Flow-Driven Corporate Finance: A Supply-Demand Approach

Hulai Zhang*

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Abstract

Integrating firm decisions into demand system asset pricing models, I develop a supply-demand framework to quantify the equilibrium effects of investor demand for stocks on firm financing and investment. This framework revises the intuitive approach to quantifying the impact of investor flows of dividing the supply elasticity by the demand elasticity of stock prices. I apply Gabaix and Koijen (2024)'s granular instrumental variable method to estimate the multipliers. The results show that a \$1 investor flow to the stock leads to an immediate \$0.012 share issuance and a total of \$0.24 share issuance over two years. A 1% investor flow leads to a 0.19% increase in firm investment over two years. The multipliers are asymmetric: firms respond more strongly to investor inflows than to outflows, and more strongly to investor flows during economic expansions than during recessions.

*Tilburg University and ESCP Business School. My correspondence is h.zhang_4@tilburguniversity.edu. I am deeply grateful to my advisors, Luc Renneboog, Jasmin Gider, and Alberta Di Giuli, for their unwavering support and guidance.

1 Introduction

Does investor demand for stocks have a real effect on firms? On one hand, trading activities in the stock market are conducted mainly between investors and do not involve firms. The supply elasticity of firms is small, indicating nearly zero capital flows to firms even when stock prices are changed by investor demand.[1] Classic asset pricing theories imply that investor demand for stocks is highly elastic and does not have a price impact, let alone a real impact, on firms.[2] On the other, firms pay attention to the stock market and actively time it.[3] The investor demand for stocks is also not as elastic as previously believed.[4] It remains an empirical question whether investor demand for stocks affects the real economy of firms. This paper develops a supply-demand framework, by adding firm decisions to Koijen and Yogo (2019)'s demand system asset pricing model, to quantify the equilibrium effects of investor demand for stocks on firm financing and investment.

There are numerous key quantity questions in academia and policymaking regarding the real impact of investor demand for stocks on firms. A first example is on the Bank of Japan's 2010 stock market quantitative easing (QE).[5] Many may question the effectiveness of a stock market QE and prefer one targeting bonds. Knowing the magnitude of the real impact of investor demand in the stock market could help the Bank of Japan determine whether it should conduct QE in stock (or bond) markets, as well as the size of its stock market QE ex ante. A second example is on the portfolio regulation of pension funds. The portfolio regulation forces pension funds to re-allocate their funds across firms, which

[1]The empirical studies on the q-theory of investment show a weak relationship between corporate investment and Tobin's q, as in Morck et al. (1990); Erickson and Whited (2000); Liu et al. (2009).

[2]See a discussion of theory-implied demand elasticity in Gabaix and Koijen (2021).

[3]See the behavior finance literature on market timing theory, as in Baker and Wurgler (2000, 2002); Baker et al. (2003)

[4]This has been documented in recent demand-based asset pricing literature, as in Koijen and Yogo (2019); Haddad et al. (2021); Van der Beck (2021).

[5]The Bank of Japan purchases ETFs that worth 3.5% of GDP from January 2011 through March 2018 (Barbon and Gianinazzi, 2019; Charoenwong et al., 2021). Barbon and Gianinazzi (2019) documents positive and persistent price impact, while Charoenwong et al. (2021) finds no impact on firms' investment.

generates differentiated flows to different firms. This portfolio regulation thus has two effects: a welfare effect and a misallocation effect of financing. These two effects should be quantified and included in decision as to whether a portfolio regulation should be implemented. A third example is on the sustainable investment. While the literature has documented the benefits of sustainable investment in reduced carbon emissions and increased green innovations,[6] it has not adequately assessed the costs of sustainable investment.[7] One potential cost is the loss of total investment and production. Knowing the magnitude of effects of sustainable investment on firms' financing, investment, and production will enable one to conduct a welfare analysis of sustainable investment.

There are two challenges to quantifying the real impact of investor flows. The first challenge arises from the bias of simultaneous equations. Suppose we can perfectly measure the investor flow by all investors; the regression of corporate decisions on the investor flow results in inconsistent estimations as in any supply-demand framework. Investor flows affect corporate decisions, which in turn affect investor flows. The supply-side parameters are unidentifiable due to endogenous investor flows. A demand shock will help. Several demand shocks in the literature are used as instruments for stock prices: mutual fund flows (Edmans et al., 2012), dividend reinvestment (Hartzmark and Solomon, 2021), and index reconstitution (Chang et al., 2015). Using these demand shocks as an instrument for investor flows would give us a consistent estimation of the real impact of investor flows. However, we cannot measure the investor flow by including all investors. We could potentially substitute it with the three aforementioned demand shocks in our regressions, which brings us to the second challenge: the measurement error bias. These demand shocks capture only part of investor flows, and they change stock prices and corporate decisions, which in turn affect

[6]These papers are Becht et al. (2023); Cenedese et al. (2023); Choi et al. (2024); Gantchev et al. (2022); Noh et al. (2023).

[7]Hartzmark and Shue (2022) finds that sustainable investment is counterproductive in that it does not reduce total carbon emissions.

other investor flows. This implies a correlation between the measurement error of demand shocks and the demand shocks themselves, resulting in an inconsistent estimation of the impact of investor flows.

