Flow-Driven Corporate Finance: A Supply-Demand Approach

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Abstract

This paper develops a supply-demand framework to quantify and decompose the effects of investor demand on corporate financing and investment. The framework extends demand-based asset pricing models by incorporating endogenous corporate decisions. Using Gabaix and Koijen (2024)'s granular instrumental variable approach, I estimate the model parameters and find that a $1 investor flow generates $0.012 in share issuance within the first quarter and a cumulative $0.24 over two years. Similarly, a 1% investor flow increases firm investment by 0.19% over two years. The results reveal significant asymmetry: firms respond more strongly to inflows than to outflows. Counterfactual analysis shows that investor preferences substantially dampen firms' investment responses to flows. The framework also provides a novel tool to evaluate firms' role in stabilizing the stock market.

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1 Introduction

Does investor demand for stocks have real effects on firms? How do investor preferences affect corporate policies in equilibrium? When a demand shock occurs in the stock market, it directly affects stock prices, which in turn shape firm financing and investment decisions—this is the direct effect of the demand shock on firms. The direct effect assumes that investor demand is exogenous and does not adjust in response to changes in firm policies. However, when investors have preferences for firm characteristics, firms' adjustments to corporate policies can influence investor demand, which subsequently affects stock prices and firm decisions, creating a feedback effect. This feedback effect may amplify or mitigate the initial impact of the demand shock on firms, depending on investor preferences. Figure 1 illustrates the propagation of the demand shock through both direct and indirect pathways.[1]

Prior literature, such as Edmans et al. (2012), Khan et al. (2012), Hau and Lai (2013), Phillips and Zhdanov (2013), Norli et al. (2015), Lee and So (2017), Dessaint et al. (2019), Bennett et al. (2020), and Xu and Kim (2022), has examined the effects of financial markets (e.g., stock prices) on firm decisions. Since this literature focuses on the effects of stock prices, it has predominantly treated investor demand as a "black box," making the direct link between investors and firms under-explored. The demand system asset pricing models starting from Koijen and Yogo (2019) make it possible to build a direct relation between investor demand and firm supply. Moreover, the impact of investor preferences on corporate policies has not been adequately quantified. This paper addresses these gaps by developing a supply-demand framework that integrates firm decisions into demand-based asset pricing models to quantify and decompose the effects of investor demand on corporate financing and investment.

Numerous key quantitative questions in academia and policymaking concern the impact of investor demand on firms. One example is sustainable investment. While previous research has documented the benefits of investor flows from dirty to clean firms in reducing carbon emissions and increasing green innovations,[2] less is known about the costs of sustainable investment. Sustainable investment generates differentiated costs of capital for dirty and clean firms, and investor preferences for green actions may push firms toward increased green investment. Hence, sustainable investment could result in misallocation

[1]Figure 1 visualizes the multiplier effect of a demand shock. The blue arrows represent the direct impact, where the demand shock influences firm decisions (e.g., financing and investment) through stock prices. The red arrows depict the feedback impact, where firms' responses alter investor demand, which further influences stock prices and firm decisions. Together, the blue and red arrows illustrate the combined multiplier effect of investor flows.

[2]See Becht et al. (2023), Cenedese et al. (2023), Choi et al. (2024), Gantchev et al. (2022), Noh et al. (2024) and Hartzmark and Shue (2023).

of financing both across firms and within individual firms. Quantifying the effects of sustainable investment on firms' financing, investment, and production will enable welfare analysis. Another example concerns the portfolio regulation of pension funds, which forces pension funds to reallocate their funds across firms. This generates differentiated capital flows and varying impacts on firms. The effects of such regulation on firms' investment and production hinge on investor preferences, which is key to determining whether and when such portfolio regulation should be implemented.[3]

Quantifying and decomposing the impact of investor demand poses several challenges. The first challenge is the simultaneous equations bias inherent in the supply-demand framework. Even if investor demand could be perfectly measured, regressing corporate decisions on investor demand would yield inconsistent estimates because investor demand affects corporate decisions, which in turn influence investor demand. This endogeneity makes supply-side parameters unidentifiable. To address this issue, prior studies have relied on demand shocks—such as mutual fund flows (Edmans et al., 2012), dividend reinvestment (Hartzmark and Solomon, 2024), and index reconstitution (Chang et al., 2015). The second challenge is measurement error bias. Since demand by all investors cannot be perfectly measured,[4] the literature uses the aforementioned demand shocks as proxies. However, these shocks capture only a portion of investor flows, and unmeasured flows from other sources are often correlated with the observed shocks. For example, mutual fund flows may correlate with dividend reinvestment flows if households reinvest dividends into mutual funds. This correlation between the demand shock and its measurement error leads to biased estimates. The third challenge lies in decomposing the effects of investor demand into direct and feedback effects. It is particularly difficult to isolate the impact of investor preferences on firms using simple regressions.

I address these challenges in two steps. First, I develop a supply-demand framework that establishes the linear relation between corporate decisions and demand shocks in the stock market. Unlike previous demand-based asset pricing models, such as those in Koijen and Yogo (2019), Haddad et al. (2025), and Van der Beck (2024), which assume an exogenously given supply side, this framework allows firms to adjust their financing and investment policies in response to investor demand. These corporate adjustments, in turn, influence investor demand (driven by investors' preferences for firm investment), further shaping corporate decisions through a feedback effect. In equilibrium, when the stock

[3] Another example is the Bank of Japan's ETF purchase program between 2011 and 2018, which accounted for 3.5% of GDP. Demand shocks propagated through firms' financing and investment decisions, potentially amplifying or mitigating its intended effects. Understanding how investor preferences affect the multiplier effects of such interventions helps policymakers assess whether and when stock market quantitative easing is effective.

[4] This is due to the lack of high-frequency holdings data, as portfolio holdings are typically available only on a quarterly basis.

market clears—meaning aggregate asset demand equals asset supply—changes in stock prices, total share supply, and firm investment collectively absorb the demand shock.

A demand shock can be decomposed into three components in equilibrium: one related to stock prices, one to total share supply, and one to firm investment. This decomposition yields several key insights. First, if firms are unable to adjust their outstanding shares or investment, stock prices alone must absorb the demand shock. In this case, the price impact of the demand shock can be identified using the demand elasticity with respect to stock prices. A lower demand elasticity implies a greater price impact of the demand shock. Second, if investors are indifferent to firm characteristics, firms can absorb the demand shock through adjustments in total share supply. Corporate equity supply directly mitigates the price impact, with the extent of moderation depending on the supply elasticity of shares. A lower supply elasticity results in a greater price impact. Third, if investors respond to firm characteristics such as investment, firms gain an additional channel to absorb the demand shock by adjusting their investment, which alters investor demand. The extent to which investment absorbs or amplifies the demand shock depends on both the supply elasticity of investment with respect to stock prices and the demand elasticity with respect to investment. Depending on investor preferences, firm investment may either mitigate or amplify the price impact of the demand shock.

The supply-demand framework combines demand-based asset pricing models, which endogenize investor demand, with production-based asset pricing models, which endogenize corporate policies. It provides closed-form relationships between investor demand and corporate decisions, demonstrating that financing and investment multipliers depend on two supply-side elasticities (for financing and investment) and two demand-side elasticities (for stock prices and investment). The interaction between a firm's supply of investment and investor preferences generates the feedback effect, through which the impact of a demand shock is either amplified or mitigated. This supply-demand framework serves as a valuable tool for quantifying the effects of investor preferences on firms.

Second, I apply the granular instrumental variable (GIV) approach, as outlined in Gabaix and Koijen (2024), to estimate the multipliers for the reduced-form relationship between firm policies and investor flows. Through the estimation of a supply-demand system, I demonstrate that the GIVs can identify the financing and investment multipliers. The key to GIV identification is that GIVs are constructed to be exogenous to common factors. To mitigate the risk of omitted factors, I use different sets of observed and latent factors to construct GIVs and examine whether the estimated multipliers from the main regressions change notably. The results in the main regressions indicate that the estimated multipliers are stable across different observed and latent factors.[5]

[5] I also provide three additional ways to justify the exogeneity of the constructed GIVs. First, I

My approach yields three main results regarding the effect of investor flows on firm financing and investment. First, the financing multipliers are 0.012 in the short horizon and 0.24 in the long horizon,[6] and the investment multipliers are zero in the short horizon and 0.19 in the long horizon. Consequently, the financing multipliers reveal that a $1 investor flow to a firm generates 1.2 cents in share issuance in the quarter of the investor flow and 24 cents in share issuance over the eight quarters following the quarter of the investor flow. The investment multipliers reveal that the firm does not respond to investor flows in the current quarter, and a 1% investor flow causes a 0.19% increase in investment by the firm over the eight quarters. A firm's investment requires planning and thus grows gradually after the demand shock. In the short run, the firm obtains very limited financing from the stock market, which is consistent with the literature showing that the stock market mainly plays an informational role rather than a financing role for firms (Bond et al., 2012). In the long run, however, the financing channel of the stock market dominates: the firm obtains sizable funds from the stock market and uses them to increase investment.

Second, the effects are asymmetric, with firms responding more strongly to investor inflows than to outflows. A $1 investor inflow causes the firm to issue $0.85 in shares, but a $1 investor outflow causes the firm to buy back only $0.005 in shares. A 1% investor inflow causes the firm's investment to increase by 0.30%, but a 1% investor outflow causes the firm's investment to decrease by only 0.15%. These results are consistent with Van Binsbergen and Opp (2019). The asymmetric reactions support the supply-side story: due to financial flexibility and irreversible investment, a firm's share issuance and investment growth adjust to investor inflows more strongly than to investor outflows.

Third, investor preferences play a crucial role in shaping firms' responses to investor flows. Counterfactual analysis reveals that shutting down investor preferences for firm characteristics reduces the impact of investor flows on firm policies by 67.4%, with reductions ranging from 30.4% to 71.7% across different elasticity estimates. These results highlight the importance of feedback effects, driven by investor preferences, in moderating the impact of investor flows on corporate decisions.

An application of the supply-demand framework demonstrates the significant role of firms in stabilizing stock prices. Allowing firms to adjust their share supply reduces the price impact of investor flows by 72.4%. Furthermore, when firms also adjust their investment, the feedback effect from investor preferences mitigates the price impact by

find that GIVs have no relationship with corporate decisions in periods before demand shocks. Second, I find that GIVs are normally distributed with a mean of zero. Third, I validate the GIV approach by showing that the constructed GIVs can capture demand shocks induced by mutual fund flows and dividend reinvestment simultaneously.

[6]The long horizon refers to the eight quarters after the investor flow since the impact of investor flows on firm financing and investment lasts for two years.

an additional 20%. These findings emphasize the pivotal role of firms in stabilizing the stock market.

The paper is structured as follows. Section 2 outlines the literature review. In Section 3, I develop a supply-demand framework for the relationships between corporate decisions and investor flows in equilibrium. Section 4 presents the data and introduces the GIV approach that is used to estimate multipliers. Section 5 validates the GIV approach in several ways and links it with demand shocks by mutual fund flows and dividend reinvestments. In Section 6, I quantify and decompose the effects of investor flows on firm's share issuance and investment. Section 7 concludes.

2 Literature Review

This paper relates to several strands of literature. Starting with Koijen and Yogo (2019), the literature on demand-based asset pricing has burgeoned. Contrary to classic asset pricing theories, the demand-based asset pricing literature documents highly inelastic asset demand by investors (Van der Beck, 2024; Haddad et al., 2025). Gabaix and Koijen (2023) linked inelastic asset demand with stock prices and documented substantial price impacts of demand shocks. In parallel, a large body of literature has focused on the supply side, such as production-based asset pricing (Cochrane, 1996; Zhang, 2005; Belo, 2010; Gomes and Schmid, 2021) and q-theory of investment (Hayashi, 1982; Erickson and Whited, 2000; Liu et al., 2009; Bolton et al., 2011; Crouzet and Eberly, 2023). This literature links corporate decisions with stock prices and tests the q-theory of investment. While both literature threads succeed in explaining behaviors on each side (either demand or supply) by assuming the other side is exogenous, little literature endogenizes both sides and tracks their interactions.[7].

This paper also relates to the literature that uses investor flows as instruments for stock prices and examines their effects on firms. Since this literature focuses on the relation between stock prices and firms, it does not measure the effects of investor preferences on firms. The first instrument is mutual fund flows. Edmans et al. (2012) measure firm-level price pressure by mutual fund redemptions, assuming that each stock was sold in proportion to the fund's beginning-of-quarter holdings. They use this measure as the instrument for stock prices and study the impact of stock prices on takeovers. Since Ed-

[7] To my knowledge, Choi et al. (2023) is the only exception, which builds a dynamic investment model with endogenous asset demand as in Koijen and Yogo (2019) to quantify the financing misallocation of latent demand. Instead of using the cost of capital to link the dynamic investment model with investor demand, my supply-demand framework relates the supply and demand sides using either the cost of capital channel (Hayashi, 1982; Cochrane, 1996; Liu et al., 2009) or the the information channel (Bond et al., 2012)

mans et al. (2012), a large number of papers use mutual fund flows to instrument stock prices and examine their real impact: Hau and Lai (2013), Lou and Wang (2018) and Dessaint et al. (2019) on corporate investment; Phillips and Zhdanov (2013) on R&D; Bennett et al. (2020) on productivity; Khan et al. (2012) on seasoned equity offerings; Norli et al. (2015) on shareholder activism; Lee and So (2017) on analyst coverage; and Xu and Kim (2022) on environmental policy.[8] The second instrument is dividend reinvestment. Most papers use dividend reinvestment to quantify the price impact of investor flows, such as Hartzmark and Solomon (2024) and Van der Beck (2024). One exception is Schmickler and Tremacoldi-Rossi (2023) who use dividend reinvestment as the instrument for stock prices and study the spillover effects of payouts on firm financing and investment decisions.[9] The third instrument is index reconstitution. Chaudhry (2024) uses Russell index reconstitution as the instrument for stock prices and studies their effect on analyst cash flow expectations. Sammon and Shim (2024) and Tamburelli (2024) link firms' share supply with demand shocks by index reconstitution.[10] My paper makes several distinct contributions to this literature. First, it moves beyond the focus on stock prices to examine the behavior of investors in the stock market. Second, it not only quantifies the multiplier effects of investor demand but also explores how investor preferences influence corporate responses. Third, the supply-demand framework developed in this paper enables counterfactual analysis, allowing for a detailed examination of the interactions between investors and firms, as well as their combined effects on prices and real outcomes.

This paper also contributes to the broader literature examining the real effects of credit supply shocks. Seminal work by Bernanke (1983) and Bernanke and Gertler (1989) argues that disruptions in credit supply within the banking system influence the real economy, a claim supported by empirical studies such as Khwaja and Mian (2008) on the cost of debt financing, Chodorow-Reich (2014) on employment, and Aghamolla et al. (2024) on

[8] Wardlaw (2020) and Schmickler (2020) question the use of mutual fund flows as the instrument for stock prices. Wardlaw (2020) finds that mutual fund flows (if corrected) are too small to generate price impact, let alone real impact, while Schmickler (2020) finds that the price impact of mutual fund flows is driven by reverse causality.

[9] Quantifying the long-term real impact of payouts may have a reverse causality issue if the long-term investment of firms or their industries or the market affects current payouts at the firm, industry and market level. This reverse causality issue can be mitigated when quantifying the short-term impact of dividend reinvestment, as in the setting of Hartzmark and Solomon (2024). This is so because the demand side is changeable, whilst the supply side remains unchanged in the short term.

[10] Replacing total investor flows with flows by index reconstitution suffers from the measurement error bias as illustrated above. While index reconstitution generates a statistically significant price impact, its predicting power for stock prices is small. I replicate the demand shocks by index reconstitution using the construction approach in Aghaee (2024). I find that the change in weights by portfolio rebalancing (due to index reconstitution) is small and the total asset under management of S&P 500 index funds is small, indicating weak price impact of these demand shocks. This result is consistent with Chang et al. (2015). The small price impact by index reconstitution makes it hard to generate real impact on firms.

hospital health outcomes. While these studies focus on the primary market and largely overlook the role of credit suppliers' preferences in shaping real outcomes, my paper shifts the focus to the stock market, investigating how stock investors' demand affects firm financing and investment decisions in equilibrium.[11]

3 Model

In this section, I establish a model of investor demand and firm supply in the stock market. Firms decide their total share supply and characteristics such as real investment. Investors form their portfolios based on stock prices and firm characteristics. Under the market clearing condition, I derive the equilibrium relationship between investor flows and firm decisions such as share issuance and fundamentals (investment). By adding corporate decisions, this model extends the demand system asset pricing models of Koijen and Yogo (2019) and Van der Beck (2024).

3.1 Firm Side

There are N firms in the market, indexed by $n = 1, \cdots, N$. Each firm n issues one security in the equity market, denoted as asset n. Each firm makes two decisions: (1) it adjusts total shares outstanding through share issuance or buybacks; (2) it adjusts its firm characteristics such as investment. Firms' total shares outstanding is denoted as $\boldsymbol{Q_t^F} = (Q_t^F(1), Q_t^F(2), \cdots, Q_t^F(N))'$, where I normalize the beginning-of-quarter shares outstanding of each firm to 1. Firms' characteristics are denoted as $\boldsymbol{X_t} = (X_t(1), X_t(2), \cdots, X_t(N))'$. These decisions depend on market conditions, $\boldsymbol{P_t} = (P_t(1), P_t(2), \cdots, P_t(N))'$. $\boldsymbol{P_t}$ is the market equity since I normalize the beginning-of-quarter shares outstanding to 1.

Below I derive the equilibrium firm decisions in a stock market. This follows the q-theory of investment literature such as Hayashi (1982), Liu et al. (2009) and Bolton et al. (2011). Corporate policies are linear functions of asset prices: $\text{diag}(\boldsymbol{X_t})^{-1}\Delta\boldsymbol{X_t} = \boldsymbol{\Lambda_t^X}\text{diag}(\boldsymbol{P_t})^{-1}\Delta\boldsymbol{P_t}$ and $\Delta\boldsymbol{Q_t^F} = \boldsymbol{\Lambda_t^F}\text{diag}(\boldsymbol{P_t})^{-1}\Delta\boldsymbol{P_t}$. To simplify the derivation, I assume a representative firm.[12]

[11] A study by Kubitza (2024) focuses on the corporate bond market and assesses the impact of insurers' bond demand on firm financing and investment. The approach of this study bears a resemblance to the literature that uses mutual fund flows as instruments. Kubitza (2024) finds that supply elasticities to bond prices are high but does not consider investor preferences. My paper adds to this research by explicitly incorporating investor preferences into a supply-demand framework to assess their influence on corporate decisions.

[12] I thus simplify the notation by ignoring the n in this subsection. For example, $(P_t(n), X_t(n), Q_t^F(n)) \stackrel{\text{def}}{=} (P_t, X_t, Q_t^F)$.

Suppose the firm's production follows the Cobb-Douglas production function:

$$Y_t = Z_t K_t^{\alpha} L_t^{1-\alpha}, \tag{1}$$

where Z_t is total factor productivity, K_t is the total capital of the firm, L_t represents other factors of production such as labor. This production function exhibits constant returns to scale (CRS) as $Y_t(sK_t, sL_t) = sY_t(K_t, L_t)$.

Labor can be perfectly adjusted, meaning that the firm hire any amount of labor at a given wage rate w_t. The firm decides its optimal labor in production by maximizing total profit (equals the total production minus the total wage of labor) as follows:

$$L_t^* = \max_{L_t}[Z_t K_t^{\alpha} L_t^{1-\alpha} - w_t L_t] = \left[\frac{(1-\alpha)Z_t K_t^{\alpha}}{w_t}\right]^{1/\alpha}. \tag{2}$$

Under this optimal labor, the profit of the firm is

$$\Pi(K_t) = \underbrace{\alpha\left(\frac{1-\alpha}{w_t}\right)^{\frac{1-\alpha}{\alpha}} Z_t^{1/\alpha}}_{\stackrel{\text{def}}{=} A_t} \cdot K_t = A_t K_t. \tag{3}$$

The profit function of the firm also shows constant return of scale (CRS).

