_{i,t} &= (1-\tau)A_t^{b_i} X_{i,t} K_{i,t}^{\alpha} + \tau\delta K_{i,t} + \tau r_f L_{i,t} \mathbb{1}_{\{L_{i,t}>0\}} - I_{i,t} - G_{i,t} + L_{i,t+1} - (1+r_l)L_{i,t} \\
K_{i,t+1} &= (1-\delta)K_{i,t} + I_{i,t} \\
G_{i,t} &= \frac{c_k}{2}\left(\frac{I_{i,t}}{K_{i,t}}\right)^2 K_{i,t} \\
\Psi_{i,t} &= c_{h0}\frac{K_{i,t}}{\Lambda_{i,t}} + \frac{c_{h1}}{2}\left(\frac{H_{i,t}}{\Lambda_{i,t}K_{i,t}}\right)^2 K_{i,t} \\
\Phi_{i,t} &= \frac{c_b}{2}\left(\frac{\Lambda_{i,t}B_{i,t}}{E_{i,t}}\right)^2 E_{i,t} \\
L_{i,t+1} &\leq \varphi K_{i,t+1}.
\end{aligned}
$$

First, when $E_{i,t} > 0$, $B_{i,t} = \frac{\tau_D}{c_b\Lambda^2}E_{i,t}$ and $O_{i,t} \equiv O_{i,t}^{+} = \left(1 - \tau_D + \frac{1}{2}\frac{\tau_D^2}{c_b\Lambda^2}\right)E_{i,t}$. Let q_t and λ_t denote the Lagrangian multipliers associated with (21) and (23). The first-order conditions with respect to I_t, K_{t+1}, and L_{t+1} are

$$
-\frac{\partial O}{\partial I} = q \tag{A.11}
$$

$$
q = \mathbb{E}\left\{M'\left[\frac{\partial V'}{\partial K'}\right]\right\} + \lambda\varphi + \frac{\partial O}{\partial \Lambda}\frac{\partial \Lambda}{\partial \phi'}\frac{\partial \phi'}{\partial K'} \tag{A.12}
$$

$$
\lambda - \mathbb{E}\left\{M'\left[\frac{\partial V'}{\partial L'}\right]\right\} = \frac{\partial O}{\partial E}\frac{\partial E}{\partial L'} + \frac{\partial O}{\partial \Lambda}\frac{\partial \Lambda}{\partial \phi'}\frac{\partial \phi'}{\partial L'} \tag{A.13}
$$

C Computation Appendix

C.1 Algorithm to Solve the Model

1. Guess portfolio holding rule $\phi'^0(K', L', S)$, value function $V^0(S)$, and investment decision $K'^0(S)$.

2. Market clearing implies $s^{R'}(\phi'^0(K', L', S), K', L', S) = s^{R'0}(K', L', S)$ and therefore we have $\Xi(s^{R'0}(K', L', S), K', L', S) = \Xi^0(K', L', S)$. We also have the $\Xi^0(K'^0(S), L'^0(S), S) = \Xi^0(S)$.

3. Use $\Xi^0(K', L', S)$, run the Value Function Iteration routine. Get $V^1(S)$ and policy functions $K'^1(S)$.

4. Given $\Xi^0(S)$ (for tomorrow's value) and $V^0(S)$, calculate $\phi'^1(K', S)$.

5. Compare distances $|\phi^1(K', S) - \phi^0(K', S)|$ and $|V^1(S) - V^0(S)|$. Update $\phi^0(K', S)$ and $V^0(S)$. If larger than tolerance, go back to step 2.

C.2 Algorithm for the Indirect Inference Estimation

C.2.1 Constructing Model Moments and the Weight Matrix

I first regress firm returns, NEI, mutual fund portfolio holding, mutual fund positions, and changes in mutual fund positions on time and firm fixed effects and extract the residual to demean all relevant variables by firm and time. I calculate two dummies indicating non-negative and non-positive NEI (excluding dividends), and use the non-demeaned NEI data to calculate the conditional means. After calculating one-period forward of returns, I drop observations with any missing variable. This results in a panel of $N = 156,080$ observations. To keep the consistency between data and the model, I calculate the impulse response functions without added firm controls. As shown in Table 6, the regression coefficients are qualitatively similar to the baseline specification reported in Figure 1.

I follow Erickson and Whited (2002) to calculate the influence functions and covary the influence functions to calculate the weight matrix.

C.2.2 Estimation

Let x_n be a vector of data of dimension J, where J is the number of relevant variables. Let b be the vector of structural parameters to be estimated. Let $y_{n,k}(b)$ be the J-dimensional simulated data vector from simulation $k = 1, \ldots, K$. Let $x = \{x_1, \ldots, x_N\}$ and $y_k(b) = \{y_{1,k}, \ldots, y_{N,k}\}$ denote the data panel and the k-th simulated panel. I estimate b by matchign a set of simulated moments, denoted as $h(y_k(b))$, with the corresponding set of actual data moments, denoted as $h(x)$. Define

$$g(x, b) = h(x) - \frac{1}{K}\sum_{k=1}^{K} h(y_k(b)). \tag{A.14}$$

The indirect inference estimator of b is then defined as the solution to the minimization of

$$\hat{b} = \arg\min_{b} g(x, b)'\hat{W} g(x, b), \tag{A.15}$$

where $\hat{W}$ is the weight matrix calculated from the influence functions.