I address these challenges in two steps. First, I develop a supply-demand framework to obtain the structural relationship between corporate decisions and investor flows. The supply-demand framework starts with the demand system asset pricing models in Koijen and Yogo (2019), Haddad et al. (2021), and Van der Beck (2021). Instead of assuming an exogenously given supply side, I allow endogenous corporate decisions in the demand system asset pricing models. When there is a demand shock in the system, the stock price, share issuance and investment of the firm adjust. When the stock market clears-that is, when the aggregate asset demand equals asset supply-the relationship between price impact, financing impact, and investment impact in equilibrium is (as I will demostrate below):

$$\Delta D_t = \boldsymbol{\zeta}_t^P \underbrace{\text{diag}(P_t)\Delta P_t}_{\text{Price Effect}} + \underbrace{\Delta Q_t^F}_{\text{Financing Effect}} - \boldsymbol{\zeta}_t^X \underbrace{\text{diag}(X_t)\Delta X_t}_{\text{Investment Effect}}.$$

When the firm does not respond to demand shocks ΔD_t, the financing and investment effects are zero, making $\text{diag}(P_t)\Delta P_t = (\boldsymbol{\zeta}_t^P)^{-1}\Delta D_t$. This simplified equation says that the price impact of investor flows can be identified using demand elasticity to stock prices. However, the price impact becomes unidentifiable if firms react to demand shocks. Stock prices can amplify the impact of investor flows on firm financing and investment decisions. When there is an investor flow, the stock price changes; this changed stock price induces the firm to adjust their financing and investment, which in turn affects investor flows and the stock price. Considering this amplification effect, the supply-demand framework in this paper yields closed-form relationships between investor flows and corporate decisions in equilibrium. Both the financing and investment multipliers are contingent on four elasticities, not just two as was naturally believed.[8] Both the financing and investment multipliers are dependent on two supply-side elasticities of financing and investment, as well as two demand-side elasticities of stock prices and investment. This framework revises the natural approach to quantifying the real impact of investor flows of dividing the supply elasticity by the demand elasticity to stock prices. In sum, the supply-demand framework indicates that we need two additional elasticities to sufficiently quantify the real impact of investor flows.

Second, I apply the granular instrument variable (GIV) method, as outlined by Gabaix and Koijen (2024), to estimate the multipliers. The GIV method subtracts investors' idiosyncratic demand shocks from quarterly portfolio holdings, as the source of aggregate investor flows to the firm. This aggregate idiosyncratic demand shock is exogenous to firm fundamentals provided that it is well constructed. Through the estimation of a supply-demand system, I demonstrate that the GIV method 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 a different set of observed and latent factors to construct GIVs and check whether the estimated multipliers from main regressions change notably. If the estimated multipliers are stable across different specifications, this indicates that the common factors are properly controlled for and that the GIVs are exogenous. The results in the main regressions indicate that the estimated multipliers are stable with different observed and latent factors. I also provide three other ways to justify the exogeneity of the constructed GIVs in this paper. First, I find that GIVs have no relationships with corporate decisions in periods ahead of demand shocks. A necessary condition of GIV exogeneity is that GIVs are unrelated to the firm's past fundamentals or expected

[8] The natural approach to quantifying the real impact of investor flows is dividing the supply elasticity to stock prices by demand elasticity to stock prices. The supply elasticity to stock prices has been estimated in the literature that studies the supply side, such as Erickson and Whited (2000), Liu et al. (2009), Edmans et al. (2012), Hau and Lai (2013), and Lou and Wang (2018). The demand elasticity to stock prices has been estimated in the literature that studies the demand side (Lou, 2012; Chang et al., 2015; Schmickler and Tremacoldi-Rossi, 2022; Koijen and Yogo, 2019; Van der Beck, 2021; Gabaix and Koijen, 2021; Hartzmark and Solomon, 2021).

fundamentals. This is supported in the regressions of firm past fundamentals on GIVs: the correlations between GIVs and firm past fundamentals are close to zero. Second, a random shock should be normally distributed around zero. I find that GIVs are normally distributed with a mean of zero. Third, I validate the GIV method by testing its correlation with well-known exogenous demand shocks in the literature, namely mutual fund flows and dividend reinvestment. If GIVs are indeed proxies for demand shocks, they should be able to capture these exogenous demand shocks induced by mutual fund flows and dividend reinvestment. The results reveal that the constructed GIVs in this paper can capture both these demand shocks at the same time. However, the R^2's of these regressions are close to zero, indicating that these demand shocks are weak predictors of GIVs. There are other sources of demand shocks embedded in the GIVs. To conclude, I use it to estimate the financing and investment multipliers.

This paper 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,[9] and the investment multipliers amount to zero in the short horizon and 0.19 in the long horizon. Consequently, the financing multipliers reveal that a $1 dollar investor flow to a firm generates 1.2 cents share issuance at the quarter of the investor flow, and 24 cents share issuance over the eight quarters after the quarter of the investor flow. The investment multipliers reveal that the firm does not respond to investor flows at the quarter, and a 1% investor flow causes 0.19% increase in investment by the firm over the eight quarters. A firm's investment requires planing 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 has an information role, rather than a financing role for firms (Bond et al., 2012). In the long run, however, the financing

[9]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.

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 the firm responding more strongly to investor inflows than to outflows. A $1 investor inflow causes the firm to issue $0.85 shares, but a $1 investor outflow causes the firm to buy back $0.005 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 growths adjust for investor inflows more strongly than those for investor outflows.

Third, investor flows are less effective in increasing firms' investment during recessions than during expansions. A 1% investor flow generates 0.25% share issuance during expansion periods and 0.14% share issuance during recession periods, indicating that a similar investor flow generates 44% less share issuance during recessions than during expansions. As for investment, a 1% investor flow generates 0.18% and 0.09% investment growths during recessions and expansions, respectively, suggesting that a similar investor flow is 50% less effective in inducing investment growth during recessions than during expansions. These results have policy implications: central banks should implement QE-like policies or that regulators should implement portfolio regulations before the occurrence of recessions.