The capital can be adjusted with a cost. The total capital of the firm accumulated as the investment minus capital depreciation, follows the path

$$K_{t+1} = (1-\delta_t)K_t + I_t. \tag{4}$$

The adjustment cost is defined as $\Phi(I_t, K_t)$, as an increasing and convex function of I_t. A commonly used adjustment cost in the literature, such as Hayashi (1982) and Liu et al. (2009), is $\Phi(I_t, K_t) = \frac{a}{2}\frac{I_t^2}{K_t}$.[13] The adjustment cost of capital may be sourced from capital installing cost, capital restructuring cost, regulation compliance cost, or so on.

Suppose the firm is fully financed by equity market. After paying the cost of investment and tax (tax rate is τ_t), the firm distribute all the remaining profit to equity holders as dividend:

$$D_t = (1-\tau_t)[\Pi(K_t) - \Phi(I_t, K_t)] - I_t + \tau_t \delta_t K_t. \tag{5}$$

If $D_t > 0$, the firm distributes profits to equity holders. If $D_t < 0$, the firm finances its operations by getting money from equity holders.

Suppose the firm lives in an unlimited and discrete time environment, it optimizes

[13]This adjustment cost satisfies the constant return of scale: $\frac{\partial \Phi(I_t,K_t)}{\partial I_t} I_t + \frac{\partial \Phi(I_t,K_t)}{\partial K_t} K_t = \Phi(I_t, K_t)$.

total discounted dividends to the existing equity holders. The objective function and constraints of the firm are

$$V_t = \max_{\{I_t, K_{t+1}\}_{t \geqslant 0}} \mathbb{E}_t \left[\sum_{s=0}^{+\infty} M_{t+s} D_{t+s} \right] = \max_{\{I_t, K_{t+1}\}_{t \geqslant 0}} D_t + \mathbb{E}_t[M_{t+1} V_{t+1}] \tag{6}$$

$$\text{s.t.} \quad K_{t+1} = (1 - \delta_t) K_t + I_t \tag{7}$$

where M_{t+s} is the discount factor at time $t + s$.

The first order condition with respect to I_t is

$$\frac{\partial V_t}{\partial I_t} = 0 = -\left[1 + (1 - \tau_t) \frac{\partial \Phi(I_t, K_t)}{\partial I_t}\right] + Q_t \tag{8}$$

where Q_t is the Lagrange multiplier before the constraint, which equals the shadow price of total capital of the firm.

The first order condition with respect to K_{t+1} is

$$\frac{\partial V_t}{\partial K_{t+1}} = 0 = \mathbb{E}_t[M_{t+1} \frac{\partial V_{t+1}}{\partial K_{t+1}}] - Q_t \tag{9}$$

Combining both first order conditions, we get the famous Tobin's Q theory of investment,

$$1 + (1 - \tau_t) \frac{\partial \Phi(I_t, K_t)}{\partial I_t} = Q_t = \mathbb{E}_t[M_{t+1} \frac{\partial V_{t+1}}{\partial K_{t+1}}] \tag{10}$$

which says that firm's investment is fully determined by its marginal Q, defined as $\mathbb{E}_t[M_{t+1} \frac{\partial V_{t+1}}{\partial K_{t+1}}]$. This equation also says that the firm adjusted its investment until its marginal cost of investment equals its marginal benefit of investment.

With the CRS assumptions, we are able to replace the marginal Q with the average Q. Lemma 1 is the theoretical result in Hayashi (1982). That is, we build the relationship between firm's investment and its market equity P_t.

Lemma 1. *The investment rate of the firm is an affine function of average Q under the constant return of scale (CRS) assumption of production and investment adjustment cost functions:*

$$1 + (1 - \tau_t) \frac{\partial \Phi(I_t, K_t)}{\partial I_t} = \frac{P_t}{K_{t+1}}. \tag{11}$$

Under the functional assumption of production and adjustment cost above, the investment rate of the firm is linear in average Q:

$$\frac{I_t}{K_t} = \frac{1}{a(1 - \tau_t)} \frac{P_t}{K_{t+1}} - \frac{1}{a(1 - \tau_t)}. \tag{12}$$

Next we derive the equilibrium relationship between firm's share issuance and the average Q. Here, we include an additional assumption that the firm's average Q should stay somewhat stable over time.

Lemma 2. *Assume the constant return of scale (CRS) of production and investment adjustment cost functions, we have the share issuance (or the negative dividend) of the firm as*

$$-\frac{D_t}{K_t} = \frac{1}{2a(1-\tau_t)}\left(\frac{P_t}{K_{t+1}}\right)^2 + \mathcal{C}_t, \tag{13}$$

where $\mathcal{C}_t$ is a term unrelated with the average Q.

Lemma 1 and Lemma 2 show that both investment rate and share issuance can be modeled as separate functions of market equity. We then arrive at the linear function of firm's investment growth and share issuance on its market equity. The proofs are in the Internet Appendix IA.1.

Proposition 1. *Assume the constant return of scale (CRS) of production and investment adjustment cost functions, firm's investment and share issuance are*

$$diag(\boldsymbol{X_t})^{-1}\Delta\boldsymbol{X_t} = \boldsymbol{\Lambda_t^X}\, diag(\boldsymbol{P_t})^{-1}\Delta\boldsymbol{P_t} \tag{14}$$

$$\Delta\boldsymbol{Q_t^F} = \boldsymbol{\Lambda_t^F}\, diag(\boldsymbol{P_t})^{-1}\Delta\boldsymbol{P_t} \tag{15}$$

where $diag(\boldsymbol{X_t})^{-1}\Delta\boldsymbol{X_t}$ and $\Delta\boldsymbol{Q_t^F}$ represent the percentage change in firm's investment rate and total shares.

The theory in this subsection posits that the firm's investment and share issuance decisions are determined only by its own market equity P_t. Thus the $\boldsymbol{\Lambda_t^X}$ and $\boldsymbol{\Lambda_t^F}$ should be diagonal, with zero spillover effects: One firm's market equity should not affect other firms' investment and share issuance. These two linear equations are widely used in the literature. For example, Morck et al. (1990) use the first equation to test whether stock prices are correlated with real economic activity such as firm's investment. Hau and Lai (2013), Lou and Wang (2018), Dessaint et al. (2019), and Schmickler and Tremacoldi-Rossi (2023) use the same first equation to build causal relationship between stock prices and firm's investment. Khan et al. (2012) use the second equation to investigate whether stock prices affect firm's equity issuance (e.g., seasoned equity offerings).

The model in this subsection is a simplified-version dynamic investment model. I simplify the firm to not suffering from any financial frictions outlined in Chapter 3 of Strebulaev et al. (2012). This simplification leads to the limitation of micro-foundations of the firm in this paper. Let's discuss the differences and limitations of my firm-side model here.

One assumption for the firm in this paper is that it does not suffer from equity financing costs. When I model the share issuance in Equation 5 as the negative dividend, I assume that the firm can get whatever amount of money from equity holders without costs. This assumption is not plausible as the firm faces different costs when issuing new shares. One cost is the underwriting fees paid to financial intermediaries (Altınkılıç and Hansen, 2000). Another cost is related to the bad signaling of equity financing. Share issuances convey bad signal to the market about the state of the firm, which induces financing costs (Leland and Pyle, 1977; Myers and Majluf, 1984). The financing cost could also be sourced from agency problems: managers over take risks when they sell shares to new shareholders due to the convex return structure. New shareholders anticipate this and punish the firm by higher financing costs (Jensen and Meckling, 1976). We can incorporate the external financing cost in our model by changing per-period cash flow in Equation (5):

$$\bar{D}_t = \underbrace{(1-\tau_t)[\Pi(K_t) - \Phi(I_t, K_t)] - I_t + \tau_t \delta_t K_t}_{\stackrel{\text{def}}{=} D_t} - \underbrace{[\eta_0 - \eta_1 D_t] \cdot \mathcal{I}[D_t < 0]}_{\stackrel{\text{def}}{=}\text{Financing Costs}}. \tag{16}$$

where the financing cost consists of the fixed and variable costs when the financing need is positive (e.g. $-D_t > 0$), as in Gomes (2001). In this setting, the model does not have an analytic solution. Estimating the model would need a structural approach as in Strebulaev et al. (2012). Normally, the financing cost is positive for firms (e.g., $\eta_0 > 0$ and $\eta_1 > 0$). In this case, the firm's investment and share issuance are less responsive to the change in stock prices.

The second assumption for the firm is that it does not manage cash holdings. I assume that firm distributes all its remaining cash flow to its shareholders as stated in Equation 5. The firm holds cash because it's cheaper than external financing. Thus, cash holdings can act as a better source of future financing needs. Regarding the cost of cash holdings, the interest from cash needs to pay taxation. Incorporating cash holdings in our model, we can getthe per-period cash flow as:

$$\bar{D}_t = \underbrace{(1-\tau_t)[\Pi(K_t) - \Phi(I_t, K_t)] - I_t + \tau_t \delta_t K_t + \overbrace{C_t - \frac{C_{t+1}}{1 + r_t(1-\tau_t)}}^{\stackrel{\text{def}}{=}\text{Net Cash}}}_{\stackrel{\text{def}}{=} D_t} - \underbrace{[\eta_0 - \eta_1 D_t] \cdot \mathcal{I}[D_t < 0]}_{\stackrel{\text{def}}{=}\text{Financing Costs}}. \tag{17}$$

The firm's share issuance and investment will be less responsive to the the negative investor flows (it can use cash reserves if under-pricing), and its share issuance will be more responsive to the positive investor flows (it can actively manage cash reserve from over-pricing). The investment may or may not be more responsive for the positive investor flows.

The third assumption in the paper is that the firm does not rely on debt financing. Again, I assume in Equation (5) that the firm can only finance its operations with equity issuance when its cash flow is negative. This leaves out the possibility that the firm can borrow from banks or from the bond holders. If the firm's debt is risk free, we can regard the debt as negative cash. We then have similar per-period cash flow as Equation (17). If the firm's debt is risky (as in Hennessy and Whited (2007)), the firm's per-period cash flow has the same structure as Equation (17), but with a smaller interest rate r_t. When debt financing is possible, the firm's share issuance and investment will be less responsive to the the negative investor flows (it can use debt if under-pricing), and its share issuance will be more responsive to the positive investor flows (it can actively manage debt reserve from over-pricing). The investment may or may not be more responsive for the positive investor flows.

To sum up, my base model has assumed no frictions in equity financing, debt financing, and cash holdings. The model enjoys the benefits of model and estimation simplicity in investigating how investors' asset demand affects firm's policies. However, the above-mentioned frictions would bias the estimation, thus a more complicated model, such as the ones reviewed in Strebulaev et al. (2012), is need. Also the estimation of the complicated model needs a structural approach. I leave this for the future step of this paper.

3.2 Investor Side

There are I investors in the market, indexed by $i = 1, \cdots, I$. The investor i firms its portfolio of N assets.[14] The ownership share of the investor i in the asset n at t is denoted as $Q_{i,t}(n)$. The optimal portfolio $\boldsymbol{Q_{i,t}} = (Q_{i,t}(1), Q_{i,t}(2), \cdots, Q_{i,t}(N))'$ is a function of asset prices $\boldsymbol{P_t} = (P_t(1), P_t(2), \cdots, P_t(N))'$, observable firm-level variables $\boldsymbol{X_t}$ (such as firm's investment) and unobservable firm-level variables $\boldsymbol{V_t} = (V_t(1), V_t(2), \cdots, V_t(N))'$: $\boldsymbol{Q_{i,t}} = \boldsymbol{Q_{i,t}}(\boldsymbol{P_t}, \boldsymbol{X_t}, \boldsymbol{V_t})$. When the equity market clears, the total supply of assets equals to the total demand of assets:

$$\boldsymbol{Q_t^F} = \sum_{i=1}^{I} \boldsymbol{Q_{i,t}} = \sum_{i=1}^{I} \boldsymbol{Q_{i,t}}(\boldsymbol{P_t}, \boldsymbol{X_t}, \boldsymbol{V_t}). \tag{18}$$

[14] I also allow these investors to invest in an outside asset such as savings or bonds. Investors can also short sale or leverage their investment over the N stocks. Thus, the total asset under management could be larger than the total dollar holdings of the investor if investing in short positions or outside asset: $\mathrm{AUM}_{i,t} \geqslant \sum_{n=1}^{N} P_t(n) Q_{i,t}(n)$; or smaller than the total dollar holdings of the investor if using leverage: $\mathrm{AUM}_{i,t} \leqslant \sum_{n=1}^{N} P_t(n) Q_{i,t}(n)$.

Since $\boldsymbol{Q_{i,t}}$ is defined as the ownership share, it is summed to one when there is no issuance of shares at t: $\sum_{i=1}^{I} \boldsymbol{Q_{i,t}} = \mathbf{1}$.

Demand elasticity is defined with respect to price as the negative ratio of the percentage change in quantity demanded over the percentage change in price:

$$\zeta_{i,t}^{P}(n,n) = -\frac{\partial \ln(Q_{i,t}(n))}{\partial \ln(P_t(n))} \quad \text{and} \quad \zeta_{i,t}^{P}(n,m) = -\frac{\partial \ln(Q_{i,t}(n))}{\partial \ln(P_t(m))}. \tag{19}$$

Given the investor-specific demand elasticity matrix $\boldsymbol{\zeta_{i,t}^{P}}$, I define the stock level price elasticity matrix as the sum of weighted investor-specific price elasticity:

$$\boldsymbol{\zeta_t^{P}} = \sum_{i=1}^{I} \text{diag}(\boldsymbol{Q_{i,t}})\boldsymbol{\zeta_{i,t}^{P}} \tag{20}$$

Similarly, I define the demand elasticity with respect to observable variables $\boldsymbol{X_t}$ as the ratio of the percentage change in quantity demanded over the percentage change in $\boldsymbol{X_t}$:

$$\zeta_{i,t}^{X}(n,n) = \frac{\partial \ln(Q_{i,t}(n))}{\partial \ln(X_t(n))} \quad \text{and} \quad \zeta_{i,t}^{X}(n,m) = \frac{\partial \ln(Q_{i,t}(n))}{\partial \ln(X_t(m))}. \tag{21}$$

Given the investor-specific demand elasticity matrix $\boldsymbol{\zeta_{i,t}^{X}}$, I define the stock level demand elasticity with respect to $\boldsymbol{X_t}$ as the sum of weighted investor-specific demand elasticity:

$$\boldsymbol{\zeta_t^{X}} = \sum_{i=1}^{I} \text{diag}(\boldsymbol{Q_{i,t}})\boldsymbol{\zeta_{i,t}^{X}}. \tag{22}$$

Assume that a shock $\Delta \boldsymbol{V_t} = (\Delta V_t(1), \Delta V_t(2), \cdots, \Delta V_t(N))'$ occurs at t. The shock could be the stock's inclusion in an index, or unobservable characteristics that attract mutual fund flow-induced purchases, or investor sentiment on the stocks. The shock triggers the change in investor demand, $\Delta \boldsymbol{D_t}$, expressed as a fraction of shares outstanding.[15] This shock also changes the asset price $\boldsymbol{P_t}$, shares outstanding $\boldsymbol{Q_t^{F}}$, and firm characteristics $\boldsymbol{X_t}$. These changes can be approximated by first-order Taylor expansion:

$$\Delta \boldsymbol{D_t} = \left(\sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{V_t}}\right) \Delta \boldsymbol{V_t}; \Delta \boldsymbol{P_t} = \frac{\partial \boldsymbol{P_t}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t}; \Delta \boldsymbol{Q_t^{F}} = \frac{\partial \boldsymbol{Q_t^{F}}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t}; \Delta \boldsymbol{X_t} = \frac{\partial \boldsymbol{X_t}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t}. \tag{23}$$

Proposition 2. *In equilibrium, the investor flow generates three effects: price effect, financing effect, and investment effect. These effects together absorb the investor flow as*

[15] Here and after, $\boldsymbol{D_t}$ represents the investor demand, rather than the firm's dividend in Section 3.1.

follows:

$$\Delta \boldsymbol{D_t} = \boldsymbol{\zeta_t^P} \underbrace{diag(\boldsymbol{P_t})^{-1}\Delta \boldsymbol{P_t}}_{\textit{Price Effect}} + \underbrace{\Delta \boldsymbol{Q_t^F}}_{\textit{Financing Effect}} - \boldsymbol{\zeta_t^X} \underbrace{diag(\boldsymbol{X_t})^{-1}\Delta \boldsymbol{X_t}}_{\textit{Investment Effect}} \tag{24}$$

Proposition 2 illustrates the firm-level demand function by all investors.[16]

This equation indicates how corporate policies (such as financing and investment) affect the stock market. Firm-level investor inflow $\Delta \boldsymbol{D_t}$ first affects the equilibrium price, and then affects firm decisions on share issuance and fundamentals. These effects adjust to account for investor inflow. If firms do not respond to the investor inflow, the price effect can be directly calculated as

$$\text{diag}(\boldsymbol{P_t})^{-1}\Delta \boldsymbol{P_t} = (\boldsymbol{\zeta_t^P})^{-1}\Delta \boldsymbol{D_t}, \tag{25}$$

which is used by Gabaix and Koijen (2023) and Van der Beck (2024) to quantify the price effect of investor flows. However, as I show in the empirical evidence, firms do respond to investor flows by adjusting their shares outstanding and fundamentals. This has two consequences: first, the price elasticity of demand is an insufficient statistic to quantify the price effect; second, the price elasticity of demand is unidentifiable using flow shocks as instruments.[17]

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[16]The linear demand function is also consistent with the demand function in Koijen and Yogo (2019). Fit in the demand function of Koijen and Yogo (2019) to below, we get

$$\begin{aligned} q_{i,t}(n) = \ln(Q_{i,t}(n)) &= \ln \frac{w_{i,t}(n)A_{i,t}}{P_t(n)} = \ln(w_{i,t}(n)) + \ln(A_{i,t}) - p_t(n) \\ &= -(1-\beta_{0,i,t})p_t(n) + \sum_{k=1}^{K-1} \beta_{k,i,t}x_{k,t}(n) + \beta_{K,i,t} + + \ln(A_{i,t}) \ln(w_{i,t}(0)) + \ln(\epsilon_{i,t}(n)) \end{aligned}$$

Therefore, the demand elasticity to price is $\zeta_{i,i}(n) = 1 - \beta_{0,i,t}$. There are two differences between the demand function in this paper and that in Koijen and Yogo (2019). First, the always zero holdings do not provide information for demand elasticity in this paper. Second, using trades for demand elasticity estimation controls for last-period portfolios and thus remove the bias from hidden investment mandate. See a discussion of trades vs. levels demand elasticity estimation in Van der Beck (2022).

[17]I do not model the bond market, but take it as exogenously given. When investors flow from bond/savings to the equity, it will reduce the cost of equity financing and increase the cost of bond financing. This will incentivize the firm to replace bond financing with equity financing, making more response in equity issuance, thus our estimated equity issuance will be biased upwards. The true cost of capital will be higher if there is bond market, making less response in investment. Thus our estimated investment growth will be biased downwards.

3.3 Equilibrium

Proposition 3. *In equilibrium, the multiplier effects of investor flow on firm's share issuance and investment are given by*

$$\Delta \boldsymbol{Q}_t^{\boldsymbol{F}} = \underbrace{\boldsymbol{\Lambda}_t^{\boldsymbol{F}}(\boldsymbol{\zeta}_t^{\boldsymbol{P}} + \boldsymbol{\Lambda}_t^{\boldsymbol{F}} - \boldsymbol{\zeta}_t^{\boldsymbol{X}}\boldsymbol{\Lambda}_t^{\boldsymbol{X}})^{-1}}_{\stackrel{def}{=}\boldsymbol{M}^{\boldsymbol{F}}} \Delta \boldsymbol{D}_t \tag{26}$$

$$diag(\boldsymbol{X}_t)^{-1}\Delta \boldsymbol{X}_t = \underbrace{\boldsymbol{\Lambda}_t^{\boldsymbol{X}}(\boldsymbol{\zeta}_t^{\boldsymbol{P}} + \boldsymbol{\Lambda}_t^{\boldsymbol{F}} - \boldsymbol{\zeta}_t^{\boldsymbol{X}}\boldsymbol{\Lambda}_t^{\boldsymbol{X}})^{-1}}_{\stackrel{def}{=}\boldsymbol{M}^{\boldsymbol{X}}} \Delta \boldsymbol{D}_t \tag{27}$$

4 Estimation

I first summarize the data sources and sample, then introduce the approach to identify the multipliers of $\Delta \boldsymbol{D}_t$ in Proposition 3. Finally, I examine the validity of the granular instrumental variable (GIV) approach.

4.1 Data and Sample

The data used in this paper include institutional equity holdings, stock returns, and firm characteristics. Institutional equity ownership in the United States is obtained from FactSet Ownership v5. FactSet sources its quarterly institutional holdings from SEC Form 13F filings. All institutional investors with assets under management above USD 100 million are required to file 13F filings quarterly. Shares outstanding are also from FactSet Ownership v5. The portfolios of households are constructed as total outstanding shares minus the sum of shares held by all institutional investors. The FactSet ownership data are available from 1999Q1. Information on stock returns and dividends comes from CRSP, while firm characteristics are from Compustat Fundamentals.

Given that this paper focuses on the real impact of investor flows on corporate policies such as investment, I exclude financial firms (SIC 6000–6999) and the utility sector (SIC 4900–4999) from the sample. For stocks, I include only common stocks listed on the NYSE, NASDAQ, or AMEX (i.e., CRSP share code 10 or 11 and exchange code 1, 2, or 3). I also exclude firms with missing data on the fundamentals from Compustat. The sample period is from 1999Q1 to 2023Q4.

4.2 Identification

To quantify the impact of investor flows on firm decisions, I need to estimate two sets of parameters: the supply-side elasticity $(\boldsymbol{\Lambda}_t^{\boldsymbol{F}}, \boldsymbol{\Lambda}_t^{\boldsymbol{X}})$ and the demand-side elasticity $(\boldsymbol{\zeta}_t^{\boldsymbol{P}}, \boldsymbol{\zeta}_t^{\boldsymbol{X}})$. However, identification of these elasticities mostly relies on finding suitable instruments for asset prices and firm fundamentals. Most of these instruments are *hypothetical* fund flows and suffer from concerns like weak instrument.[18] In the following, I demonstrate that it is possible to directly identify the impact of investor flows by measuring $\Delta \boldsymbol{D_t}$ in Proposition 3 directly from investor holdings.

I estimate the impact of investor flows on firm decisions using the granular instrumental variables (GIV) approach in Gabaix and Koijen (2024). The intention of the GIV approach is to aggregate investors' idiosyncratic demand shocks to the asset level. Given that investors' idiosyncratic demand shocks are uncorrelated with firms' fundamentals, this aggregated demand shock at the asset level is also orthogonal to the firm's fundamentals, ensuring the identification of supply-side parameters. Previous papers have used this intuition to estimate the causal effects of financial markets, such as mutual fund flows (Edmans et al., 2012), dividend reinvestment (Hartzmark and Solomon, 2024), and index reconstitution (Chang et al., 2015). The differences between this paper and the previous literature are the source of flows and the weights of aggregation. The GIV approach provides a more flexible and reliable framework for causally estimating the impact of financial markets.

I start the identification by estimating the supply-side parameters. To do so, I quantify two supply elasticities $(\lambda^F(n), \lambda^X(n))$ using the following two equations:

$$\Delta Q_t^F(n) = \lambda^F(n) R_t(n) + \mu_t(n) \tag{28}$$

$$\Delta x_t(n) = \lambda^X(n) R_t(n) + \nu_t(n) \tag{29}$$

where $R_t(n) = \frac{P_t(n) - P_{t-1}(n)}{P_{t-1}(n)}$ (the percentage change in market equity, e.g., stock return), $\Delta Q_t^F(n) = Q_t^F(n) - 1$ (the percentage change in firm's total shares outstanding)[19], and $\Delta x_t(n) = \frac{X_t(n) - X_{t-1}(n)}{X_{t-1}(n)}$(the percentage change in firm's investment rate). Firm's share issuance and investment depend on the change in market equity $R_t(n)$, and supply side shocks. According to Lemma 1 and Lemma 2, these supply shocks include shocks to the investment adjustment cost and corporate tax rate.

Next, I quantify two demand elasticity $(\zeta^P(n), \zeta^X(n))$ at the firm level, which are aggregated from investor-level demand elasticity. Therefore, I estimate the demand function for investors to get their demand elasticity:

$$\Delta q_{i,t}(n) = -\zeta^P(n) R_t(n) + \zeta^X(n) \Delta x_t(n) + \gamma_i(n) \eta_t(n) + \varepsilon_{i,t}(n) \tag{30}$$

[18] These fund flows are *hypothetical* since they assume an approach to aggregate investor-level flows to the firm level, rather than using the realized firm-level flows induced by investor-level flows. Section 5 will discuss these details.

[19] This definition of $\Delta Q_t^F(n)$ represents the percentage change in firm's total shares outstanding as I normalize the beginning-of-period shares outstanding as one.

where $\Delta q_{i,t}(n) = \frac{Q_{i,t}(n) - Q_{i,t-1}(n)}{Q_{i,t-1}(n)}$ (the percentage change in total shares held), $R_t(n) = \frac{P_t(n) - P_{t-1}(n)}{P_{t-1}(n)}$ (the percentage change in market equity, e.g., stock return), $\Delta x_t(n) = \frac{X_t(n) - X_{t-1}(n)}{X_{t-1}(n)}$ (the percentage change in firm's investment rate). Changes in investor's portfolio holdings are not only determined by firm's asset price and investment (the explained part), but also by demand shocks. We further group the demand shock into the systemic demand shock $\gamma_i(n)\eta_t(n)$ and the idiosyncratic demand shock $\varepsilon_{i,t}(n)$. To model the systemic demand shock, I use a factor model with dimension r: $\gamma_i(n)\eta_t(n) = \sum_{f=1}^{r} \gamma_i^f(n)\eta_t^f(n)$. I take the first factor for stock n to be constant over time, e.g., $\eta_t^1(n) = \eta^1(n)$. The other factors could be the macroeconomic variables such as GDP growth (e.g., $\eta_t^f(n) = \eta_t^f$), or firm-specific factors such as book-to-market, size, profitability, and etc. The remaining part in shares change $\Delta q_{i,t}(n)$ is assigned as investor's idiosyncratic demand shock $\varepsilon_{i,t}(n)$. Examples of the idiosyncratic demand shock are unexpected mutual fund flows, dividend reinvestment, index reconstitution, capital requirement on some institutions, investment mandate shift, and etc.

Now let's discuss the assumptions needed for the identification.

Assumption 1. *The idiosyncratic shocks to investors are uncorrelated with the systemic demand shock and the supply side shocks:*

$$\varepsilon_{i,t}(n) \perp \eta_t(n) \tag{31}$$

$$\varepsilon_{i,t}(n) \perp \mu_t(n), \nu_t(n) \tag{32}$$

This key assumption is that the error term $\varepsilon_{i,t}(n)$ captures the unexplained idiosyncratic demand of the investor, which is not explained by macroeconomic factors (e.g., GDP growth, interest rates) or firm-level factors (e.g., firm fundamentals). Consider, for instance, an idiosyncratic shock induced by unexpected mutual fund flows. When a mutual fund experiences a sudden, large outflow from its investors, its demand for the stocks in its portfolio drops sharply, leading to a fire sale of portfolio stocks. Provided the fund flow is unexpected, this drop in demand is independent of stock prices, firm fundamentals, or macroeconomic conditions.[20] In such cases, this flow-driven demand shock can serve as an instrument for stock returns and change in investment, enabling the estimation of demand and supply elasticity.[21] With the granular instrumental variables

[20]Identifying unexpected and meaningful fund flows poses challenges. The literature often employs a threshold of 5% of the fund's total assets: if the total dollar outflow exceeds this threshold, it is classified as unexpected and meaningful. Expected outflows, driven by macroeconomic factors or portfolio characteristics, are typically small and exhibit smooth variation over time. Fund outflows that are less than 5% total assets do not force funds to trade quickly and likely do not generate large price impacts.

[21]A potential limitation of using mutual fund flow-driven demand shocks as the instrument is the risk of weak instruments. Unexpected mutual fund flows are relatively rare and may lack sufficient magnitude to produce substantial price effects at the firm level.

(GIV) approach, I isolate the idiosyncratic demand shock by extracting the unexplained component of demand after controlling for as many relevant factors as possible in the investor's demand function.[22] This approach mirrors the logic of factor models in asset pricing (Ross, 1976), where idiosyncratic risks are the residuals after accounting for systematic risk factors. Similarly, if all relevant factors $\eta_t(n)$ are incorporated into the demand function (30), the error term $\varepsilon_{i,t}(n)$ should represent the idiosyncratic demand shock (Gabaix and Koijen, 2024).[23] Since including every possible factor is impractical, I adopt a parsimonious set, guided by the principle that the additional factor should be included only if it meaningfully enhances the explanation of investor demand, consistent with Fama and French (1993) and Hou et al. (2020).

The extracted idiosyncratic shock is unrelated with supply side shocks. Suppose there is a productivity shock to the firm. Since this productivity shock affects all investors' demand, it will be detected by $\eta_t(n)$.[24] Investors have different response to this productivity shock, to the degree of the factor loading $\gamma_i(n)$. Incorporating this productivity shock as a factor in demand functions, the extracted idiosyncratic demand shock is unrelated with supply side shocks.

This logic inspires my strategy to justify the exogeneity of $\varepsilon_{i,t}(n)$. If all necessary factors are accounted for, the estimated $\varepsilon_{i,t}(n)$ should remain stable when an additional factor is introduced. As a result, the findings from the main regressions should be robust whether we use the idiosyncratic demand shock derived from the current set of factors or the one augmented with an additional factor. To further validate that $\varepsilon_{i,t}(n)$ represents the idiosyncratic demand shock, I employ two more justifications. First, I assess whether $\varepsilon_{i,t}(n)$ correlates with well-known demand shocks, such as unexpected mutual fund flows or dividend reinvestments. If $\varepsilon_{i,t}(n)$ is truly idiosyncratic, it should reflect these known shocks. Second, I investigate whether $\varepsilon_{i,t}(n)$ is associated with pre-period firm fundamentals. While idiosyncratic demand shocks may influence current and future fundamentals, they should not be predictable from pre-period fundamentals.

Assumption 2. *Homogeneous demand elasticity across investors and time for each asset:*

$$\zeta^P_{i,t}(n) = \zeta^P(n) \tag{33}$$

$$\zeta^X_{i,t}(n) = \zeta^X(n) \tag{34}$$

[22] Some flows are anticipatory: investors flow to a firm in anticipation of higher stock return (expected return). The expect return is based on systemic risk and can be expressed as factors and factor loadings. As we remove the systemic demand shocks out by $\gamma_i(n)$, the idiosyncratic demand shock does not suffer from this anticipatory flow issue.

[23] This idiosyncratic shock could be sourced from shocks to investors, such as unexpected fund flows, unexpected income from dividend payment, or capital requirement.

[24] I use the latent factor to capture this productivity shock.

Assumption 2 posits that demand elasticity is homogeneous across investors for a given asset but allows for heterogeneity across assets. This assumption is adopted for three primary reasons. First, it permits heterogeneity in firm-level demand elasticity, which is essential for capturing various firm responses to similar investor flows. Our regressions can generate heterogeneous responses to investor flow across firms. Second, the rise of exchange-traded funds (ETFs) and benchmarking practices during the sample period (1999–2023) has driven financial institutions toward passive investing strategies, resulting in increasingly similar demand elasticities among these institutions over time.[25] Third, this assumption simplifies the construction of the granular instrumental variable (GIV), facilitating the quantification of the impact of investor flows.

Despite its simplification in instrument construction, this assumption introduces two notable limitations. First, the own-price and own-investment elasticity are determined solely by the stock's price, investment, and market share. While one might expect stocks with more substitutes–those sharing similar characteristics–to exhibit greater demand elasticity, Assumption 2 implies that own-demand elasticity remains unchanged even as the number of substitutes increases, contradicting economic intuition. Second, cross-stock elasticity depends only on the stock's own price, investment and market share, suggesting that substitution patterns are independent of other stock characteristics. This conflicts with the expectation that stocks with similar characteristics should exhibit higher cross-stock demand elasticity.

Assumption 3. *Homogeneous supply elasticity across time for each firm:*

$$\Lambda_t^F(n) = \Lambda^F(n) \tag{35}$$

$$\Lambda_t^X(n) = \Lambda^X(n) \tag{36}$$

Assumption 4. *No spillover effects in supply:*

$$\Lambda_t^F(n,m) = \frac{\partial \ln(Q_t^F(n))}{\partial \ln(P_t(m))} = 0 \tag{37}$$

$$\Lambda_t^X(n,m) = \frac{\partial \ln(X_t(n))}{\partial \ln(P_t(m))} = 0 \tag{38}$$

The above two assumptions regulate supply elasticity. Assumption 3 says that a firm's investment and issuance are similarly responsive to market equity over time. This assumption is satisfied in our sample period 1999–2023 as there are not structural change that affects firm's supply elasticity (given other factors fixed). Assumption 4 is derived

[25]This trend is evident in Figure 3 of Koijen and Yogo (2019), which illustrates that demand elasticity was highly heterogeneous prior to 1999 but has become more homogeneous thereafter. A similar pattern is documented by Haddad et al. (2025).

from Lemma 1 and Lemma 2: the firm's investment and share issuance decisions are determined only by its own market equity P_t.

Now let's discuss the procedure to estimate the parameters with data. We can re-write Equation (30) as

$$\Delta q_{i,t}(n) = \underbrace{-\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n)}_{\stackrel{\text{def}}{=}\beta_t(n)} + \underbrace{\gamma_i(n)\eta_t(n)}_{\stackrel{\text{def}}{=}\alpha_i(n)+\sum_{f=2}^{r}\gamma_i^f(n)\eta_t^f(n)} + \varepsilon_{i,t}(n) \tag{39}$$

$$= \beta_t(n) + \alpha_i(n) + \sum_{f=2}^{r}\gamma_i^f(n)\eta_t^f(n) + \varepsilon_{i,t}(n) \tag{40}$$

We can run the regression on the panel data $I \times T$ (fix firm n) to extract the idiosyncratic shock for given set of factors $\eta_t(n)$.[26] The key to get the idiosyncratic demand shock is the choice of factors $\eta_t(n)$. I adopt a parsimonious set of factors, guided by the principle that the additional factor should be included only if it meaningfully enhances the explanation of investor demand, consistent with Fama and French (1993) and Hou et al. (2020): the error term is then the idiosyncratic demand shock.

Given the idiosyncratic demand shock $\varepsilon_{i,t}(n)$, I define the so-called granular instrumental variable (GIV) as

$$z_t(n) \stackrel{\text{def}}{=} \sum_{i=1}^{I}[S_{i,t}(n) - E_i(n)]\varepsilon_{i,t}(n) \tag{41}$$

where $S_{i,t}(n)$ is the time-varying value weight $S_{i,t}(n) = \frac{Q_{i,t-1}(n)}{\sum_{i=1}^{I} Q_{i,t-1}(n)}$, $E_i(n)$ is the time-invariant weight. Since $\varepsilon_{i,t}(n)$ is orthogonal to the systemic factors and supply side shocks, the GIV $z_t(n)$ is orthogonal to them.

The following proposition shows that the coefficients of $\boldsymbol{\Delta D_t}$ in Proposition 3 can be identified from $z_t(n)$.

Proposition 4. *The coefficients in Proposition 3 are identifiable by regressing $\Delta Q_t^F(n)$ and $\Delta x_t(n)$ on $z_t(n)$.*

$$\Delta Q_t^F(n) = M^F(n)z_t(n) + \xi_t(n) \tag{42}$$

$$\Delta x_t(n) = M^X(n)z_t(n) + \upsilon_t(n) \tag{43}$$

where $M^F(n) = \lambda^F(n)[\zeta^P(n) + \lambda^F(n) - \zeta^X(n)\lambda^X(n)]^{-1}$, $M^X(n) = \lambda^X(n)[\zeta^P(n) + \lambda^F(n) - \zeta^X(n)\lambda^X(n)]^{-1}$, and $z_t(n) \perp \xi_t(n), \upsilon_t(n)$.

[26] I is the number of investors and T is the number of sample period.

I now summarize the estimation procedure. This procedure follows the general framework of Gabaix and Koijen (2024) but makes two modifications to adapt to the specific setting of this paper: (1) I include firm-specific factor $\eta_t(n)$. This is achievable since we have a panel data for each stock. (2) I rely on the Bootstrap to correcting standard errors rather than using a loop algorithm to update $\sigma_i^2(n)$. This is because the GIV $z_t(n)$ is a generated regressor, which gives a consistent estimation of the coefficients but an inconsistent estimation of the standard errors.[27]

Before calculating the GIV, I aggregate institutional holdings to nine investor groups: brokers, hedge funds, long-term investors, private banking, small active, large active, small passive, large passive, and households. I use these nine aggregated groups as investors in the GIV estimation.[28] The factors $\eta_t(n)$ consist of observable factors $\eta_t^o(n)$ and latent factors $\eta_t^l(n)$. I use $\sigma_i^2(n) = \max(\sigma_i^2(n), \text{median}(\sigma_i^2(n)))$ to ensure a reasonable weight on the aggregations.

Step 1: Calculate the volatility $\sigma_i^2(n)$ of $\Delta q_{i,t}(n)$ for investor i and asset n.

This step is to calculate the time-invariant weight $E_i(n) = \frac{1/\sigma_i^2(n)}{\sum_{i=1}^{I} 1/\sigma_i^2(n)}$. Since this weight is to give less weight to data points with high volatile demand, it can achieve the lowest standard errors in parameter estimation, thus efficiency. In my setting of using the Bootstrap, this time-invariant weight can be randomly chosen, for example. $E_i = \frac{1}{I}$ could also work. I still use $E_i(n) = \frac{1/\sigma_i^2(n)}{\sum_{i=1}^{I} 1/\sigma_i^2(n)}$ to follow closely with the literature (Gabaix and Koijen, 2024).

Step 2: For each asset n, run the panel regression on the $I \times T$ panel

$$\Delta q_{i,t}(n) = \alpha_i(n) + \beta_t(n) + \gamma_i(n)\eta_t^o(n) + \epsilon_{i,t}(n) \tag{44}$$

[27]Since the GIV is constructed from the residuals of Equation (44), the OLS standard errors of the estimated multipliers in regressions (45) and (46) overestimate the true standard errors; this means that my estimated multipliers would have higher statistical significance for the corrected standard errors. I also calculate the bootstrap standard errors for each regression and investigate whether the OLS standard errors affect my inference. The results reveal that the difference between bootstrap standard errors and OLS standard errors is nearly zero. That is, the OLS standard errors do not affect my inference. This also indicates that the weight (defined from the $\sigma_i^2(n)$) is reasonably defined. Thus, for simplicity, I report the OLS standard errors for regressions.