Related Literature. This paper relates to a number of strands of literature. Starting with Koijen and Yogo (2019), the literature on demand-based asset pricing has been burgeoning. Contrary to classic asset pricing theories, the demand-based asset pricing literature documents highly inelastic asset demand by investors (Van der Beck, 2021; Haddad et al., 2021). Gabaix and Koijen (2021) linked the inelastic asset demand with stock prices and documented a substantial price impact 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 the behaviors of each side (either demand or supply side) by assuming the other side is fixed, there is scarce literature that combines both sides and track their interactions.[10] My paper fills this gap by integrating both sides in a supply-demand framework.

This paper also relates to the literature that uses investor flows as the instrument for stock prices and examines their real effects on firms. The first instrument of exogenous price pressure is the mutual fund flow. 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 holding. They use this measure as the instrument for stock prices and study the impact of stock prices on takeovers. Since Edmans 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. However, 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. The second instrument of exogenous price pressure is dividend reinvestment of investors. Most papers use dividend

[10]To the best of 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 a dynamic investment model, my supply-demand framework models the supply side using the ideas of q-theory of investment as in Hayashi (1982), Cochrane (1996), and Liu et al. (2009).

reinvestment to quantify the price impact of investor flows, such as Hartzmark and Solomon (2021) and Van der Beck (2021). One exception is Schmickler and Tremacoldi-Rossi (2022) who use dividend reinvestment as the instrument for stock prices and study the spillover effects of payouts on firm financing and investment decisions. Quantifying the long-term real impact of payouts has a reverse causality issue: The long-term investment of firms or their industries or the market affects current payouts at the firm, industry and market level.[11] The third instrument of exogenous price pressure is index reconstitution. Chaudhry (2023) uses Russel 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.[12] While index reconstitution generates a statistically significant price impact, its predicting power for stock prices is small.[13] The small price impact by index reconstitution makes it hard to generate real impact on forms. My paper adds to this literature on two aspects. First, my paper goes beyond stock prices to emphasize investor flows and their real effects on firms. Second, I use the realized investor flows by all investors, which mitigates the measurement error bias.

This paper also relates to the broad literature that examines the real effects of credit supply shocks. Influential contributions by Bernanke (1983) and Bernanke and Gertler (1986) argue that credit supply shocks in the banking system affect the real economy, a claim substantiated by empirical studies on different aspects of the real economy: Khwaja and Mian (2008) on the cost of debt financing, Chodorow-Reich (2014) on employment, Aghamolla et al. (2024) on hospital health outcomes. While these papers focus on the primary market,

[11]This reverse causality issue can be mitigated when quantifying the short-term impact of dividend reinvestment, as in the setting of Hartzmark and Solomon (2021). This is so because the demand side is changeable, whilst the supply side remains unchanged in the short term.

[12]Replacing total investor flows with flows by index reconstitution suffers from the measurement error bias as illustrated above.

[13]I replicate the demand shocks by index reconstitution using the construction methodology in Aghaee (2022). 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).

it remains unknown whether it holds in the stock market. I fill the gap by examining to what extent the investor demand in the stock market affects firm financing and investment decisions.[14]

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

2 Model

In this section, I establish a model of investor demand in the stock market and derive the equilibrium relationship between investor flow and firm decisions, such as share issuance and fundamentals (investment). By adding corporate decisions, this model extends the demand system asset pricing models as of Koijen and Yogo (2019), Haddad et al. (2021), and Van der Beck (2021).

There are I investors and N firms in the market. Each firm n issues one security in the equity market, denoted as the asset n. Each firm makes two decisions: (1) It adjusts total shares outstanding by share issuance or buyback; (2) It adjusts its firm characteristics such as investment. Firms' total shares outstanding is denoted as $Q_t^F = (Q_t^F(1), Q_t^F(2), \cdots, Q_t^F(N))'$, where I normalize beginning-of-the-quarter shares outstanding of each firm as 1. Firms' characteristics are denoted as $X_t = (X_t(1), X_t(2), \cdots, X_t(N))'$. These decisions are de-

[14]A study by Kubitza (2021) focuses on the corporate bond market and assesses the impact of insurers' bond demand on firm financing and investment. The methodology of this study bears a resemblance to the literature that utilizes mutual fund flows as instruments, as both employ a proportion of investors. Kubitza (2021) complements my paper by showing that supply elasticities to bond prices are high.

pendent on market conditions such as stock prices. $P_t(n)$ is the stock price of asset n, which is also the market equity since I normalize the beginning-of-the quarter shares outstanding as 1. The I investors, indexed by $i = 1, ..., I$, form their portfolios of these N assets.[15] The share of ownership of the investor i in the asset n at t is denoted as $Q_{i,t}(n)$. The optimal portfolio $Q_{i,t} = (Q_{i,t}(1), Q_{i,t}(2), \cdots, Q_{i,t}(N))'$ is a function of asset prices $P_t = (P_t(1), P_t(2), \cdots, P_t(N))'$, observable variables X_t (such as firm characteristics) and unobservable variables $V_t = (V_t(1), V_t(2), \cdots, V_t(N))'$ (such as demand shocks): $Q_{i,t} = Q_{i,t}(P_t, X_t, V_t)$. When the equity market clears, the total supply of asset equals to the total demand of assets:

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

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

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:

$$\zeta_{i,t}^P(n) = -\frac{\partial \ln(Q_{i,t}(n))}{\partial \ln(P_t(n))}. \tag{2}$$

In the same way, I define cross-price elasticity as

$$\zeta_{i,t}^P(n, m) = -\frac{\partial \ln(Q_{i,t}(n))}{\partial \ln(P_t(m))}. \tag{3}$$