[28]This aggregation aims to alleviate the effects of investors having zero holdings. Nonetheless, using either aggregated investors or individual investors does not affect my main findings. Consider two mutual funds (from the same institution type): A+ and A-. Their holdings of Apple Inc. from 2022Q1 to 2022Q4 are (0,100,0,100) for A+, and (200,0,200,0) for A-. Our dependent variable in estimation for both funds will be (., ., -1,.) for A+ and (.,-1,.,-1) for A-. The holdings from 0 to a positive number will not be captured by our dependent variable, while the holdings from a positive number to 0 can be. This will lose information for holdings from 0 to a positive number. With limited information, we are not able to estimate elasticity of Funds A+ and A-. However, if we aggregate them (assume they have same elasticity), we get holdings as (200,100,200,100) and the dependent variable as (.,-.5,+1,-.5). We do not lose information for funds whose holdings from 0 to a positive number. We are also able to quantify the elasticity for Funds A+ and A- in this situation.

using $E_i(n)$ as regression weights. Calculate the residual $\epsilon_{i,t}(n)$.

This step is from Equation (39).

Step 3: Extract latent factors $\eta_t^l(n)$ by running the principal component algorithm (PCA) on $\sqrt{E_i(n)}\epsilon_{i,t}(n)$. Calculate the residuals $\varepsilon_{i,t}(n)$ of regressing $\epsilon_{i,t}(n)$ on $\eta_t^l(n)$. Calculate the GIV $z_t(n)$ using $\varepsilon_{i,t}(n)$ as in Equation (41).

For any given stock n, I have a panel $I \times T$ consisting of $\sqrt{E_i(n)}\epsilon_{i,t}(n)$ for each investor i over T periods. I then run PCA on this panel to get $r-1$ factors ($\eta_t^1, \eta_t^2...$ with the size $1 \times T$) and factor loadings ($\gamma_i^1, \gamma_i^2...$). Then the idiosyncratic shock will be calculated as the error term, which is then aggregated to generate GIV.

Step 4: Run simple time series regressions for each asset n.

$$\Delta Q_t^F(n) = M^F(n)z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t(n) + \xi_t(n) \tag{45}$$

$$\Delta x_t(n) = M^X(n)z_t(n) + \alpha^X(n) + \gamma^X(n)\eta_t(n) + \upsilon_t(n) \tag{46}$$

5 Validating the Granular Instrumental Variable

The first condition for the GIV—the relevance condition—requires a few large idiosyncratic shocks by a few large investors.[29] A few sizable idiosyncratic shocks to large investors or sectors could significantly affect aggregate demand, changing stock prices and further affecting firms' policies. This relevance condition is satisfied in the U.S. setting because financial institutions are quite concentrated and there are frequent demand shocks on them: capital requirement regulations on banks (Amiti and Weinstein, 2018), portfolio regulations on pension funds and brokers, extreme flows to mutual funds and hedge funds, etc.

The second condition for the GIV approach—the exogeneity condition— requires random shocks to investors that are orthogonal to common macro trends, such as GDP growth. The GIV is exogenous by construction, given that I properly control for common factors. To mitigate the risk of omitted factors, I add additional observed and latent factors and check whether the coefficients of $z_t(n)$ change significantly. If the coefficients are stable across different specifications, this indicates that the common factors are properly controlled and the demand shocks are exogenous. The results in the main regressions (45) and (46) indicate that the coefficients are stable with different observed and latent factors. I examine the validity of the exogeneity condition in three additional ways. First, I demonstrate that the GIV $z_t(n)$ bears no relation with corporate decisions

[29]Consider two cases: (1) large shocks to small investors; (2) small shocks to large investors. Both cases will not generate sizable price impact, let alone real impact on firms. The first case is due to small weights for large shocks in aggregation, while the second case is due to small shocks for large weighted investors.

in periods ahead of demand shocks. $z_t(n)$ measures a demand shock that is unrelated to the firm's past fundamentals or expected fundamentals. Thus, an exogenous $z_t(n)$ should be uncorrelated with past fundamentals, which is supported in the regressions of firm past fundamentals on $z_t(n)$.[30] Second, a random demand shock should be normally distributed around zero. To verify this, I plot the histogram of $z_t(n)$ and find that it is well approximated by a normal distribution with zero mean, as shown in Figure 2. About 65% of the GIV $z_t(n)$ is within one standard deviation from zero, which indicates that the demand by institutional investors is quite stable. In addition to stable asset demand, demand shocks are equally distributed on both sides of zero, indicating that my results are robust to both investor inflows and outflows. Third, I validate the GIV $z_t(n)$ by assessing its correlation with well-known demand shocks in the literature: mutual fund flows and dividend reinvestment. If GIV $z_t(n)$ is indeed a proxy for demand shocks, it should be able to capture these exogenous demand shocks induced by mutual fund flows and dividend reinvestment. Note that these demand shocks from mutual fund flows and dividend reinvestment are *hypothetical* as they make assumptions about how demand shocks at the stock level are aggregated from fund-level demand shocks. Each of the demand shocks only explains part of the aggregate demand shocks since there are other sources of demand shocks.

In the sections below, I show the link between the GIV $z_t(n)$ and mutual fund flows and dividend reinvestment.[31]

5.1 Mutual Fund Flows

Investor redemptions from mutual funds, particularly sizable ones, exert significant pressure on funds to liquidate their stock holdings. Conversely, investor inflows prompt mutual funds to purchase additional shares of stocks already in their portfolios. Consequently, the mutual fund flow-driven demand shock satisfies the relevance condition.

[30] I also link the GIV with macroeconomic variables such as GDP growth, inflation rate and unemployment rate in the US. The results are shown in Table IA.I. Although the GIV is weakly related to the inflation rate, the results show that GIVs are not correlated with macroeconomic factors in general. The results are expected since we already incorporate macro factors to calculate the idiosyncratic demand shocks.

[31] I also link the GIV $z_t(n)$ with demand shocks induced by index reconstitution. In construction of demand shocks using the approach in Aghaee (2024), I show in regressions that index reconstitution-driven demand shocks hardly predict the GIV. This could be due to several reasons. First, many index reconstitutions, such as the Russell index, are infrequent events, which is not suitable for our quarterly data. Second, index reconstitution has only a significant impact on marginal firms, not on the whole sample. Aghaee (2024) utilizes the S&P 500 index reconstitution to calculate demand shocks for all S&P 500 firms. Although the S&P 500 index reconstitution is relatively frequent and affects many large firms, its impact on asset demand is very limited. This is because the change in weights by portfolio rebalancing is small and the total asset under management of S&P 500 index funds is small. The regression results show that these demand shocks are too small to detect a relationship with the GIV.

To construct this firm-level demand shock, we use hypothetical portfolio weights derived from previously disclosed holdings of mutual funds. This approach ensures that the demand shock reflects only the mechanical expansion or contraction of a fund's existing positions triggered by investor flows to mutual funds, rather than discretionary trades that might stem from shifts in the fund's assessment of a stock's fundamentals. Moreover, such flows are unlikely to be influenced by investors' expectations regarding future share issuance or investment growth at the firm level. Thus, this firm-level mutual fund flow-driven demand shock satisfies the exclusion condition.[32]

Mutual fund flows are used as a shock to stock prices to study the effect of stock price on corporate policies. For example, Edmans et al. (2012) use mutual fund redemption as a shock to the stock price and investigate how stock prices affect the likelihood of being a M&A target. Hau and Lai (2013) use fire sales by distressed mutual funds as shocks to stock underpricing and study the effect of stock underpricing on corporate investment. Lou and Wang (2018) use mutual fund redemption to study its effect on corporate investment. Dessaint et al. (2019) used mutual fund redemption as an instrument for peer firms' stock prices and investigated how corporate investment responds to peer firm's stock price. The idea of measuring the price pressure from mutual fund flows comes from Coval and Stafford (2007), who use observed sales of mutual funds. This measure of price pressure embeds not merely a non-fundamental shock as the observed fund sales may reflect information in the decision. Edmans et al. (2012) and papers later[33] overcome this problem by using the beginning-of-quarter holdings. This approach assumes that funds sell each stock in proportion to the beginning-of-quarter portfolio holdings upon redemption. To better capture the price pressure of mutual fund flows, Edmans et al. (2012) used aggregate stock level flows scaled by end-of-quarter dollar volume. However, as pointed out by Wardlaw (2020), this volume-adjusted flow is inadvertently a direct function of the return of the quarter. To overcome this, I follow Wardlaw (2020) and use the flow-to-stock as a measure of non-fundamental demand shock induced by mutual fund flows.

Mutual fund data comes from two sources. The quarterly portfolio holdings of mutual funds are obtained from Thomson Reuters S12, the fund returns and total net asset values are taken from the CRSP Mutual Fund Database. The fund returns are accumulated at

[32] Fund flows may not be exogenous to firm fundamentals in the first place, as retail investors may chase past performance. The correlation between fund flows and stock returns for portfolio firms may come from reverse causality: stock returns in the portfolio drive fund flows, rather than fund flows drive stock returns via demand pressure. It's possible to develop a two-layer asset demand system: the first layer is the demand function for household on funds; the second layer is the demand function of assets by funds. Darmouni et al. (2022) utilize this two-layer asset demand system to investigate the fragility in the corporate bond market.

[33] For example, Khan et al. (2012), Norli et al. (2015), Lee and So (2017), Lou and Wang (2018), Dessaint et al. (2019) and Xu and Kim (2022).

the quarter level. I combine these two databases using MFLINKS.[34] Below, I illustrate the procedure to define the aggregate demand shock induced by mutual fund flows, denoted as $MFFlow_t(n)$.

To calculate mutual fund flows, I first aggregate multiple share classes of each mutual fund using the beginning-of-month total net asset as weights. I then calculate the quarterly net flows to mutual fund i during quarter t as

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + RET_{i,t})}{TNA_{i,t-1}} \tag{47}$$

where $TNA_{i,t}$ is the end-of-quarter total net asset of mutual fund i, and $RET_{i,t}$ is the quarterly return of mutual fund i.

I assume that the mutual fund reinvests its flow into stocks in proportion to its portfolio holdings at the beginning of the quarter. The aggregate stock-level flow is then the sum of *hypothetical* flows to each stock by all mutual funds, defined as

$$MFFlow_t(n) = \sum_{i=1}^{I} Q_{i,t-1}(n) Flow_{i,t} \tag{48}$$

where $Q_{i,t-1}(n)$ is the ownership share of stock n by mutual fund i at the beginning of the quarter.

Next, I run the following regression:

$$z_t(n) = \beta \times MFFlow_t(n) + \delta_t + \phi_i + \epsilon_t(n). \tag{49}$$

If the GIV $z_t(n)$ is a proxy for investor flows, the estimated β should be positive. The regression results are shown in Table 1.

Column (1) presents the result of regressing $z_t(n)$ on $MFFlow_t(n)$, with quarter fixed effects. The quarter fixed effects address the concern that the calculated $z_t(n)$ may differ between quarters for all firms. This concern is reasonable since an idiosyncratic shock to an investor would transfer to all firms that this investor holds. The stock-level demand shocks are thus correlated within each quarter and differ across quarters. The result of column (1) shows a strong relationship between $z_t(n)$ and demand shocks induced by mutual fund flows. However, R^2 of this regression is close to zero, indicating that the demand shock by mutual funds is a weak predictor of $z_t(n)$.

Column (2) uses both firm and quarter fixed effects to address the concern that investor flows differentiate across firms. The result of column (1) shows a positive but

[34] Here I use all mutual funds who hold at least one stock in my sample. My results do not change if mutual funds are restricted to US domestic equity funds.

insignificant relationship between $z_t(n)$ and demand shocks induced by mutual fund flows. The R^2 has increased hugely, indicating huge heterogeneous investor flows across firms.

Many papers use only fund flows that deviate more than 5% from zero (e.g. $|Flow_{i,t}| \geqslant 5\%$) to define hypothetical demand shocks by mutual fund flows.(Edmans et al., 2012; Lou and Wang, 2018; Dessaint et al., 2019; Wardlaw, 2020) Several reasons justify the use of large inflows and outflows only. First, small mutual fund flows could be absorbed by internal cash or external liquidity providers of the mutual fund. Second, transaction costs prevent mutual funds from trading stocks for small flows. As such, small flows would not trigger trades by mutual funds. Hence, I use mutual fund flows that deviate more than 5% to define aggregate flows and use these stock level flows to replicate the regressions. The regression results using these updated flows are given in columns (3) to (4). These regressions yield the same results: demand shocks from mutual fund flows can predict $z_t(n)$, and investor flows vary across firms.

Regressions on mutual fund flows suggest that GIV $z_t(n)$ is weakly positively correlated with the demand shocks of mutual fund flows.

5.2 Dividend Reinvestment

This section links GIV $z_t(n)$ with another source of demand shocks: payouts from portfolio firms. For each investor, the total payout from the stocks they receive creates a fund inflow. This fund inflow leads to positive demand shocks of the fund, which ends up with positive demand shocks to the portfolio firms the fund preciously held. Thus, the relevance condition satisfies. I rely on dividend payment dates rather than announcement dates to define the fund flows. When the interval between dividend announcement and payment is sufficiently long, the payment itself conveys no new fundamental information about the firm. To compute the demand shock for a given stock, I consider dividend payments from other stocks within the fund's portfolio, excluding the stock's own dividend, thereby minimizing the influence of firm-specific information embedded in its payout. Consistent with the approach used for mutual fund flows, we base this calculation on the fund's previously disclosed holdings. As a result, the demand shock arising from dividend reinvestment reflects only the mechanical expansion or contraction of a fund's existing positions, driven by uninformed fund flows. This firm-level dividend reinvestment-driven demand shock thus satisfies the exclusion restriction.

To define these fund flows, we rely on dividend payment dates. When the interval between dividend announcement and payment is sufficiently long, the payment itself conveys no new fundamental information about the firm. To compute the demand shock for a given stock, we consider dividend payments from other stocks within the fund's portfolio, excluding the stock's own dividend, thereby minimizing the influence of firm-specific information embedded in its payout. Consistent with the approach used for mutual fund flows, we base this calculation on the fund's previously disclosed holdings. As a result, the demand shock arising from dividend reinvestment reflects only the mechanical expansion or contraction of a fund's existing positions, driven by uninformed fund flows. This firm-level dividend reinvestment-driven demand shock thus fulfills the exclusion restriction.

Several papers have used dividend reinvestment as a substitute for mutual fund flows to study similar questions. For example, Schmickler and Tremacoldi-Rossi (2023) develops the demand shocks on the date of the dividend payment and highlighted its impact on stock prices. They then use this dividend reinvestment as an instrument for stock prices and revealed a positive relationship between the stock price and firm investment. Hartzmark and Solomon (2024) also used dividend payments to build their demand shocks, called the predictable uninformed flow, and used this flow as an instrument of price pressure to estimate the macro-elasticity of the stock market. Van der Beck (2024) built on Schmickler and Tremacoldi-Rossi (2023) to estimate the demand elasticity of equity investors with respect to stock prices. He then used this demand function for equity investors to investigate how sustainable investing has affected stock returns over the past decade.

I follow Schmickler and Tremacoldi-Rossi (2023) to construct the quarterly demand shocks using dividend reinvestment. The information on the stock dividend comes from CRSP. I restrict dividends to cash payouts: the distribution type *disttype* is among "CD", "CG" and "CP". Investors receive fund inflows on the payment dates; therefore, the quarterly dividend reinvestment is based on the dividend payment dates. Dividend payments are adjusted by corporate policies using *cfacshr*. Linking the dividend information with the quarterly institutional holdings data from FactSet, I calculate the aggregate demand shock induced by dividend reinvestment. I denote this stock-level demand shock as $DivFlow$.

As in the definition of investor flows driven by mutual funds, I first calculate the quarterly net inflows to investor i during quarter t as

$$Flow_{i,t} = \frac{\sum_n Div_t(n) \times Q_{i,t-1}(n)}{AUM_{i,t-1}} \tag{50}$$

where $Div_t(n)$ is the total dividend payment to shareholders of firm n at quarter t, $Q_{i,t-1}(n)$ is the ownership share of firm n that investor i holds at the beginning of quarter t, and $AUM_{i,t-1}$ is the beginning-of-quarter asset under management of investor i.

I assume that investors reinvest their flows from dividend payments to stocks in proportion to their portfolio holdings at the beginning of the quarter. The aggregate stock-level flow is then the sum of *hypothetical* flows to each stock by all investors, defined as

$$DivFlow_t(n) = \sum_{i=1}^{I} Q_{i,t-1}(n) Flow_{i,t} \tag{51}$$

where $Q_{i,t-1}(n)$ is the ownership share of stock n by investor i at the beginning of the quarter. Since $DivFlow_t(n)$ is censored from below zero, I use a dummy variable $HighDivFlow_t(n)$ in regressions, where $HighDivFlow_t(n)$ is defined as one if it's among the top 25% dividend-driven flows.

Next, I run the following regression:

$$z_t(n) = \beta \times HighDivFlow_t(n) + \delta_t + \phi_i + \epsilon_t(n). \tag{52}$$

If GIV $z_t(n)$ is a proxy for investor flows, the estimated β should be positive. The regression results are shown in Table 1.

Column (5) presents the result of regressing $z_t(n)$ on $HighDivFlow_t(n)$ with quarter fixed effects. The quarter fixed effects address the concern that the calculated $z_t(n)$ may differ between quarters for all firms, which is the case when an idiosyncratic shock to an investor transfers to all the firms it holds. The result of column (5) shows a strong relationship between $z_t(n)$ and demand shocks induced by dividend reinvestment. The hypothetical demand shock driven by dividend reinvestment can significantly predict $z_t(n)$.

Column (6) uses both quarter and firm fixed effects to the regression to address the concern that investor flows vary across firms. The result of column (6) reveals a similar correlation between $z_t(n)$ and the demand shocks induced by dividend reinvestment in column (5). The R^2 has increased hugely, indicating huge heterogeneous investor flows across firms.

Hartzmark and Solomon (2013) showcase that investors chase stocks with dividend payments. However, the above-defined $DivFlow_t(n)$ does not consider this, making it an inappropriate measure of demand shocks induced by dividend reinvestment. To address this issue, I modify the definition of $DivxFlow_t(n)$ by taking the dividend payment of the stock itself out to calculate its firm-level demand shock induced by other stocks' payouts. I denote this modified demand shock as $DivxFlow_t(n)$, which is calculated as

$$DivxFlow_t(n) = \sum_{i=1}^{I} Q_{i,t-1}(n) \frac{\sum_{m \neq n} Div_t(m) \times Q_{i,t-1}(m)}{AUM_{i,t-1}}. \tag{53}$$

Since $DivxFlow_t(n)$ is censored from below zero, I also use a dummy variable $HighDivxFlow_t(n)$ in regressions, where $HighDivxFlow_t(n)$ is defined as one if it's among the top 25%

dividend-driven flows. I replicate the regressions using this modified demand shock $HighDivxFlow_t(n)$. The results are shown in columns (7) to (8) in Table 1. They give the same results: demand shocks by dividend reinvestment forecast $z_t(n)$ significantly.

In summary, the regressions on dividend reinvestment indicate that the granular instrumental variable $z_t(n)$ indeed captures demand shocks by dividend reinvestment.

5.3 Discussion

The generated granular instrumental variable $z_t(n)$ should be able to capture all kinds of demand shocks, including being able to capture demand shocks by mutual fund flows and dividend reinvestment at the same time. I assess this point in regressions with both demand shocks:

$$z_t(n) = \beta_1 \times MFFlow_t(n) + \beta_2 \times HighDivxFlow_t(n) + \delta_t + \phi_i + \epsilon_t(n). \quad (54)$$

I expect both β_1 and β_2 to be significant and positive.

Columns (9) indicates a significant positive relationship between the GIV and demand shocks by large-than-5% mutual fund flows and dividend reinvestment. This result implies that the GIV captures both demand shocks at the same time. Without firm fixed effects, hypothetical demand shocks caused by mutual fund flows or dividend reinvestment are too small to generate a big impact on stock prices. This is especially true for corporate policies, since firms require a large price impact to compensate for the adjustment costs of changing corporate decisions. Wardlaw (2020) revisits the literature that uses mutual fund flows as a source of demand shocks to build a causal relationship between stock prices and corporate decisions, examining Edmans et al. (2012) on M&A, Lee and So (2017) on analyst coverage, and Lou (2012) on corporate investment. Using the corrected measure of investor flows (the $MFFlow_t(n)$ in this paper), he finds that firm-level demand shocks induced by mutual fund flows do not affect stock price, analyst coverage, and corporate decisions.