Given the investor-specific demand elasticity matrix $\boldsymbol{\zeta}_{i,t}^P$, I define the stock level price elas-

[15] I also allow these investors to invest in an outside asset. This makes the budget constraint condition for each investors: $\text{AUM}_{i,t} \geqslant \sum_{n=1}^{N} P_t(n) Q_{i,t}(n)$. The total dollar value of an investor's holdings on N firms should be equal or less than the investor's asset under management.

ticity matrix as the sum of weighted investor-specific price elasticity:

$$\boldsymbol{\zeta}_t^P = \sum_{i=1}^{I} \text{diag}(Q_{i,t}) \boldsymbol{\zeta}_{i,t}^P. \tag{4}$$

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

$$\zeta_{i,t}^X(n) = \frac{\partial \ln(Q_{i,t}(n))}{\partial \ln(X_t(n))}. \tag{5}$$

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

$$\boldsymbol{\zeta}_t^X = \sum_{i=1}^{I} \text{diag}(Q_{i,t}) \boldsymbol{\zeta}_{i,t}^X. \tag{6}$$

I assume that a shock $\Delta V_t = (\Delta V_t(1), \Delta V_t(2), \cdots, \Delta V_t(N))'$ occurs at t. Its impact on investor flow D_t, asset price P_t, shares outstanding Q_t^F, and firm characteristics X_t can be approximated by first-order Taylor expansion:

$$\Delta D_t = \left(\sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial V_t} \right) \Delta V_t; \Delta P_t = \frac{\partial P_t}{\partial V_t} \Delta V_t; \Delta Q_t^F = \frac{\partial Q_t^F}{\partial V_t} \Delta V_t; \Delta X_t = \frac{\partial X_t}{\partial V_t} \Delta V_t. \tag{7}$$

Lemma 1. *In equilibrium, the impacts satisfy the following relationship:*

$$\Delta D_t = \boldsymbol{\zeta}_t^P \underbrace{diag(P_t) \Delta P_t}_{\textit{Price Effect}} + \underbrace{\Delta Q_t^F}_{\textit{Financing Effect}} - \boldsymbol{\zeta}_t^X \underbrace{diag(X_t) \Delta X_t}_{\textit{Investment Effect}} \tag{8}$$

Investor inflow ΔD_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

$$\text{diag}(P_t)\Delta P_t = (\boldsymbol{\zeta}_t^P)^{-1}\Delta D_t, \tag{9}$$

which is used by Gabaix and Koijen (2021) and Van der Beck (2021) 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.

As in the q-theory of investment literature such as Hayashi (1982), Liu et al. (2009) and Bolton et al. (2011), I assume that the firm's response is a linear function of asset prices: $\Delta Q_t^F = \boldsymbol{\Lambda}^F \text{diag}(P_t)\Delta P_t$ and $\text{diag}(X_t)\Delta X_t = \boldsymbol{\Lambda}^X \text{diag}(P_t)\Delta P_t$. The impact of investor flow on firm's share issuance and characteristics is given in the following proposition.

Proposition 1. *In equilibrium, the impact of investor flow on firm's share issuance and other fundamentals is given by*

$$\Delta Q_t^F = \underbrace{\boldsymbol{\Lambda}^F(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}^F - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}^X)^{-1}}_{\overset{def}{=} M^F} \Delta D_t \tag{10}$$

$$diag(X_t)\Delta X_t = \underbrace{\boldsymbol{\Lambda}^X(\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}^F - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}^X)^{-1}}_{\overset{def}{=} M^X} \Delta D_t \tag{11}$$

3 Estimation

I first summarize the data sources and sample, then introduce the method to identify the multipliers of ΔD_t in Proposition 1. Finally, I check the validity of the granular instrumental variable (GIV) method.

3.1 Data and Sample

The data used in this paper represents institutional equity ownership, 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 the 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 only include common stocks that are listed on the NYSE, NASDAQ, or AMEX, (i.e., CRSP share code 10 or 11 and the 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.

3.2 Identification

To quantify the impact of investor flow on firm decisions, I need to find a measure of investor demand shock ΔD_t, which is a challenge. Alternatively, I could estimate two sets of parameters: the supply-side elasticities $(\mathbf{\Lambda}^F, \mathbf{\Lambda}^X)$ and the demand-side elasticities $(\boldsymbol{\zeta}^P, \boldsymbol{\zeta}^X)$, which will also identify the impact of investor flow on firm decisions. 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.[16] In the following, I

[16] 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 4 will

demonstrate that it is possible to directly identify the coefficients of ΔD_t in Proposition 1 by deriving the demand shocks from investor holdings.

I estimate the impact of investor flow on firm decisions using the granular instrument variables (GIV) method in Gabaix and Koijen (2024). The intention of the GIV method is to aggregate investor idiosyncratic shocks at the asset level. This aggregated shock is orthogonal to the firm's fundamentals, ensuring the identification of supply side parameters. Many 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, 2021), 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 method provides a more flexible and reliable framework for causally estimating the impact of financial markets.