I replicate the regressions using quarter and firm fixed effects. The regressions in column (10) give similar results: the GIV could capture both demand shocks at the same time and mutual fund flow-driven demand shocks are no longer significant. The relation is also economically significant: when there is a top 25% flow driven by dividend reinvestment, the GIV increases by 0.004. Compared with the average (-0.081) and median (-0.009) of GIV. Compared with the median of within-firm standard deviation of the GIV (0.057), the relation between dividend reinvestment-driven demand shocks and the GIV is economically significant.

6 The Real Effects of Investor Flows

This section investigates the effect of investor flows on firm financing and investment decisions. First, I report the financing multiplier of investor flows in the short and long horizons. Next, I show the investment multiplier of investor flows in both short and long horizons. After presenting the two multipliers, I analyze whether the multipliers vary over time. Specifically, I compare the multipliers during economic recessions and expansions.

6.1 Financing Multipliers

Firms may take advantage of demand shocks in the stock market. If market demand is highly elastic, investors can absorb the demand shocks of other market participants, leaving limited room for firms to exploit the demand shocks. However, when market demand is inelastic, investors cannot absorb demand shocks, which gives firms a chance to exploit this by issuing more shares to satisfy positive demand shocks and buying back shares to absorb negative demand shocks.

The regressions are based on Equation (45) and study how firm share issuance responds immediately to investor flows. In addition, I assume that financing multipliers are equal across firms, making the modified regression equation as

$$\Delta Q_t^F(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{55}$$

where the net share issuance $Q_t^F(n)$ is defined as the percentage change in shares outstanding at the quarterly level. The shares outstanding are from FactSet and adjusted for stock splits. Using shares outstanding to define net share issuance has been widely adopted in the literature, e.g., by Baker and Wurgler (2000), Pontiff and Woodgate (2008), and Greenwood and Hanson (2012). $Q_t^F(n)$ is the broadest definition of net equity issuance. Any event that affects equity supply is included, such as equity offerings, insider option exercises, and convertible bond exercises. Investor demand for a firm may depend on the firm's time-constant intrinsic characteristics, which in turn affect firm share issuance decisions. Thus, I add firm fixed effects $\alpha^F(n)$ to the regressions to mitigate this concern. The results of contemporaneous regressions are shown in Table 2.

In column (1), I construct the GIV $z_t(n)$ using the only observable factor: quarterly *GDP Growth Rate*. The quarterly GDP growth rates are collected from the Federal Reserve Bank of St. Louis. Then I include this generated GIV in the regression. Investor demand functions could respond differently to the quarterly GDP growth rate. When GDP-induced demand aggregates across investors to firm level, the GDP growth rate could induce investor demand changes differently, ultimately affecting firm share issuance.

To control for this effect, I add firm×GDP growth rates fixed effects in the regressions. The result reveals that GIV $z_t(n)$ is significantly and positively related to the quarterly issuance of shares by the firm. The multiplier is 0.012, implying that a \$1 investor flow to a firm generates 1.2 cents in share issuance by the firm in the quarter. The supply side (i.e., the firm) can absorb 1.2% of total demand shocks from the demand side (i.e., investors) in the short horizon.

In column (2), I add one latent factor to the construction of the GIV. The idea of a firm-specific latent factor, which is subtracted by the principal component algorithm (PCA), is to capture as much heterogeneity in investor demand as possible.[35] Aggregating investor flows (driven by the latent factor) at the firm level yields firm-specific flows due to this latent factor. In the regressions, I add interaction effects firm×GDP growth rate and firm×latent factor as control variables to mitigate the financing effects of both factors (the GDP growth and the latent factors). The regression result yields a similar number as in column (1): the financing multiplier is significantly positive and equals 0.012.

Following Gabaix and Koijen (2023), I add a second latent factor to mitigate the risk of omitted factors of GIVs. I use the PCA to subtract two latent factors for each firm. Using the GIV $z_t(n)$ constructed by means of three factors (the GDP growth and the two latent factors), I rerun the share issuance regression. Column (3) presents the results with all fixed effects and controls. Adding a second latent factor does not change the multiplier: a \$1 investor flow induces share issuance of 1.2 cents in the quarter.

There may be macro-factors that impact all firms similarly, such as a macro-productivity shock or the market-wide cost of issuing shares. To control for these time-varying common effects, I add quarter fixed effects and replicate the regressions, of which the results are presented in columns (4) to (6). The results are similar to those of columns (1) to (3): Again, a \$1 investor flow significantly causes the firm to issue 1.2 cents in new shares in the quarter.

A demand shock or investor flow that does not reverse should have a persistent impact on firm's total shares outstanding. To examine the evolution of share issuance induced by an investor flow at quarter t, the following regressions are run by changing the period of share issuance from two quarters before to sixteen quarters after the investor flows at quarter t.

$$\Delta Q^F_{t+h}(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{56}$$

where $h \in \{-2, -1, 0, 1, \cdots, 16\}$.[36] Figure 3 plots the estimated multipliers of share

[35]Similarly to the GDP growth rate, the latent factor could induce different responses by different investors. That is, investors have different sensitivities to the latent factor.

[36]I have re-estimated the firm's policies with demand shocks at respective quarter as controls:

$$\Delta Q^F_{t+h}(n) = M^F z_t(n) + M^F_{t+h} z_{t+h}(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n)$$

issuance for different horizons. The $h = 0$ or the quarter horizon equal to zero gives exactly the same multiplier as above: 0.012. The figure clearly shows that there is a jump in firm's share issuance in the quarter of investor flows. The firm continues to issue new shares to the market even after the demand shock at quarter t. The impact of a demand shock at the quarter t lasts up to eight quarters. For these eight quarters after the demand shock, the firm absorbs around 1% of the demand shocks for each quarter.[37] The financing multipliers before the quarter of investor flows are close to zero, indicating that $z_t(n)$ is unrelated to the firm's past share issuance. This result suggests that the GIV is exogenous.

I now turn to the financing multipliers for the long horizon. Figure 3 depicts that a firm issues shares over the short and long horizons after an investor flow. To estimate long-term multipliers, I replace the share issuance at quarter t in Equation (45) by the cumulative share issuance at quarters t to $t + 8$. The regression equation is

$$\Delta Q^F_{t,t+8}(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{57}$$

where $Q^F_{t,t+8}(n)$ is the cumulative share issuance from quarter t to $t + 8$ of firm n. The regression results are shown in Panel A of Table 3. Columns (1) to (3) use differently constructed GIV, which yield similar financing multipliers: 0.24. A \$1 dollar investor flow to a firm generates \$24 cents share issuance by the firm over eight quarters. The supply side could absorb 24% of total demand shocks over a long horizon. Columns (4) to (6) add quarter fixed effects to control for time-varying common trends. These regressions give slightly larger multipliers of approximately 0.26. The multipliers in the short and long horizons indicate that a firm reacts immediately and absorbs about 25% of the demand shocks in the long run.[38]

Using shares outstanding to define net share issuance may contaminate firm financing decisions and exercise of insider options and convertible bonds. The percentage change in shares outstanding provides a noisy measure of firm's net share issuance. I thus use a direct measure of firm's financing from the stock market, namely the dollar amount of

I plot the newly-estimated M^F from the equation in Figure IA.I. The result is similar as before. It suggests that the demand shock at quarter t can have lasting effect on firm's share issuance. The coefficient will not change if GIVs are not correlated over time: $z_{t+h}(n) \perp z_t(n)$. Then the regressions without controlling $z_{t+h}(n)$ still give the consistent estimation of M^F.

[37] In the one quarter after the demand shock, the share issuance jumps down to zero. This could be due to the fact that the firm issues shares in quarter t that are shelf-registered to be issued and would have been issued in quarter $t + 1$ (Altı and Sulaeman, 2012; Khan et al., 2012; Henderson et al., 2023).

[38] I replicate the results here when adding firm-level control variables in regressions. These controls include ROA, Cash Holdings, Tobin's Q, KZ-index, and Tangibility. The results do not change, as shown in Figure IA.II. I test the non-linear relationship between long-term share issuance and investor flows. The results, shown in Figure IA.III, suggest limited non-linear effects.

share issuance divided by total assets. This measure is calculated using Compustat data:

$$NetIssue_t(n) = \frac{SSTK_t(n) - PRSTK_t(n)}{AT_{t-1}(n)}, \tag{58}$$

where $SSTK_t(n)$ is the quarterly sale of common and preferred stock, $PRSTK_t(n)$ is the quarterly purchase of common and preferred stock, and $AT_{t-1}(n)$ is the beginning-of-quarter total assets. The cumulative net share issuance in quarters t to $t+8$ is the sum of $NetIssue_t(n)$ of these nine quarters. The results of regressing cumulative net share issuance on GIV are shown in Panel B of Table 3. Columns (1) to (3) use differently constructed GIV, which yield stable financing multipliers: 0.02. A 1% investor flow to a firm generates 0.02% net share issuance to total assets by the firm in eight quarters. Columns (4) to (6) give similar multipliers of net share issuance to total assets after controlling for quarter fixed effects.

I conclude that the firm responds within the first quarter by issuing 1.2% new shares to satisfy investors' extra demand. The firm acts as a large supplier of shares to the market over the long run. The firm absorbs 24% demand shocks over eight quarters or increases 0.02% net share issuance to total assets for the 1% investor flow in eight quarters.

Do firms react differently to investor inflows and outflows? On the demand side, a firm is expected to respond to investor outflows more than to inflows, which is because frictions in the stock market contribute to a higher degree of share buybacks during investor outflows than share issuance during investor inflows. Investors prefer share buybacks to share issuance since share buybacks signal good performance of the firm while share issuance signals the opposite. In this sense, a firm should conduct more share buybacks (at investor outflows) than issuance (at investor inflows). On the supply side, a firm would react more to investor inflows than to outflows. This is because the firm tend to increase its cash holdings through share issuance as a response to investor inflows, which makes them more financially flexible. Share buybacks would leave the firm with lower cash holdings, making them more financially constrained. I test these views in Table 4.

To run the regression, I split the GIV $z_t(n)$ into two parts: net inflow $z_t^+(n)$ and net outflow $z_t^-(n)$. Net inflow is defined as the maximum of positive investor flow and zero, $z_t^+(n) = \max(z_t(n), 0)$. Net outflow is defined as the opposite of the minimum of negative investor flow and zero, $z_t^-(n) = -\min(z_t(n), 0)$. I thus replace $z_t(n)$ with $z_t^+(n)$ and $z_t^-(n)$ in the regression:

$$\Delta Q^F_{t,t+8}(n) = M^{F+} z_t^+(n) + M^{F-} z_t^-(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{59}$$

Panel A of Table 4 shows the asymmetric reactions to investor inflows and outflows. Similarly to the previous regressions, I use three versions of GIV and different sets of fixed effects and control variables. The results in Panel A give statistical and economically significant multipliers of share issuance, but statistical and economically insignificant multipliers of share buybacks: a firm increases share issuance in the case of net investor inflows but not share buyback in the case of net investor outflows. For example, Column (3) gives a multiplier of 0.853 for share issuance and 0.005 for share buyback. This means that a \$1 investor inflow causes the firm to issue \$0.85 shares to the market in eight quarters, while a \$1 investor outflow causes the firm to buy back \$0.005 shares in eight quarters. The direct measure of firm's net issuance produces similar results: a 1% investor inflow leads to 0.08% net issuance to total assets in eight quarters, while a 1% investor outflow leads to nearly zero net share buybacks. The results of share issuance and buybacks indicate that a firm responds more to investor inflows than to outflows, which supports the supply-side story. A firm exploits positive demand shocks to increase their cash holdings and remains unaffected by negative demand shocks.

6.2 Investment Multipliers

When market demand is inelastic, an investor flow allows the firm to issue shares for financing. The firm then utilizes this financing to increase its investment. I investigate how a firm changes its investment after an investor flow.

There is a large body of literature that examines the investment-Q relationship or whether market valuation causally impacts firm investment decisions. These papers include Hayashi (1982), Erickson and Whited (2000), Edmans et al. (2012), Lou and Wang (2018), Dessaint et al. (2019), and others. The challenge in answering this question is the simultaneity issue using stock prices as an independent variable. Stock prices affect corporate decisions, which in turn affect stock prices. These papers utilize natural experiments (instruments) that generate variations in stock prices that are orthogonal to firm fundamentals. These instruments are mutual fund flows, dividend reinvestment, and index reconstitution. However, as shown in Section 5 and in Wardlaw (2020), these demand shocks are too small to generate a large impact on stock prices. Using these instruments, Wardlaw (2020) failed to replicate the significant effects of stock prices on corporate investment. It should be noted that these instruments are not guaranteed to be exogenous. Mutual fund flows and dividend reinvestment may be related to the fundamentals in equilibrium. For example, households would invest their money more in mutual funds when they expect better future economic conditions. Similarly, dividend reinvestment would be higher if firms expect better market condition in the future and thus a higher payout in the present. Again, I use Gabaix and Koijen (2024)'s GIV approach to address this issue and link investor flows with corporate investment decisions directly. I replace Tobin's Q with GIV $z_t(n)$ in the investment-Q regressions.

The regressions, as in Equation (46), study the immediate response of firm investment decisions to an investor flow. As before, I assume that the investment multipliers are the same between firms. Thus, the modified regression equation is

$$\Delta x_t(n) = M^X z_t(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n) \tag{60}$$

where the investment growth $\Delta x_t(n)$ is defined as the percent change in investment rate. The investment rate is calculated by dividing quarterly capital expenditures (*capxq*) by the beginning-of-quarter property, plant, and equipment (*ppentq*). To mitigate the concern that firm's investment may be contingent on firm intrinsic characteristics such as technology and culture, I add firm fixed effects $\alpha^X(n)$ to control for firm-specific time-consistent factors. The results of the contemporaneous regressions are given in Table 5.

The GIVs are constructed using different factors. The GIV in column (1) is constructed by one observable factor: quarterly *GDP growth rate*. Like in factor models, firms' investment could respond to *GDP growth rate* differently due to different investment-GDP sensitivity. Column (2) adds one latent factor, constructed by means of the PCA. Column (3) adds the second latent factor to construct the GIV. Firm×factors are included as controls in each regression. Columns (4) to (6) add extra quarter fixed effects to control for time-varying common effects. The results reveal that within the quarter of the investor flow, a firm's investment does not change. There are two explanations: First, a firm's investment does not react to stock market dynamics, as demonstrated in the literature that documents a weak relationship between corporate investment and Tobin's Q (Blanchard et al., 1993; Hall, 2001). Second, the firm needs some time to adjust its investment after investor flows. In the following, I show the evolution of investment after the investor flows, which reveals that the firm does indeed respond, but requires some time to respond.

A demand shock or investor flow has a persistent impact on firm investment. To examine the evolution of investment growth for investor flows in quarter t, the following regressions are performed by changing the period of investment growth from two quarters before to sixteen quarters after investor flow in quarter t.

$$\Delta x_{t+h}(n) = M^X z_t(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n) \tag{61}$$

where $h \in \{-2, -1, 0, 1, \cdots, 16\}$. Figure 4 plots the evolution of investment growth. The quarter $h = 0$ gives the same multiplier as above: a firm does not change its investment at the quarter of investor flows. Furthermore, the investment multipliers before the investor flows are close to zero, indicating that $z_t(n)$ is unrelated to the firm's past investment. This result suggests that the GIV is exogenous. For quarters after investor flows, Figure 4 shows that a firm's investment grows gradually in the first six quarters after investor flows.

Next, I turn to the investment multipliers over the long horizon. Figure 3 illustrates that a firm gradually increases its investment in about six to eight quarters after an investor flow. To estimate long-term multipliers, I replace the investment growth rate at quarter t in Equation (46) by the cumulative investment growth at quarters t to $t+8$. The regression equation is

$$\Delta x_{t,t+8}(n) = M^X z_t(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n) \tag{62}$$

where $\Delta x_{t,t+8}(n)$ is the cumulative investment growth from quarter t to $t+8$ of firm n. The regression results are shown in Table 6. Columns (1) to (3) use differently constructed GIV, which yield quite similar investment multipliers: 0.19. A 1% investor flow to a firm thus causes 0.19% increase in investment by the firm in eight quarters. Columns (4) to (6) add quarter fixed effects to control for time-varying common trends. These regressions give smaller multipliers around 0.12. A firm therefore actively changes its investment over the long run after investor flows.

Do firms change their investments differently for investor inflows versus outflows? The demand side story is the same as above when share issuance is discussed: stock market frictions contribute to more disinvestment during investor outflows than more investment during investor inflows due to asymmetric information. On the supply side, a firm responds more to investor inflows than to outflows; this is because the firm faces different adjustment costs for investment and disinvestment. When firm investment is lumpy and irreversible, disinvestment is more costly than investment. I test these views in Table 7.

The regression equation is

$$\Delta x_{t,t+8}(n) = M^{X+} z_t^+(n) + M^{X-} z_t^-(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n). \tag{63}$$

where $z_t^+(n)$ and $z_t^-(n)$ are net inflows and net outflows. Net inflow is defined as $z_t^+(n) = \max(z_t(n), 0)$. Net outflow is defined as $z_t^-(n) = -\min(z_t(n), 0)$. Panel A of Table 7 presents the asymmetric reactions to investor inflows and outflows. The results give statistical and economically significant multipliers of investor inflows. However, for investor outflows, I either obtain a significant but smaller multiplier or an insignificant multiplier, compared to those for investor inflows. In column (3) as an example, the results indicate that a 1% investor inflow causes the firm's investment to increase by 0.30%, but a 1% investor outflow causes the firm's investment to decrease by only 0.15%. The results thus indicate that a firm's investment decisions respond more to investor inflows than to outflows, which is consistent with Van Binsbergen and Opp (2019). This result supports the supply-side story: due to irreversible investment, a firm's investment growths for investor inflows and outflows are asymmetric.[39]

6.3 The Decomposition of Multipliers

The multiplier effects can be decomposed into two parts: direct and indirect impact of investor flows. By shutting down the investors' preference to firm investment (e.g., $\boldsymbol{\zeta}_t^X = 0$), I get the direct impact of investor flows as

$$\Delta Q_t^F = \boldsymbol{\Lambda}_t^F(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F)^{-1}\Delta D_t \tag{64}$$

$$\text{diag}(X_t)^{-1}\Delta X_t = \boldsymbol{\Lambda}_t^X(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F)^{-1}\Delta D_t \tag{65}$$

which assume that demand side does not respond to changes in corporate investment (thus no feedback effects). The differences between the direct impact and the multipliers in Proposition 3 are the feedback effects of investor flows. Feedback effects capture the extent to which investor preferences for firm characteristics influence corporate investment decisions. To compare the feedback effect with the direct effect, I define

$$\Delta^X = \frac{\boldsymbol{\Lambda}_t^X(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F - \boldsymbol{\zeta}_t^X\boldsymbol{\Lambda}_t^X)^{-1}\Delta D_t}{\boldsymbol{\Lambda}_t^X(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F)^{-1}\Delta D_t} - 1 = \frac{(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F - \boldsymbol{\zeta}_t^X\boldsymbol{\Lambda}_t^X)^{-1}}{(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F)^{-1}} - 1. \tag{66}$$

Δ^X captures how much the feedback effect diminishes the direct effect of investor flows.

I follow a two-step approach to calculate Δ^X. First, I estimate the price multiplier by regressing cumulative stock returns $R_{t,t+8}(n)$ over quarters t to $t+8$ on the demand shock:

$$R_{t,t+8}(n) = M^P z_t(n) + \alpha^P(n) + \gamma^P(n)\eta_t + \xi_t(n). \tag{67}$$

[39]This fact points to the modification of our investment adjustment costs to

$$\Phi(I_t, K_t) = \begin{cases} \frac{a_1}{2}\frac{I_t^2}{K_t}, & \text{if } I_t \geqslant 0 \\ \frac{a_2}{2}\frac{I_t^2}{K_t}, & \text{if } I_t < 0 \end{cases}$$

where $a_1 < a_2$.