The GIV method starts from the following supply-demand system:

$$\Delta q_{i,t}(n) = -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \gamma_i(n)\eta_t + \varepsilon_{i,t}(n) \tag{12}$$

$$\Delta Q_t^F(n) = \lambda^F(n)R_t(n) + \mu_t(n) \tag{13}$$

$$\Delta x_t(n) = \lambda^X(n)R_t(n) + \nu_t(n) \tag{14}$$

where $\Delta q_{i,t}(n) = \frac{Q_{i,t}(n)-Q_{i,t-1}(n)}{Q_{i,t-1}(n)}$, $\Delta Q_t^F(n) = Q_t^F(n) - 1$, and $\Delta x_t(n) = \frac{X_t(n)-X_{t-1}(n)}{X_{t-1}(n)}$. $\varepsilon_{i,t}(n)$ stands for the idiosyncratic demand shocks, which satisfy $\varepsilon_{i,t}(n) \perp \eta_t, \mu_t(n), \nu_t(n)$. The parameters of interest here are the supply elasticities $(\lambda^F(n), \lambda^X(n))$ and the demand elasticities $(\boldsymbol{\zeta}^P(n), \boldsymbol{\zeta}^X(n))$. For the estimation, I assume $\zeta_{i,t}^P(n) = \zeta^P(n)$ and $\zeta_{i,t}^X(n) = \zeta^X(n)$, which means that the demand elasticities of asset n are the same between investors and over time. I define three weights $S_{i,t}(n) = \frac{Q_{i,t-1}(n)}{\sum_{i=1}^I Q_{i,t-1}(n)}$, $E_i(n) = \frac{1/\sigma_i^2(n)}{\sum_{i=1}^I 1/\sigma_i^2(n)}$, and $S_{i,t}(n) - E_i(n)$. $\sigma_i^2(n)$ is the variance of $\varepsilon_{i,t}(n)$. I aggregate the demand equation (12) to the asset level with

discuss these details.

these three weights:

$$\widetilde{\Delta q_t(n)} = -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \widetilde{\gamma(n)}\eta_t + \widetilde{\varepsilon_t(n)} \tag{15}$$

$$\overline{\Delta q_t(n)} = -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \overline{\gamma(n)}\eta_t + \overline{\varepsilon_t(n)} \tag{16}$$

$$\widehat{\Delta q_t(n)} = \widehat{\gamma(n)}\eta_t + z_t(n). \tag{17}$$

I define the granular instrumental variable (GIV) $z_t(n)$ as

$$z_t(n) \overset{\text{def}}{=} \sum_{i=1}^{I}[S_{i,t}(n) - E_i(n)]\varepsilon_{i,t}(n) \tag{18}$$

First, $z_t(n)$ is orthogonal to η_t, leading to identification of $\widehat{\gamma(n)}$. $z_t(n)$ can be calculated as the residual of Equation (17). Second, $z_t(n)$ is orthogonal to $\mu_t(n), \nu_t(n)$, leading to the identification of $\lambda^F(n)$ and $\lambda^X(n)$. I can estimate the supply side parameters by the following two moment conditions:

$$\mathbb{E}\left[z_t(n)[\Delta Q_t^F(n) - \lambda^F(n)R_t(n)]\right] = 0 \tag{19}$$

$$\mathbb{E}\left[z_t(n)[\Delta x_t(n) - \lambda^X(n)R_t(n)]\right] = 0 \tag{20}$$

The supply elasticities can be estimated as: $\lambda^F(n) = \mathbb{E}[z_t(n)\Delta Q_t^F(n)]/\mathbb{E}[z_t(n)R_t(n)]$ and $\lambda^X(n) = \mathbb{E}[z_t(n)\Delta x_t(n)]/\mathbb{E}[z_t(n)R_t(n)]$. The relevance condition $\mathbb{E}[z_t(n)R_t(n)] \neq 0$ is satisfied if $\zeta_t^P(n) \neq 0$: when demand shocks affect asset prices.

However, I move beyond the separate estimation of supply side parameters to identify the coefficients of ΔD_t in Proposition 1 directly. The left-hand side of Equation (15) is the weighted average of $\Delta q_{i,t}(n)$, which equals the share issuance in equilibrium, $\Delta Q_t^F(n)$. I replace $\Delta Q_t^F(n)$ and $\Delta x_t(n)$ with equations (13) and (14), and rearrange Equation ((15)), which yields a reduced-form relationship between $R_t(n)$ and $z_t(n)$. Furthermore, the following proposition shows that the coefficients of ΔD_t in Proposition 1 can be identified directly from $z_t(n)$.

Proposition 2. *The coefficients in Proposition 1 are identifiable by regressing $\Delta Q_t^F(n)$ and $\Delta x_t(n)$ on $z_t(n)$.*

$$\Delta Q_t^F(n) = M^F(n)z_t(n) + \xi_t(n) \tag{21}$$

$$\Delta x_t(n) = M^X(n)z_t(n) + \upsilon_t(n) \tag{22}$$

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 $z_t(n) \perp \xi_t(n), \upsilon_t(n)$.

I now summarize the estimation procedure. This procedure follows the general framework of Gabaix and Koijen (2024) but makes several modifications to adapt to the specific aims of this paper. I first 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.[17] The factors η_t consist of observable factors η_t^o and latent factors η_t^l. I use the $\sigma_i^2(n) = \max(\sigma_i^2(n), \text{median}(\sigma_i^2(n)))$ to ensure reasonable weight on aggregations. These steps are followed:

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

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

$$\Delta q_{i,t}(n) = \alpha_i(n) + \beta_t(n) + \gamma_i(n)\eta_t^o + \epsilon_{i,t}(n) \tag{23}$$

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

[17] This aggregation aims to alleviate the effects of investors having zero holdings. Nonetheless, usinging either aggregated investors or individual investors does not affect my main findings.

3. Extract latent factors η_t^l 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 η_t^l. Calculate the GIV $z_t(n)$ using $\varepsilon_{i,t}(n)$ as in Equation (18).