Buyback frictions could be another reason for this asymmetry. If buyback is more costly than issuance, we should observe the asymmetry as outlined in the paper.However, we normally consider that issuance is more costly than buyback. This is capture by the financing cost: $[\eta_0 - \eta_1 D_t] \cdot \mathcal{I}[D_t < 0]$. The financing cost is positive for firms (e.g., $\eta_0 > 0$ and $\eta_1 > 0$). Examining which channel dominates needs us to quantify the parameters with structural estimation.

M^P identifies the price multiplier $(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}_t^X)^{-1}$. The results, shown in Table 8, indicate a price multiplier of 0.266 ($M^P = 0.266$). Using the price multiplier, I calculate the supply elasticity of total shares to stock prices as 0.887 ($\Lambda^F = 0.236/0.266 = 0.887$), and the supply elasticity of investment to stock prices as 0.707 ($\Lambda^X = 0.188/0.266 = 0.707$).

Second, I conduct the back-of-the-envelop calculation of direct effects using the elasticity estimates $\boldsymbol{\zeta}_t^P$ in the literature.[40] These estimates of demand elasticity fall into two categories. The first category uses stock trades as instruments. The sources of stock trades or flows are: mutual fund flows in Lou (2012); Peng and Wang (2021); Li (2022); Van der Beck (2022), dividend reinvestment in Schmickler and Tremacoldi-Rossi (2023); Hartzmark and Solomon (2013); Van der Beck (2024), index reconstitution in Chang et al. (2015), GIV in Gabaix and Koijen (2023), Morningstar Ratings driven flows in Ben-David et al. (2022), pension fund rebalance in Da et al. (2018), and cash flows restricted by IPO rules in Li et al. (2021). [41] The other category uses structural estimation to identify demand elasticities. Choi et al. (2023) utilizes indirect inference (allowing interactions between demand and supply sides) and Koijen and Yogo (2019) builds on investment mandates.

Using the parameters above, I calculate the direct impact of investor flows and the extent to which feedback effects diminish these direct impacts. Table 9 presents the results, which show that the direct effects of investor flows on firm financing and investment are substantial. For instance, with a demand elasticity of 0.339, as estimated by Choi et al. (2023), a 1% investor flow directly generates a 0.724% increase in total shares and a 0.576% increase in investment over two years. However, the feedback effects significantly reduce these direct impacts. Investors respond to changes in firms' investment decisions, which further affects stock prices and alter firm policies. These feedback loops diminish the magnitude of share issuance and investment growth by 67.4%. Across different demand elasticity estimates, the calculated direct impact of investor flows on share issuance ranges from 0.34% to 0.84%, while the direct impact on investment ranges from 0.27% to 0.67% for a 1% investor flow. The reduction caused by feedback effects is substantial, by 30.4% to 71.7%.[42] These findings underscore the critical role of investors' preference in moderating the overall impact of investor flows on firm financing and investment.

[40] Gabaix and Koijen (2023) compile these estimations of $\boldsymbol{\zeta}_t^P$ in their Table 1.

[41] When firms are able to adjust their policies after investor demand shocks, the elasticity estimates actually capture $(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}_t^X)$ rather than $\boldsymbol{\zeta}_t^P$ if firms' responses are not well controlled. When firms are not able to adjust to investor flows, such as in high frequency data, these elasticity estimates reflect true demand elasticities.

[42] The magnitude of this reduction depends heavily on the estimated demand elasticity. Predictable demand shocks, such as dividend reinvestments, tend to yield higher elasticity estimates, which may overstate the true elasticity. In contrast, unpredictable shocks, such as GIV, index reconstitution, and mutual fund flows, typically result in lower and potentially more accurate elasticity estimates.

6.4 Discussion

Gabaix and Koijen (2023) propose the inelastic market hypothesis, suggesting that the stock market's volatility stems from the low demand elasticity of investors. Their model assumes an exogenous supply side, meaning firms do not react to investor flows. Under this assumption, the price impact of investor flows is given by $(\boldsymbol{\zeta}_t^P)^{-1}$.[43] However, if firms respond to investor demand shocks, the price impact of investor flows will be moderated by firms' responses. The supply-demand framework developed in this paper provides a tool to analyze the role of firms in determining the price impact of investor flows.

Firms affects the stock market in two key ways as of the supply-demand framework. First, they adjust equity supply through share issuance or buybacks. When investors have a positive demand shock, stock prices rise, prompting firms to issue new shares, which counteracts the price increase. Conversely, when investors experience a negative demand shock, stock prices fall, leading firms to buy back shares, which counteracts the price decrease. Firms' adjustment in shares effectively moderates the price impact of investor flows. Second, firms adjust their investment, which interacts with investor preferences to influence investor demand via feedback effects. If investors are averse to increased firm investment, higher investment in response to rising stock prices reduces investor demand, which in turn lowers stock prices. On the other hand, if investors favor higher investment, increased investment amplifies investor demand, further boosting stock prices. Thus, firm investment decisions can either mitigate or amplify the price impact of investor flows, depending on investor preferences for firm characteristics.

To evaluate the role of share issuance in stabilizing stock prices, I allow firms to adjust their share supply while keep feedback effects inactive ($\boldsymbol{\zeta}_t^X = 0$ or $\boldsymbol{\Lambda}_t^X = 0$) in the model. Under this assumption, the price impact is $(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F)^{-1}$. Column (3) of Table 10 presents the results, showing that firms significantly reduce the price impact of investor flows by adjusting shares outstanding. For example, using the demand elasticity estimate from Choi et al. (2023), a \$1 inflow raises stock prices by \$2.95 if the firm does not adjust its share supply or investment. However, this increase is reduced to \$0.82 when firms issue or repurchase shares, mitigating 72.4% of the price impact. Across different demand elasticity estimates, firms' share adjustments reduce the price impact by 33.9% to 83.5%.

To check how firm's share issuance could affect the stock prices, I allow firms to adjust their supply of shares in the model. I still shut down the feedback effects, that is $\boldsymbol{\zeta}_t^X = 0$ or $\boldsymbol{\Lambda}_t^X = 0$. The price impact under this assumption is $(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F)^{-1}$. The column (3) of Table 10 shows the price multipliers under the assumption that firms can react to

[43] Column (2) of Table 10 lists the price multipliers of investor flows under the exogenous supply-side assumption, which are substantial–for example, 5 in Koijen and Yogo (2019) and Gabaix and Koijen (2023).

demand shocks by changing their shares outstanding. The results show that firms can moderate a huge proportion of the price impact of flows from inelastic investors. For example, using the demand elasticity estimate in Choi et al. (2023), the stock price goes up by \$2.95 for every \$1 inflow, if the firm does not adjust its shares outstanding and investment. However, its stock price goes up by \$0.82, if the firm can issue or buyback shares in response to demand shocks. This result indicates that firm's adjustment of its total shares outstanding would mitigate the price impact of investor flows by 72.4%. Across different demand elasticity estimates, the mitigations by firms' adjustment of shares outstanding are high, ranging from 33.9% to 83.5%.

To examine how firms' investment decisions further influence stock prices, I allow for investment adjustments in the model. The price multiplier becomes $(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}_t^F - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}_t^X)^{-1}$. Column (5) of Table 10 shows that firms' investment decisions, combined with investor preferences, can further mitigate the price impact of investor flows by 20%, based on a demand elasticity of 0.339.

These results demonstrate that firms play a vital role in stabilizing stock prices. By adjusting share supply and investment, firms significantly mitigate the price impact of investor flows.

7 Conclusion

This paper quantifies and decomposes the multiplier effects of investor asset demand in the stock market on firm financing and investment. I develop a supply-demand framework that extends demand-based asset pricing models by incorporating firms' endogenous decisions. This framework bridges production-based asset pricing with demand-based asset pricing, offering a novel tool to analyze how investor flows influence corporate decisions. By including the supply side, the framework not only quantifies the multiplier effects but also decomposes them into direct and feedback effects, highlighting the critical role of investor preferences in shaping firm decisions. The framework yields closed-form relationships between investor flows and corporate policies, enabling straightforward estimation of financing and investment multipliers. Unlike models that assume an exogenous supply or demand side, the multipliers in this framework depend on four elasticities, with the additional elasticities capturing the feedback effects.

The financing and investment multipliers are estimated using the granular instrumental variable (GIV) approach, which calculates investors' idiosyncratic demand shocks as a source of aggregate flows to firms. The results show that firms respond immediately to positive demand shocks by issuing shares, with share issuance and investment growth continuing for up to two years. Over the long horizon, firms absorb 24% of demand shocks through share issuance, and they increase investment by 19% for a 100% demand shock. Responses are asymmetric, with firms reacting more strongly to inflows than outflows and more strongly during economic expansions than recessions. The asymmetry reflects that firms' decisions are more sensitive to their own objective function than to financial frictions, suggesting the efficiency of the stock market.

Counterfactual analysis reveals that investor preferences for firm characteristics significantly affect firm responses. Investor preferences through feedback effects reduce the impact of investor flows on firm financing and investment by 67.4%.

The supply-demand framework also sheds light on the role of firms in stabilizing stock prices. Counterfactual analysis demonstrates that firms play a critical role in mitigating price impact of investor flows: adjustments in share supply alone reduce the price impact by 72.4%, while firms' investment, combined with investor preferences, provides an additional 20% mitigation. These findings emphasize the importance of firms as active participants in maintaining stock market stability.

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Table 1. Validity of the GIV approach: Mutual Fund Flows and Dividend Reinvestment

This table shows how GIVs $z_t(n)$ capture demand shocks induced by mutual fund flows and dividend reinvestment. The GIVs are constructed using three factors: the GDP growth rate and two latent factors. Columns 1–4 show the regressions of GIVs on investor flows induced by mutual fund flows:

$$z_t(n) = \beta \times MFFlow_t(n) + \delta_t + \phi_i + \epsilon_t(n),$$

where $MFFlow_t(n)$ is the quarterly firm-level investor flow induced by all mutual fund flows (columns 1–2) or the firm-level investor flow induced by mutual fund flows that deviate more than 5% from zero (columns 3–4). Columns 5–8 show the regressions of GIVs on investor flows induced by dividend reinvestment:

$$z_t(n) = \beta \times HighDivFlow_t(n) + \delta_t + \phi_i + \epsilon_t(n),$$

where $HighDivFlow_t(n)$ is defined as the top 25% of $DivFlow_t(n)$ (quarterly firm-level investor flows induced by dividend reinvestment of all institutional investors). Investor flows in columns 7–8 use $HighDivxFlow_t(n)$ (the top 25% of the modified $DivxFlow_t(n)$, calculated by excluding the dividend payment of the stock itself). Columns 9–10 show the regressions of GIVs on investor flows induced by both mutual fund flows and dividend reinvestment:

$$z_t(n) = \beta_1 \times MFFlow_t(n) + \beta_2 \times DivxFlow_t(n) + \delta_t + \phi_i + \epsilon_t(n).$$

Columns 9–10 use $MFFlow_t(n)$ (only mutual fund flows that deviate more than 5% from zero) and $HighDivxFlow_t(n)$ (reinvestment that excludes the dividend payment of the stock itself). Standard errors are clustered by firm and reported in parentheses. $^{*}p < .1$;$^{**}p < .05$;$^{***}p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep. Var.: $z_t(n)$	Mutual Fund Flows				Dividend Reinvestment				Both	
MFFlow	0.002***	0.000								
	(0.001)	(0.000)								
MFFlow5%			0.002***	0.000					0.001***	0.000
			(0.000)	(0.000)					(0.000)	(0.000)
High DivFlow					0.067***	0.004***				
					(0.004)	(0.001)				
High DivxFlow							0.066***	0.004***	0.066***	0.004***
							(0.004)	(0.001)	(0.004)	(0.001)
Quarter FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Firm FEs		Yes		Yes		Yes		Yes		Yes
Obs.	359745	359745	359745	359745	359745	359745	359745	359745	359745	359745
R^2	0.004	0.437	0.004	0.437	0.011	0.437	0.011	0.437	0.011	0.437

Table 2. Financing Decisions in the Short Horizon

This table shows how firm financing decisions respond to investor flows in the short horizon. The regressions are

$$\Delta Q_t^F(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n).$$

The dependent variable $\Delta Q_t^F(n)$ is the percentage change in total shares outstanding in quarter t of firm n. The main independent variable, the GIVs $z_t(n)$, is constructed using different sets of factors: the GDP growth rate in columns (1) and (4); the GDP growth rate and one latent factor in columns (2) and (5); the GDP growth rate and two latent factors in columns (3) and (6). η_1 and η_2 are the two latent factors. Standard errors are clustered by firm and quarter and reported in parentheses. $^*p < .1;^{**} p < .05;^{***} p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t(n)$	0.012***	0.012***	0.012***	0.012***	0.012***	0.012***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Obs.	38150	38150	38150	38150	38150	38150
R^2	0.481	0.485	0.485	0.484	0.488	0.488
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Table 3. Financing Decisions in the Long Horizon

This table shows how firm financing decisions respond to investor flows over the eight quarters after demand shocks. The GIVs are constructed using different sets of factors: the GDP growth rate in columns (1) and (4); the GDP growth rate and one latent factor in columns (2) and (5); the GDP growth rate and two latent factors in columns (3) and (6). Panel A shows the regressions of share issuance on GIVs:

$$\Delta Q^F_{t,t+8}(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n).$$

$\Delta Q^F_{t,t+8}(n)$ is the cumulative percentage change in total shares outstanding from quarter t to $t+8$ of firm n. Panel B shows the regressions of net stock sales on GIVs:

$$NetIssue_{t,t+8}(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n).$$

$NetIssue_{t,t+8}(n)$ is the total dollar amount of net share issuance divided by total assets over the quarters from t to $t+8$. η_1 and η_2 are the two latent factors. Standard errors are clustered by firm and quarter and reported in parentheses. $^*p < .1;^{**}\,p < .05;^{***}\,p < .01$.

Panel A: Share Issuance

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t(n)$	0.235***	0.236***	0.236***	0.262***	0.263***	0.263***
	(0.041)	(0.042)	(0.042)	(0.045)	(0.045)	(0.045)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.571	0.573	0.573	0.576	0.578	0.578
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Panel B: Net Stock Sales

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t(n)$	0.021***	0.021***	0.021***	0.015**	0.015**	0.015**
	(0.007)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.748	0.749	0.749	0.760	0.761	0.761
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Table 4. Asymmetric Financing Decisions in the Long Horizon

This table shows how firm financing decisions respond differently to investor inflows versus outflows over the eight quarters after demand shocks. The GIVs are constructed using different sets of factors: the GDP growth rate in columns (1) and (4); the GDP growth rate and one latent factor in columns (2) and (5); the GDP growth rate and two latent factors in columns (3) and (6). Panel A shows the regressions of share issuance on GIVs:

$$\Delta Q^F_{t,t+8}(n) = M^{F+} z_t^+(n) + M^{F-} z_t^-(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n),$$

where $\Delta Q^F_{t,t+8}(n)$ is the cumulative percentage change in total shares outstanding from quarter t to $t+8$ of firm n. GIVs $z_t(n)$ are split into two parts: the investor inflow $z_t^+(n)$ and the investor outflow $z_t^-(n)$. The investor inflow is defined as the maximum of positive investor flow and zero, $z_t^+(n) = \max(z_t(n), 0)$. The investor outflow is defined as the opposite of the minimum of negative investor flow and zero, $z_t^-(n) = -\min(z_t(n), 0)$. Panel B shows the regressions of net stock sales on GIVs:

$$NetIssue_{t,t+8}(n) = M^{F+} z_t^+(n) + M^{F-} z_t^-(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n),$$

where $NetIssue_{t,t+8}(n)$ is the total dollar amount of net share issuance divided by total assets over the quarters from t to $t+8$. η_1 and η_2 are the two latent factors. Standard errors are clustered by firm and quarter, and reported in parentheses. $^*p < .1$;$^{**}\ p < .05$;$^{***}\ p < .01$.

Panel A: Share Issuance

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t^+(n)$	0.850***	0.853***	0.853***	0.873***	0.876***	0.876***
	(0.173)	(0.173)	(0.173)	(0.170)	(0.170)	(0.170)
$z_t^-(n)$	0.005	0.005	0.005	-0.025	-0.025	-0.025
	(0.044)	(0.045)	(0.045)	(0.046)	(0.046)	(0.046)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.573	0.575	0.575	0.577	0.579	0.579
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Panel B: Net Stock Sales

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t^+(n)$	0.074***	0.076***	0.076***	0.068***	0.069***	0.069***
	(0.021)	(0.021)	(0.021)	(0.019)	(0.020)	(0.020)
$z_t^-(n)$	-0.000	-0.000	-0.000	0.006	0.006	0.006
	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.748	0.749	0.749	0.761	0.761	0.761
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Table 5. Investment Growth in the Short Horizon

This table shows how firm investment decisions respond to investor flows in the short horizon. The regressions are

$$\Delta x_t(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n).$$

The dependent variable $\Delta x_t(n)$ is the quarterly growth rate of investment in quarter t of firm n, where firm investment is defined as capital expenditures divided by the beginning-of-quarter property, plant, and equipment. The main independent variable, the GIVs $z_t(n)$, is constructed using different sets of factors: the GDP growth rate in columns (1) and (4); the GDP growth rate and one latent factor in columns (2) and (5); the GDP growth rate and two latent factors in columns (3) and (6). η_1 and η_2 are the two latent factors. Standard errors are clustered by firm and quarter and reported in parentheses. $^*p < .1$;$^{**}\,p < .05$;$^{***}\,p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t(n)$	-0.016	-0.018	-0.018	-0.021	-0.023	-0.023
	(0.051)	(0.051)	(0.051)	(0.047)	(0.047)	(0.047)
Obs.	29821	29821	29821	29821	29821	29821
R^2	0.443	0.444	0.444	0.450	0.452	0.452
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Table 6. Investment Growths in the Long Horizon

This table shows how firm investment decisions respond to investor flows over the eight quarters after demand shocks. The regressions are

$$\Delta x_{t,t+8}(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n).$$

$\Delta x_{t,t+8}(n)$ is the cumulative growth rate of firm investment from quarter t to $t+8$ of firm n, where firm investment is defined as capital expenditures divided by the beginning-of-quarter property, plant, and equipment. The main independent variable, the GIVs $z_t(n)$, is constructed using different sets of factors: the GDP growth rate in columns (1) and (4); the GDP growth rate and one latent factor in columns (2) and (5); the GDP growth rate and two latent factors in columns (3) and (6). η_1 and η_2 are the two latent factors. Standard errors are clustered by firm and quarter, and reported in parentheses. $^*p < .1;^{**} p < .05;^{***} p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t(n)$	0.184***	0.188***	0.188***	0.118***	0.120***	0.120***
	(0.057)	(0.058)	(0.058)	(0.043)	(0.044)	(0.044)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.461	0.463	0.463	0.481	0.484	0.484
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Table 7. Asymmetric Investment Growths in the Long Horizon

This table shows how firm investment decisions respond differently to investor inflows versus outflows over the eight quarters after demand shocks. The regressions are

$$\Delta x_{t,t+8}(n) = M^{F+} z_t^+(n) + M^{F-} z_t^-(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n).$$

$\Delta x_{t,t+8}(n)$ is the cumulative growth rate of firm investment from quarter t to $t+8$ of firm n, where firm investment is defined as capital expenditures divided by the beginning-of-quarter property, plant, and equipment. The GIVs are constructed using different sets of factors: the GDP growth rate in columns (1) and (4); the GDP growth rate and one latent factor in columns (2) and (5); the GDP growth rate and two latent factors in columns (3) and (6). GIVs $z_t(n)$ are split into two parts: the investor inflow $z_t^+(n)$ and the investor outflow $z_t^-(n)$. The investor inflow is defined as the maximum of positive investor flow and zero, $z_t^+(n) = \max(z_t(n), 0)$. The investor outflow is defined as the opposite of the minimum of negative investor flow and zero, $z_t^-(n) = -\min(z_t(n), 0)$. η_1 and η_2 are the two latent factors. Standard errors are clustered by firm and quarter, and reported in parentheses. $*p < .1$;** $p < .05$;*** $p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t^+(n)$	0.289***	0.297***	0.297***	0.214***	0.221**	0.221**
	(0.094)	(0.097)	(0.097)	(0.080)	(0.083)	(0.083)
$z_t^-(n)$	-0.143**	-0.145**	-0.145**	-0.080	-0.081	-0.081
	(0.067)	(0.069)	(0.069)	(0.053)	(0.055)	(0.055)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.461	0.463	0.463	0.481	0.484	0.484
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Table 8. Stock Returns in the Long Horizon

This table shows how stock prices respond to investor flows over the eight quarters after demand shocks. The regressions are

$$R_{t,t+8}(n) = M^P z_t(n) + \alpha^P(n) + \gamma^P(n)\eta_t + \xi_t(n).$$

$R_{t,t+8}(n)$ is the cumulative stock returns over quarters t to $t+8$ of firm n. The main independent variable, the GIVs $z_t(n)$, is constructed using different sets of factors: the GDP growth rate in columns (1) and (4); the GDP growth rate and one latent factor in columns (2) and (5); the GDP growth rate and two latent factors in columns (3) and (6). η_1 and η_2 are the two latent factors. Standard errors are clustered by firm and quarter, and reported in parentheses. $^*p < .1;^{**}\,p < .05;^{***}\,p < .01$.