4. Run the simple time series regressions for each asset n.

$$\Delta Q_t^F(n) = M^F(n)z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{24}$$

$$\Delta x_t(n) = M^X(n)z_t(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n) \tag{25}$$

I use the generated regressor $z_t(n)$ in regressions (24) and (25) in the last step, which gives a consistent estimation of coefficients but inconsistent estimation of standard errors. Since the GIV is the residual of Equation (17), the OLS standard errors of estimated multipliers in regressions (24) and (25) over-estimate the true standard errors; this means that my estimated multipliers would have a 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. Thus, for simplicity, I report the OLS standard errors for regressions.

4 Validating the Granular Instrumental Variable

The first condition, namely the relevance condition, for the GIV in this paper requires a few large idiosyncratic shocks and a few large investors. The few idiosyncratic shocks to large investors or sectors could significantly affect aggregate demand. This condition is satisfied in my setting.

The second condition, the exogeneity condition, for the GIV method requires random shocks to investors that are orthogonal to common macro trends, such as GDP growth. The GIV is exogenous by construction, given that we 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 (24) and (25) 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 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 $z_t(n)$. 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 1. 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 the 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. Thus, I expect a low R^2 when regressing GIV to these demand shocks, which my results support.

In the sections below, I show the link between the GIV $z_t(n)$ and mutual fund flows and dividend reinvestment.[18]

4.1 Mutual Fund Flows

Investor redemption from mutual funds, especially large ones, could place great pressure on mutual funds to sell the stocks they hold. Investor inflows to mutual funds could lead mutual funds to buy stocks that they already hold in their portfolio. Thus, mutual fund flows could be a source of demand shocks to stocks.

Mutual fund flows are used as a shock to stock prices for studying the effect of stock price on corporate policies. For example, Edmans et al. (2012) use mutual fund redemption as a shock to 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 price pressure from mutual fund flows comes initially 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

[18]I also link the GIV $z_t(n)$ with demand shocks induced by index reconstitution. Constructing the demand shocks using the methodology in Aghaee (2022), 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 fit for our quarterly data. Second, index reconstitution has only a significant impact on marginal firms, not on the whole sample. Aghaee (2022) 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.

decision. Edmans et al. (2012) and papers afterward[19] overcome this problem by using the beginning-of-quarter holdings. This method 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 the quarter level. I combine these two databases using MFLINKS.[20] Below, I illustrate the procedure for defining 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

$$Flow_{i,t} = \frac{TNA_{i,t} - TNA_{i,t-1}(1 + RET_{i,t})}{TNA_{i,t-1}} \tag{26}$$

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

[19] 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).

[20] 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.

hypothetical flows to each stock by all mutual funds, defined as

$$MFFlow_t(n) = \sum_{i=1}^{I} Q_{i,t-1}(n) Flow_{i,t} \tag{27}$$

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:

$$z_t(n) = \beta \times MFFlow_t(n) + \delta_t + \epsilon_t(n). \tag{28}$$

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

Column (1) presents the result of regressing $z_t(n)$ on $MFFlow_t(n)$. Using the construction method of $z_t(n)$, the GIV $z_t(n)$ has already absorbed the firm fixed effects. Column (1) ignores quarter fixed effects by assuming that $z_t(n)$ does not vary between quarters. The result of column (1) is a strong relationship between $z_t(n)$ and demand shocks induced by mutual fund flows. The hypothetical demand shock driven by mutual fund flows can significantly predict $z_t(n)$. However, the R^2 of this regression is close to zero, indicating that the demand shock by mutual funds is a weak predictor of $z_t(n)$; this is true since mutual funds only account for a proportion of all investors. There are also many other sources for demand shocks by mutual funds, such as dividend reinvestment, discussed below.

Column (2) adds quarter fixed effects to the regression. 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 (2) shows a similar relationship between $z_t(n)$ and demand shocks induced by mutual fund flows as in column (1). The R^2 in column (2) increases slightly, but is still close to zero, indicating that the demand shock induced by the mutual fund can weakly forecast $z_t(n)$ even if the variations in the quarter are controlled for.

Column (3) uses two-way (firm and quarter) clustering to address the concern that the generated $z_t(n)$ has correlated errors over time for each firm. The result does not change after clustering by both quarter and firm. The demand shocks induced by mutual fund flows show a significant relationship with $z_t(n)$. But the near zero R^2 indicates that the demand shock by mutual fund is a weak predictor of $z_t(n)$.

Many papers use only fund flows that deviate more than 5% from zero (e.g. $|Flow_{i,t}| \geqslant 5\%$) to define the 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 deviating more than 5% to define the aggregate flows, and use these stock level flows to replicate the regressions. The regression results using these updated flows are given in columns (4) to (6). These regressions yield the same results: demand shocks from mutual fund flows can predict $z_t(n)$, but their predicting power is low.

The regressions on the mutual fund flows suggest that GIV $z_t(n)$ can capture the demand shocks of the mutual fund flows. The results also indicate that there are more sources of demand shocks than in mutual fund flows in $z_t(n)$.

4.2 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 as the mutual flow. This fund inflow leads to positive demand shocks.

Several papers have used dividend reinvestment as a substitute for mutual fund flows to study similar questions. For example, Schmickler and Tremacoldi-Rossi (2022) 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 stock price and firm investment. Hartzmark and Solomon (2021) 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 (2021) built on Schmickler and Tremacoldi-Rossi (2022) 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 (2022) to construct the quarterly demand shocks using dividend reinvestment. The stock dividend information 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

$$Flow_{i,t} = \frac{\sum_n Div_t(n) \times Q_{i,t-1}(n)}{AUM_{i,t-1}} \tag{29}$$

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

$$DivFlow_t(n) = \sum_{i=1}^{I} Q_{i,t-1}(n) Flow_{i,t} \tag{30}$$

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

Next, I run the following regression:

$$z_t(n) = \beta \times DivFlow_t(n) + \delta_t + \epsilon_t(n). \tag{31}$$

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

Column (1) presents the result of regressing $z_t(n)$ on $DivFlow_t(n)$ without adding fixed effects. The granular instrumental variable $z_t(n)$ has already absorbed the firm fixed effects in its construction. Column (1) further assumes that $z_t(n)$ does not vary between quarters. The result of column (1) 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 $z_t(n)$. However, the R^2 of this regression is 0.004, indicating that the demand shock caused by dividend reinvestment is a weak predictor of $z_t(n)$.

Column (2) adds quarter fixed effects to the regression. 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 stock level demand shocks are thus correlated within each quarter and differ across quarters. However, the result of column (2) reveals a similar correlation between $z_t(n)$ and the demand shocks induced by dividend reinvestment in column (1). The R^2 in column (2) increases to

0.012, which is still close to zero, indicating that the demand shock induced by dividend reinvestment can weakly forecast $z_t(n)$ even if quarter variations are controlled for.

Column (3) uses two-way (firm and quarter) clustering to address the concern that the generated $z_t(n)$ has correlated errors over time for each firm. The result does not change after clustering by both quarter and firm. Demand shocks induced by dividend reinvestment have a significant relationship with $z_t(n)$. The near-zero R^2 indicates that the demand shock caused by dividend reinvestment is a weak predictor of $z_t(n)$.

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

$$DivxFlow_t(n) = \sum_{i=1}^{I} Q_{i,t-1}(n) \frac{\sum_{m \neq n} Div_t(m) \times Q_{i,t-1}(m)}{AUM_{i,t-1}}. \tag{32}$$

I replicate the regressions using this modified demand shock $DivxFlow_t(n)$. The results are shown in columns (4) to (6) in Panel B of Table 1. They give the same results: demand shocks by dividend reinvestment forecast $z_t(n)$, but their forecasting power is limited.

In summary, the regressions on dividend reinvestment indicate that the granular instrumental variable $z_t(n)$ indeed captures demand shocks by dividend reinvestment. However, there are more sources of demand shocks in $z_t(n)$.

4.3 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:

$$z_t(n) = \beta_1 \times MFFlow_t(n) + \beta_2 \times DivxFlow_t(n) + \delta_t + \epsilon_t(n). \tag{33}$$

I expect both β_1 and β_2 to be significant and positive. The regression results are shown in Panel C of Table 1.

Columns (1) to (3) indicate a significant positive relationship between the granular instrument variable and demand shocks by total flows from mutual funds and dividend reinvestment. This result implies that the GIV captures both demand shocks at the same time. The small R^2 in these regressions points to the weak prediction power of both demand shocks for the GIV. Hypothetical demand shocks caused by mutual fund flows or dividend reinvestment are too small to generate a big impact on stock prices. And 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 fails to affect stock price, analyst coverage, and corporate decisions.

I replicate the regressions using demand shocks from dividend reinvestment and large-than-5% mutual fund flows. The regressions in columns (4) to (6) give similar results as in columns (1) to (3): the GIV could capture both demand shocks at the same time. The results show by the low R^2's that there are more sources of demand shocks in the GIV.

5 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.

5.1 Financing Multipliers

Firms might take advantage of demand shocks in the stock market. If market demand is very elastic, investors could absorb the demand shocks of other market participants, leaving limited room for the firm to exploit the demand shocks. However, when market demand is inelastic, investors cannot absorb demand shocks, which gives the firm a chance to exploit this by issuing more shares to satisfy positive demand shocks and buyback shares to absorb negative demand shocks.

The regressions are based on Equation (24) and study how firm share issuance immediately responds to investor flows. In addition, I assume that financing multipliers are equal across firms, making the modified regression equation as

$$\Delta Q_t^F(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{34}$$

where the net share issuance $Q_t^F(n)$ is defined as the percent 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 the GIV $z_t(n)$ is significantly and positively related to firm quarterly issuance of shares. The multiplier is 0.012, implying that a \$1 dollar investor flow to a firm generates 1.2 cents share issuance by the firm for the quarter. The supply side, namely the firm, could absorb 1.2% of total demand shocks from the demand side, or the investors in the short horizon.

In column (2), I add one latent factor to the construction of the GIV. The idea of the firm-specific latent factor, which is subtracted by the principal component algorithm (PCA), is to capture as much heterogeneity in investor demand as possible.[21] 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 that in column (1): the financing multiplier is significantly positive and equals 0.012.

[21] 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.

Following Gabaix and Koijen (2021), 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 dollar investor flow induces the issuance of shares at the quarter for an amount of 1.2 cents.

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 dollar investor flow significantly causes the firm to issue new shares of 1.2 cents at 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.

$$\Delta Q^F_{t+h}(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{35}$$

where $h \in \{-2, -1, 0, 1, \cdots, 16\}$. Figure 2 plots the estimated multipliers of share 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 every quarter.[22] 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 2 depicts that a firm issues shares over both the short and long horizons after an investor flow. To estimate long term multipliers, I replace the share issuance at quarter t in Equation (24) by the cumulative share issuance at quarters t to $t+8$. The regression equation is

$$\Delta Q^F_{t,t+8}(n) = M^F z_t(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{36}$$

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 give 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.

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 share

[22] 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).

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

$$NetIssue_t(n) = \frac{SSTK_t(n) - PRSTK_t(n)}{AT_{t-1}(n)}, \tag{37}$$

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 summation 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 inflow and outflows? On the demand side, a firm is expected to respond to investor outflows more than to inflows, which is because the 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.