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t(n)$	0.266***	0.266***	0.266***	0.155***	0.154***	0.154***
	(0.047)	(0.048)	(0.048)	(0.031)	(0.032)	(0.032)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.471	0.474	0.474	0.553	0.555	0.555
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm×GDP Growth	Yes	Yes	Yes	Yes	Yes	Yes
Firm×η_1		Yes	Yes		Yes	Yes
Firm×η_2			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Table 9. The Decomposition of Multipliers

This table presents the decomposition of the financing and investment multipliers of investor flows. Column (1) reports estimates of demand elasticity with respect to stock prices from the literature. Column (2) shows the impact of investor flows on share issuance under the assumption that investors have no preference for firm investment. Column (3) presents the impact of investor flows on firm investment growth, also assuming no investor preference for firm investment. Column (4) quantifies the extent to which investor preferences for investment influence firms' investment responses to investor flows.

		(1)	(2)	(3)	(4)
Literature	Methodology	ζ^P	$\frac{\mathbf{\Lambda}^F}{(\zeta^P+\mathbf{\Lambda}^F)}$	$\frac{\mathbf{\Lambda}^X}{(\zeta^P+\mathbf{\Lambda}^F)}$	Δ^X
Choi et al. (2023)	Simulated Method of Moments	0.339	0.724	0.576	-67.4%
Koijen and Yogo (2019)	Investment Mandate	0.200	0.816	0.650	-71.1%
Gabaix and Koijen (2023)	GIV	0.211	0.808	0.643	-70.8%
Lou (2012)	Mutual Fund Flows	0.833	0.516	0.411	-54.2%
Peng and Wang (2021)	Mutual Fund Flows	0.208	0.810	0.645	-70.9%
Li (2022)	Mutual Fund Flows	0.175	0.835	0.665	-71.7%
Van der Beck (2022)	Mutual Fund Flows	0.833	0.516	0.411	-54.2%
Ben-David et al. (2022)	Morningstar Ratings	0.189	0.825	0.657	-71.4%
Schmickler and Tremacoldi-Rossi (2023)	Dividend Reinvestment	1.250	0.415	0.331	-43.2%
Van der Beck (2024)	Dividend Reinvestment	1.730	0.339	0.270	-30.4%
Hartzmark and Solomon (2024)	Dividend Reinvestment	0.526	0.628	0.500	-62.4%
Chang et al. (2015)	Index Reconstitution	0.625	0.587	0.467	-59.8%
Da et al. (2018)	Pension Fund Rebalance	0.455	0.661	0.527	-64.3%
Li et al. (2021)	IPO Restriction	0.220	0.801	0.638	-70.6%

Table 10. The Decomposition of Price Multipliers

This table presents the decomposition of price multipliers for investor flows. Column (1) lists estimates of demand elasticity with respect to stock prices from the literature. Column (2) reports the price multiplier under the assumption that firms are exogenous, as in traditional demand-based asset pricing models. Column (3) provides the price multiplier when firms can issue shares but feedback effects on investor demand are excluded. Column (4) quantifies the extent to which firms' share issuance mitigates the price multiplier. Column (5) captures the combined effect of firms' share issuance and investor feedback in reducing the price multiplier.

		(1)	(2)	(3)	(4)	(5)
Literature	Methodology	ζ^P	$\frac{1}{\zeta^P}$	$\frac{1}{(\zeta^P+\Lambda^F)}$	Δ^F	Δ^{X+F}
Choi et al. (2023)	Simulated Method of Moments	0.339	2.951	0.816	-72.4%	-91.0%
Koijen and Yogo (2019)	Investment Mandate	0.200	5.000	0.920	-81.6%	-94.7%
Gabaix and Koijen (2023)	GIV	0.211	4.730	0.910	-80.8%	-94.4%
Lou (2012)	Mutual Fund Flows	0.833	1.200	0.581	-51.6%	-77.8%
Peng and Wang (2021)	Mutual Fund Flows	0.208	4.800	0.913	-81.0%	-94.5%
Li (2022)	Mutual Fund Flows	0.175	5.700	0.941	-83.5%	-95.3%
Van der Beck (2022)	Mutual Fund Flows	0.833	1.200	0.581	-51.6%	-77.8%
Ben-David et al. (2022)	Morningstar Ratings	0.189	5.300	0.929	-82.5%	-95.0%
Schmickler and Tremacoldi-Rossi (2023)	Dividend Reinvestment	1.250	0.800	0.468	-41.5%	-66.8%
Van der Beck (2024)	Dividend Reinvestment	1.730	0.578	0.382	-33.9%	-54.0%
Hartzmark and Solomon (2024)	Dividend Reinvestment	0.526	1.900	0.707	-62.8%	-86.0%
Chang et al. (2015)	Index Reconstitution	0.625	1.600	0.661	-58.7%	-83.4%
Da et al. (2018)	Pension Fund Rebalance	0.455	2.200	0.745	-66.1%	-87.9%
Li et al. (2021)	IPO Restriction	0.220	4.550	0.903	-80.1%	-94.2%

Figure 1. The Multiplier Effect of a Demand Shock

This figure shows how a shock in investor demand propagates through stock prices and firm decisions. The blue arrows show the direct impact of a demand shock, which affects firm decisions (such as financing and investment) through stock prices. Moreover, firms' responses alter investor demand, further affecting stock prices and firm decisions, thereby creating the indirect impact (the feedback effect) of a demand shock, as shown by the red arrows. The blue and red arrows together show the multiplier effect of a demand shock.

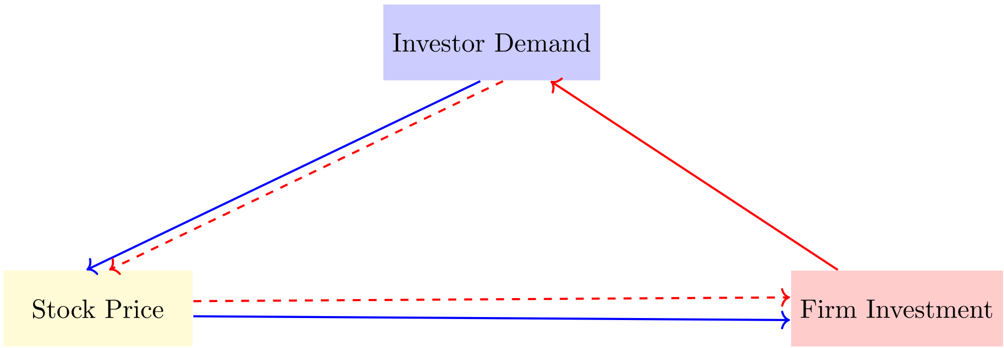


Figure 2. The Distribution of GIV $z_t(n)$

This figure shows the distribution of the GIVs. The firm-quarter GIVs are constructed using three factors: the GDP growth rate and two latent factors. The GIVs are trimmed to be equal to or larger than -1.

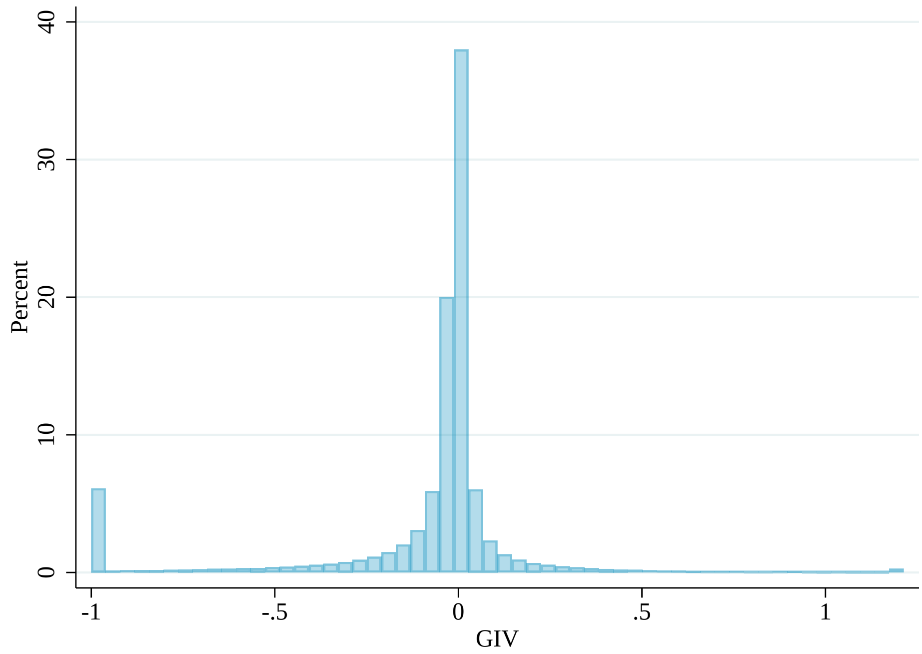


Figure 3. The Evolution of Financing Decisions in Response to Investor Flows

This figure shows the evolution of firm financing decisions over several quarters in response to demand shocks. The firm-quarter GIVs are constructed using three factors: the GDP growth rate and two latent factors. The figure plots the coefficients M_h^F and its 95% confidence interval of the regressions:

$$\Delta Q_{t+h}^F(n) = M_h^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n)$$

where $h \in \{-2, -1, 0, 1, \cdots, 16\}$.

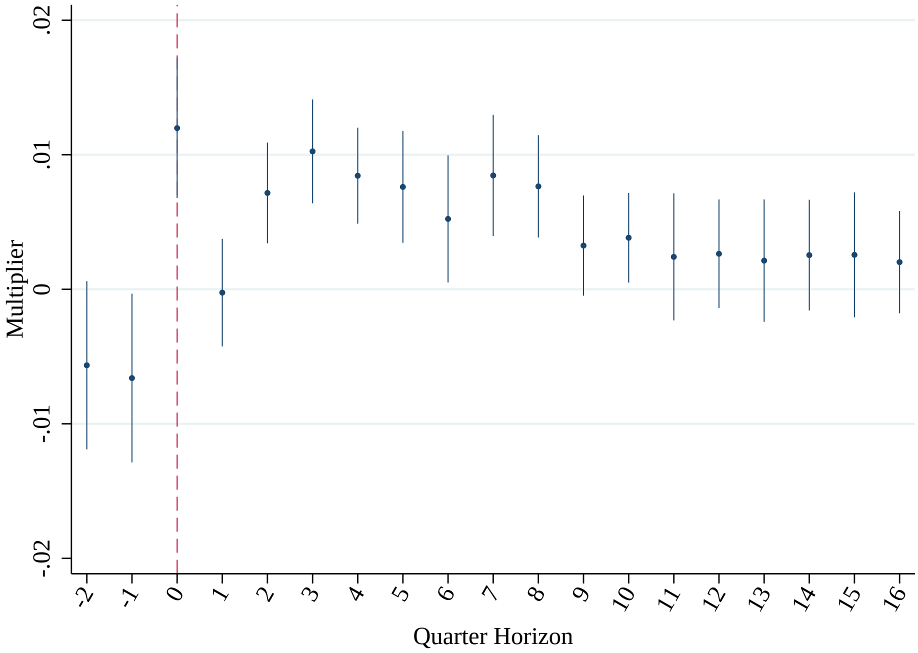
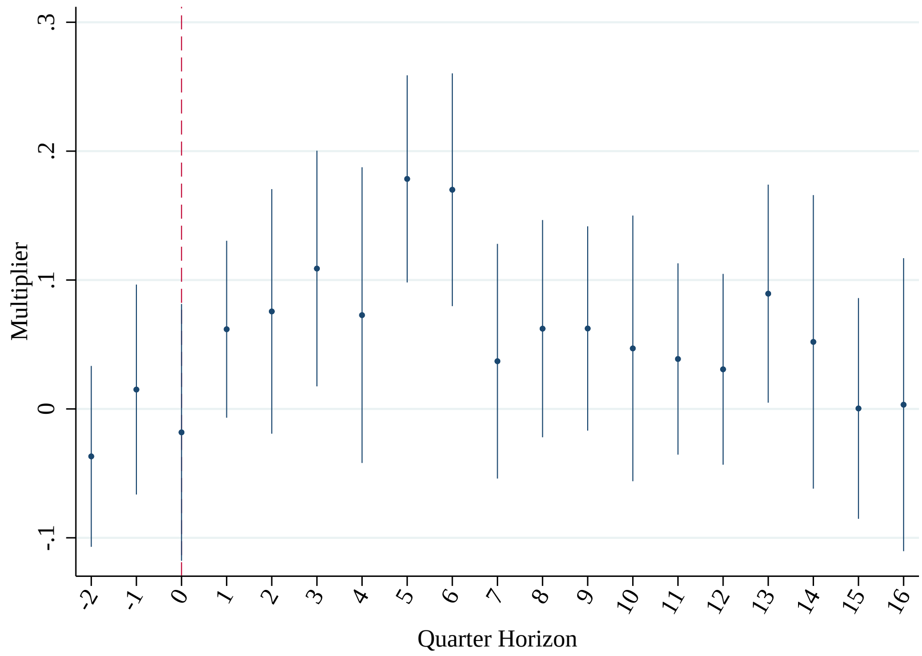


Figure 4. The Evolution of Investment Growth in Response to Investor Flows

This figure shows the evolution of firm investment growth over several quarters in response to demand shocks. The firm-quarter GIVs are constructed using three factors: the GDP growth rate and two latent factors. The figure plots the coefficients M_h^X and its 95% confidence interval of the regressions:

$$\Delta x_{t+h}(n) = M_h^X z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n)$$

where $h \in \{-2, -1, 0, 1, \cdots, 16\}$.



Internet Appendix for "Flow-Driven Corporate Finance: A Supply-Demand Approach"

IA.1 Proofs

Proof of Proposition 1. First, I prove Lemma 1. Applying the Envelope Theorem to the firm's objective function, I get

$$
\begin{aligned}
\frac{\partial V_{t+1}}{\partial K_{t+1}} =& \frac{\partial D_{t+1}}{\partial K_{t+1}} + \mathbb{E}\left[M_{t+2}\frac{\partial V_{t+2}}{\partial K_{t+1}}\right] \quad \text{(IA.1)} \\
=& (1-\tau_{t+1})\left[\frac{\partial \Pi(K_{t+1})}{\partial K_{t+1}} - \frac{\partial \Phi(I_{t+1}, K_{t+1})}{\partial K_{t+1}}\right] + \tau_{t+1}\delta_{t+1} \\
&+ (1-\delta_{t+1})\mathbb{E}_{t+1}\left[M_{t+2}\frac{\partial V_{t+2}}{\partial K_{t+2}}\right] \quad \text{(IA.2)} \\
=& (1-\tau_{t+1})\left[\frac{\partial \Pi(K_{t+1})}{\partial K_{t+1}} - \frac{\partial \Phi(I_{t+1}, K_{t+1})}{\partial K_{t+1}}\right] + \tau_{t+1}\delta_{t+1} \\
&+ (1-\delta_{t+1})\left[1 + (1-\tau_{t+1})\frac{\partial \Phi(I_{t+1}, K_{t+1})}{\partial I_{t+1}}\right] \quad \text{(IA.3)}
\end{aligned}
$$

The term in (IA.2) utilizes the Envelope Theorem on the path of total capital

$$K_{t+2} = (1-\delta_{t+1})K_{t+1} + I_{t+1}.$$

The term in (IA.3) utilizes Equation (10).

Combining the above equation with Equation (10), I get

$$
\begin{aligned}
&\left[1+(1-\tau_t)\frac{\partial\Phi(I_t,K_t)}{\partial I_t}\right]K_{t+1} && \text{(IA.4)}\\
=&\mathbb{E}_t M_{t+1}\{(1-\tau_{t+1})[\frac{\partial\Pi(K_{t+1})}{\partial K_{t+1}}K_{t+1}-\frac{\partial\Phi(I_{t+1},K_{t+1})}{\partial K_{t+1}}K_{t+1}]+\tau_{t+1}\delta_{t+1}K_{t+1}\\
&+(1-\delta_{t+1})[1+(1-\tau_{t+1})\frac{\partial\Phi(I_{t+1},K_{t+1})}{\partial I_{t+1}}]K_{t+1}\} && \text{(IA.5)}\\
=&\mathbb{E}_t M_{t+1}\{(1-\tau_{t+1})[\frac{\partial\Pi(K_{t+1})}{\partial K_{t+1}}K_{t+1}-\frac{\partial\Phi(I_{t+1},K_{t+1})}{\partial K_{t+1}}K_{t+1}]+\tau_{t+1}\delta_{t+1}K_{t+1}\\
&+[1+(1-\tau_{t+1})\frac{\partial\Phi(I_{t+1},K_{t+1})}{\partial I_{t+1}}](K_{t+2}-I_{t+1})\} && \text{(IA.6)}\\
=&\mathbb{E}_t M_{t+1}\{(1-\tau_{t+1})[\frac{\partial\Pi(K_{t+1})}{\partial K_{t+1}}K_{t+1}-\frac{\partial\Phi(I_{t+1},K_{t+1})}{\partial K_{t+1}}K_{t+1}-\frac{\partial\Phi(I_{t+1},K_{t+1})}{\partial I_{t+1}}I_{t+1}]\\
&-I_{t+1}+\tau_{t+1}\delta_{t+1}K_{t+1}+Q_{t+1}K_{t+2}\} && \text{(IA.7)}\\
=&\mathbb{E}_t M_{t+1}\{(1-\tau_{t+1})[\Pi(K_{t+1})-\Phi(I_{t+1},K_{t+1})]-I_{t+1}+\tau_{t+1}\delta_{t+1}K_{t+1}+Q_{t+1}K_{t+2}\} && \text{(IA.8)}\\
=&\mathbb{E}_t M_{t+1}[D_{t+1}+Q_{t+1}K_{t+2}] && \text{(IA.9)}
\end{aligned}
$$

Thus, I get an iterating function of Q_tK_{t+1}:

$$
\begin{aligned}
Q_tK_{t+1}=&\mathbb{E}_t M_{t+1}[D_{t+1}+Q_{t+1}K_{t+2}] && \text{(IA.10)}\\
=&\lim_{T\to+\infty}\mathbb{E}_t\left[\sum_{s=1}^{T-1}M_{t+s}D_{t+s}+(\prod_{s=1}^{T-1}M_{t+s})K_{t+T}\right] && \text{(IA.11)}\\
=&\mathbb{E}_t\sum_{s\geqslant 1}M_{t+s}D_{t+s} && \text{(IA.12)}\\
=&V_t-D_t && \text{(IA.13)}\\
=&P_t && \text{(IA.14)}
\end{aligned}
$$

I have therefore proved the Q-theory of investment under CRS assumptions:

$$\left[1+(1-\tau_t)\frac{\partial\Phi(I_t,K_t)}{\partial I_t}\right]=\frac{P_t}{K_{t+1}} \tag{IA.15}$$

I can further replace $\frac{\partial\Phi(I_t,K_t)}{\partial I_t}$ with our explicit functional form and get

$$\frac{I_t}{K_t}=\frac{1}{a(1-\tau_t)}\frac{P_t}{K_{t+1}}-\frac{1}{a(1-\tau_t)} \tag{IA.16}$$

This equation says that the firm's investment rate is a linear function of its average Q.

Next, I prove Lemma 2. Replacing the investment rate in Equation 5 with the investment rate in Lemma 1, I get

$$
\begin{aligned}
D_t =& (1-\tau_t)[\Pi(K_t) - \Phi(I_t, K_t)] - I_t + \tau_t \delta_t K_t && \text{(IA.17)}\\
=& (1-\tau_t)[\Pi(K_t) - \frac{a}{2}\frac{I_t^2}{K_t}] - I_t + \tau_t \delta_t K_t && \text{(IA.18)}\\
=& (1-\tau_t)[\Pi(K_t) - \frac{a}{2}\left(\frac{1}{a(1-\tau_t)}\frac{P_t}{K_{t+1}} - \frac{1}{a(1-\tau_t)}\right)^2 K_t] \\
& - \left(\frac{1}{a(1-\tau_t)}\frac{P_t}{K_{t+1}} - \frac{1}{a(1-\tau_t)}\right) K_t + \tau_t \delta_t K_t && \text{(IA.19)}\\
=& -\frac{K_t}{2a(1-\tau_t)}\left(\frac{P_t}{K_{t+1}}\right)^2 + \cdots && \text{(IA.20)}
\end{aligned}
$$

The other terms without average Q are left in the dots.

Rearranging the formula, I can get the relationship between equity financing and Q_t.

$$
-\frac{D_t}{K_t} = \frac{1}{2a(1-\tau_t)}\left(\frac{P_t}{K_{t+1}}\right)^2 + \mathcal{C}_t \tag{IA.21}
$$

where $\mathcal{C}_t$ is a term unrelated with the average Q or the market equity P_t.

The last step is to prove the proposition. For simplicity, I denote the investment and share supply functions as $X_t = f(P_t, \mu_t)$ and $Q^F = g(P_t, \nu_t)$. X_t and Q^F are firm's investment rate and share issuance, respectively. Suppose a small shock to market equity, say dP_t, I can get the percentage changes in the investment rate and total share as

$$
\frac{dX_t}{X_t} = \frac{\frac{\partial f(P_t,\mu_t)}{\partial P_t} dP_t}{X_t} = \underbrace{\frac{\partial f(P_t,\mu_t)/X_t}{\partial P_t/P_t}}_{\stackrel{\text{def}}{=} \zeta_t^X} \frac{dP_t}{P_t} \tag{IA.22}
$$

$$
\frac{dQ_t^F}{Q_t^F} = \frac{\frac{\partial g(P_t,\nu_t)}{\partial P_t} dP_t}{Q_t^F} = \underbrace{\frac{\partial g(P_t,\nu_t)/Q_t^F}{\partial P_t/P_t}}_{\stackrel{\text{def}}{=} \zeta_t^F} \frac{dP_t}{P_t} \tag{IA.23}
$$

□

Proof of Proposition 3. Let's start from the proof of Proposition 2. Suppose a shock $\Delta \boldsymbol{V_t} = (\Delta V_t(1), \Delta V_t(2), \cdots, \Delta V_t(N))'$, we can get the first order Taylor approximations of each variable as

$$\Delta \boldsymbol{D_t} = \left(\sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{V_t}}\right) \Delta \boldsymbol{V_t} \tag{IA.24}$$

$$\Delta \boldsymbol{Q_t^F} = \frac{\partial \boldsymbol{Q_t^F}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t} \tag{IA.25}$$

$$\Delta \boldsymbol{P_t} = \frac{\partial \boldsymbol{P_t}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t} \tag{IA.26}$$

$$\Delta \boldsymbol{X_t} = \frac{\partial \boldsymbol{X_t}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t} \tag{IA.27}$$

where all the left hand variables are vectors with length N. Take derivatives of Equation (18) with respect to the unobservable $\boldsymbol{V_t}$ on both sides,

$$\frac{\partial \boldsymbol{Q_t^F}}{\partial \boldsymbol{V_t}} = \sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{V_t}} + \left(\sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{P_t}}\right) \frac{\partial \boldsymbol{P_t}}{\partial \boldsymbol{V_t}} + \left(\sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{X_t}}\right) \frac{\partial \boldsymbol{X_t}}{\partial \boldsymbol{V_t}} \tag{IA.28}$$

After a shock $\Delta \boldsymbol{V_t}$, we get

$$\frac{\partial \boldsymbol{Q_t^F}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t} = \sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t} + \left(\sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{P_t}}\right) \frac{\partial \boldsymbol{P_t}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t} + \left(\sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{X_t}}\right) \frac{\partial \boldsymbol{X_t}}{\partial \boldsymbol{V_t}} \Delta \boldsymbol{V_t} \tag{IA.29}$$

$$= \Delta \boldsymbol{D_t} + \left(\sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{P_t}}\right) \Delta \boldsymbol{P_t} + \left(\sum_{i=1}^{I} \frac{\partial \boldsymbol{Q_{i,t}}}{\partial \boldsymbol{X_t}}\right) \Delta \boldsymbol{X_t} \tag{IA.30}$$

$$= \Delta \boldsymbol{D_t} - \left(\sum_{i=1}^{I} \text{diag}(\boldsymbol{Q_{i,t}}) \boldsymbol{\zeta_{i,t}^P} \text{diag}(\boldsymbol{P_t})^{-1}\right) \Delta \boldsymbol{P_t} + \left(\sum_{i=1}^{I} \text{diag}(\boldsymbol{Q_{i,t}}) \boldsymbol{\zeta_{i,t}^X} \text{diag}(\boldsymbol{X_t})^{-1}\right) \Delta \boldsymbol{X_t} \tag{IA.31}$$

$$= \Delta \boldsymbol{D_t} - \boldsymbol{\zeta_t^P} \text{diag}(\boldsymbol{P_t})^{-1} \Delta \boldsymbol{P_t} + \boldsymbol{\zeta_t^X} \text{diag}(\boldsymbol{X_t})^{-1} \Delta \boldsymbol{X_t} \tag{IA.32}$$

Note the left hand side equals $\Delta \boldsymbol{Q_t^F}$. Re-arrange the above equation, we get Proposition 2.

$$\Delta \boldsymbol{D_t} = \boldsymbol{\zeta_t^P} \text{diag}(\boldsymbol{P_t})^{-1} \Delta \boldsymbol{P_t} + \Delta \boldsymbol{Q_t^F} - \boldsymbol{\zeta_t^X} \text{diag}(\boldsymbol{X_t})^{-1} \Delta \boldsymbol{X_t}. \tag{IA.33}$$

Combined with $\Delta \boldsymbol{Q_t^F} = \boldsymbol{\Lambda_t^F} \text{diag}(\boldsymbol{P_t})^{-1} \Delta \boldsymbol{P_t}$ and $\text{diag}(\boldsymbol{X_t})^{-1} \Delta \boldsymbol{X_t} = \boldsymbol{\Lambda_t^X} \text{diag}(\boldsymbol{P_t})^{-1} \Delta \boldsymbol{P_t}$, the above equation becomes

$$\Delta \boldsymbol{D_t} = \boldsymbol{\zeta_t^P} \text{diag}(\boldsymbol{P_t})^{-1} \Delta \boldsymbol{P_t} + \boldsymbol{\Lambda_t^F} \text{diag}(\boldsymbol{P_t})^{-1} \Delta \boldsymbol{P_t} - \boldsymbol{\zeta_t^X} \boldsymbol{\Lambda_t^X} \text{diag}(\boldsymbol{P_t})^{-1} \Delta \boldsymbol{P_t}. \tag{IA.34}$$

Solve this equation, we can get the price impact of the demand shock $\Delta \boldsymbol{D_t}$. We can also get the financing and investment effects after we know the price impact of the demand shock.

$$\text{diag}(\boldsymbol{P_t})^{-1}\Delta\boldsymbol{P_t} = (\boldsymbol{\zeta_t^P} + \boldsymbol{\Lambda_t^F} - \boldsymbol{\zeta_t^X}\boldsymbol{\Lambda_t^X})^{-1}\Delta\boldsymbol{D_t} \tag{IA.35}$$
$$\Delta\boldsymbol{Q_t^F} = \boldsymbol{\Lambda_t^F}(\boldsymbol{\zeta_t^P} + \boldsymbol{\Lambda_t^F} - \boldsymbol{\zeta_t^X}\boldsymbol{\Lambda_t^X})^{-1}\Delta\boldsymbol{D_t} \tag{IA.36}$$
$$\text{diag}(\boldsymbol{X_t})^{-1}\Delta\boldsymbol{X_t} = \boldsymbol{\Lambda_t^X}(\boldsymbol{\zeta_t^P} + \boldsymbol{\Lambda_t^F} - \boldsymbol{\zeta_t^X}\boldsymbol{\Lambda_t^X})^{-1}\Delta\boldsymbol{D_t} \tag{IA.37}$$

□

Proof of Proposition 4. I start from estimating the following demand-supply system,

$$\Delta q_{i,t}(n) = -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \gamma_i(n)\eta_t + \varepsilon_{i,t}(n) \tag{IA.38}$$
$$\Delta Q_t^F(n) = \lambda^F(n)R_t(n) + \mu_t(n) \tag{IA.39}$$
$$\Delta x_t(n) = \lambda^X(n)R_t(n) + \nu_t(n) \tag{IA.40}$$

Aggregate the demand over all investors using the weight $S_{it}(n) = \frac{Q_{i,t-1}(n)}{\sum_{i=1}^I Q_{i,t-1}(n)}$, we get

$$\begin{aligned}
&\sum_{i=1}^I S_{i,t}(n)\Delta q_{i,t}(n)\\
=& -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \left(\sum_{i=1}^I S_{i,t}(n)\gamma_i(n)\right)\eta_t + \left(\sum_{i=1}^I S_{i,t}(n)\varepsilon_{i,t}(n)\right) && \text{(IA.41)}\\
=& -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \widetilde{\gamma(n)}\eta_t + \widetilde{\varepsilon_t(n)} && \text{(IA.42)}\\
=& -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \widetilde{\gamma(n)}\eta_t + \overline{\varepsilon_t(n)} + z_t(n) && \text{(IA.43)}
\end{aligned}$$

Note that the left hand side, the aggregate demand shock, must equal the supply $\Delta Q_t^F(n)$ in equilibrium. Put Equation (28) and (29) into the above, we get

$$R_t(n) = [\zeta^P(n) + \lambda^F(n) - \zeta^X(n)\lambda^X(n)]^{-1}z_t(n) + \widetilde{\gamma(n)}\eta_t + \overline{\varepsilon_t(n)} + \zeta^X(n)\nu_t(n) - \mu_t(n) \tag{IA.44}$$

Then we get the equations for share issuance and fundamentals:

$$\Delta Q_t^F(n) = \underbrace{\lambda^F(n)[\zeta^P(n) + \lambda^F(n) - \zeta^X(n)\lambda^X(n)]^{-1}}_{=M^F(n)} z_t(n) + \xi_t(n) \tag{IA.45}$$
$$\Delta x_t(n) = \underbrace{\lambda^X(n)[\zeta^P(n) + \lambda^F(n) - \zeta^X(n)\lambda^X(n)]^{-1}}_{=M^X(n)} z_t(n) + \upsilon_t(n) \tag{IA.46}$$

where the two error terms are

$$\xi_t(n) = \lambda^F(n)\widetilde{\gamma(n)}\eta_t + \lambda^F(n)\overline{\varepsilon_t(n)} + \lambda^F(n)\zeta^X(n)\nu_t(n) - \lambda^F(n)\mu_t(n) + \mu_t(n) \quad \text{(IA.47)}$$

$$\upsilon_t(n) = \lambda^X(n)\widetilde{\gamma(n)}\eta_t + \lambda^X(n)\overline{\varepsilon_t(n)} + \lambda^X(n)\zeta^X(n)\nu_t(n) - \lambda^X(n)\mu_t(n) + \nu_t(n) \quad \text{(IA.48)}$$

Since $z_t(n) \perp \eta_t, \nu_t(n), \mu_t(n), \overline{\varepsilon_t(n)}$, $z_t(n)$ is orthogonal to $\xi_t(n)$ and $\upsilon_t(n)$. See also Proposition 1 in Gabaix and Koijen (2024).

□

IA.2 Additional Tables

Table IA.I. GIVs and Macroeconomic Variables

This table shows how the GIVs are related with macroeconomic variables such as GDP growth rate, inflation rate and unemployment rate in the US. η_1 and η_2 are the two latent factors. Standard errors are clustered by firm and quarter, and reported in parentheses. $*p < .1;^{**} p < .05;^{***} p < .01$.

Dep. Var.: $z_t(n)$	(1)	(2)	(3)
GDP Growth	-0.019		
	(0.231)		
Inflation		-2.067*	
		(1.217)	
Unemployment Rate			0.004
			(0.003)
Firm FEs	Yes	Yes	Yes
Firm×η_1	Yes	Yes	Yes
Firm×η_2	Yes	Yes	Yes
Obs.	118610	118610	118610
R^2	0.341	0.342	0.341

IA.3 Additional Figures

Figure IA.I. The Evolution of Financing Decisions with Controls

This figure presents the evolution of firm financing decisions over several quarters in response to demand shocks. The firm-quarter GIVs are constructed using three factors: the GDP growth rate and two latent factors. The figure plots the coefficients M_h^F and its 95% confidence interval of the regressions:

$$\Delta Q_{t+h}^F(n) = M_h^F z_t(n) + M_{t+h}^F z_{t+h}(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n)$$

where $h \in \{-2, -1, 0, 1, \cdots, 16\}$.

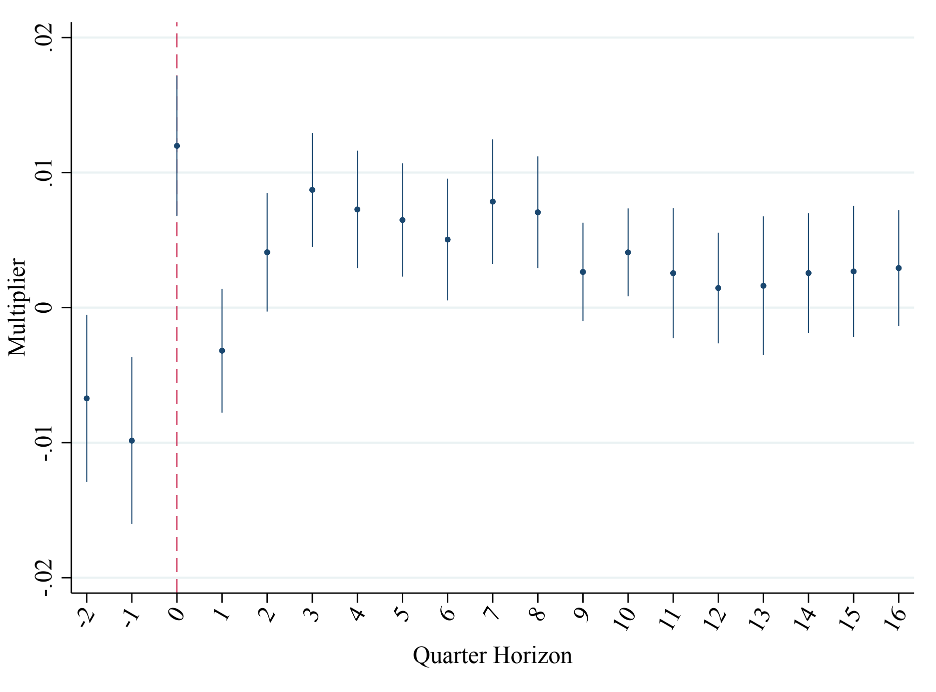


Figure IA.II. The Evolution of Financing Decisions with Control Variables

This figure presents the evolution of firm financing decisions over several quarters in response to demand shocks. The firm-quarter GIVs are constructed using three factors: the GDP growth rate and two latent factors. The figure plots the coefficients M_h^F and its 95% confidence interval of the regressions:

$$\Delta Q_{t+h}^F(n) = M_h^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n)$$

where $h \in \{-2, -1, 0, 1, \cdots, 16\}$. Control variables include ROA, Cash Holdings, Tobin's Q, KZ-index, and Tangibility.

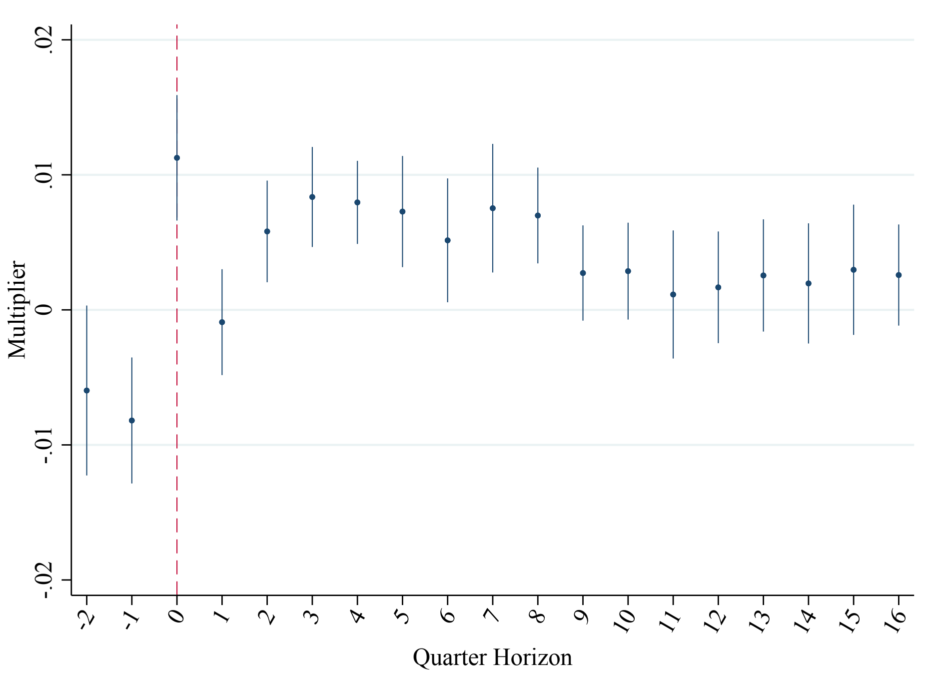


Figure IA.III. The Asymmetric Response of Financing Decisions

This figure presents the asymmetric response of firm financing decisions to different level demand shocks. This table shows how firm financing decisions respond to investor flows over the eight quarters after different level demand shocks. The GIVs are constructed using factors: the GDP growth rate and two latent factors. The regressions are

$$\Delta Q^F_{t,t+8}(n) = M^F \sum_{q>1}^{5} z^q_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n).$$

$z^q_t(n)$ is the group of GIVs, 5 represents the largest investor inflows. $\Delta Q^F_{t,t+8}(n)$ is the cumulative percentage change in total shares outstanding from quarter t to $t + 8$ of firm n. Standard errors are clustered by firm and quarter, and reported in parentheses. $^*p < .1$;$^{**}\ p < .05$;$^{***}\ p < .01$.