The 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 $z_t^-(n)$. The net inflow is defined as the maximum of the positive investor flow and zero, $z_t^+(n) = \max(z_t(n), 0)$. The net outflow is defined as the opposite of the minimum of the 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:

$$\Delta Q^F_{t,t+8}(n) = M^{F+} z_t^+(n) + M^{F-} z_t^-(n) + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \tag{38}$$

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 to negative demand shocks.

5.2 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 examining 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 answering this question is the simultaneity issue using stock prices as the 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 4 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 relate to fundamentals in equilibrium. For example, households would invest their money more to 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 method to tackle 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 per Equation (25), 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

$$\Delta x_t(n) = M^X z_t(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n) \tag{39}$$

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 the firm's 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 the 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 literature documenting 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. Below, 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 flow 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.

$$\Delta x_{t+h}(n) = M^X z_t(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n) \tag{40}$$

where $h \in \{-2, -1, 0, 1, \cdots, 16\}$. Figure 3 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 3 shows that a firm's investment grows gradually in the first six quarters of the investor flow.

Next, I turn to the investment multipliers over the long horizon. Figure 2 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 (25) by the cumulative investment growth at quarters t to $t + 8$. The regression equation is

$$\Delta x_{t,t+8}(n) = M^X z_t(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n) \tag{41}$$

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 investment 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 dis-investment 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 dis-investment. When firm investment is lumpy and irreversible, dis-investment is more costly than investment. I test these views in Table 7.

The regression equation is

$$\Delta x_{t,t+8}(n) = M^{X+} z_t^+(n) + M^{X-} z_t^-(n) + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n). \tag{42}$$

where $z_t^+(n)$ and $z_t^-(n)$ are net inflows and net outflows. The net inflow is defined as $z_t^+(n) = \max(z_t(n), 0)$. The 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 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.

5.3 Multipliers in Recessions vs Expansions

The asymmetric reactions to investor inflows and outflows suggest the importance of supply side factors, such as financial flexibility and investment irreversibility. Some macro factors could also affect the supply side and generate another form of asymmetry, particularly different reactions over time. In this section, I examine corporate financing and investment decisions during economic recessions and expansions.

The study of different flow-driven corporate policies during recessions and expansions has important policy implications. Suppose that there is a quantitative easing targeting the stock market, such as the Bank of Japan's QE in 2010. Policy makers would like to know when they should implement the QE to obtain the largest impact in terms of the highest growth in firm investment. Should this QE be implemented before the recession or during the recession? Another example considers the investment regulation of pension funds. When should the regulation be implemented to minimize total loss of firm investment? This is a welfare maximization problem. A third example regards the sustainable investing. There is ongoing debate regarding the productivity of sustainable investing (Becht et al., 2023; Cenedese et al., 2023; Choi et al., 2024; Gantchev et al., 2022; Hartzmark and Shue, 2022; Noh et al., 2023). Whether sustainable investing increases or decreases green investments or results in carbon reductions may depend on when the sustainable investing is implemented. Sustainable investing may well generate a larger impact on firm green investment during recessions since high-emission firms have higher incentive to attract funding during times of financial constraint (Bansal et al., 2022). Comparing the financing and investment multipliers during recessions versus expansions offers answers to the questions in the above three examples.

I use the definition of economic recessions and expansions as NBER.[23] The recession periods in my sample are 2001Q1 to 2001Q4, 2007Q4 to 2009Q2, and 2020Q1 to 2020Q2, which are evenly distributed over our sample periods 1999Q1 to 2023Q4, alleviating the concern that a coincidental period could make our results. The remaining quarters are economic expansion periods.

I first check the different share issuance during recessions and expansions. I run the regression with GIV and a dummy variable for economic recession periods. To obtain the

[23] https://www.nber.org/research/data/us-business-cycle-expansions-and-contractions

coefficient of GIV times the recession dummy, the regression removes the firm fixed effects times GDP growth rate controls.

$$\Delta Q^F_{t,t+8}(n) = M^F_1 z_t(n) + \beta Recession_t + M^F_2 z_t(n) \times Recession_t + \alpha^F(n) + \gamma^F(n)\eta_t + \xi_t(n) \quad (43)$$

where $Recession_t$ is a dummy variable that equals one if the quarters are in 2001Q1 to 2001Q4, 2007Q4 to 2009Q2, and 2020Q1 to 2020Q2

The parameter M^F_1 measures the effect of investor flows on share issuance during economic expansions. The parameter M^F_2 measures the gap of share issuance between expansions and recessions after investor flows. Panel A of Table 8 gives the results. A 1% investor flow generates 0.25% share issuance during expansion periods and 0.14% (= 0.248%−0.111%) share issuance during recession periods. This indicates that a similar investor flow generates 44% less share issuance during economic recessions.

I then check the different investment growth during recessions and expansions. The following regression with GIV and a recession dummy would estimate the differing responses in firm real investment during recessions versus expansions. To obtain the coefficient of GIV times the recession dummy, the regression removes the firm fixed effects times GDP growth rate controls.

$$\Delta x_{t,t+8}(n) = M^X_1 z_t(n) + \beta Recession_t + M^X_2 z_t(n) \times Recession_t + \alpha^X(n) + \gamma^X(n)\eta_t + \upsilon_t(n) \quad (44)$$

Panel B of Table 8 shows quite similar results as the share issuance results. A 1% investor flow generates 0.18% investment growth during expansion periods and 0.09% (= 0.183%−0.095%) investment growth during recession periods. This indicates that a similar investor flow generates 50% less investment growth during economic recessions.

In sum, the results in this subsection reveal that investor flows are more effective in increasing firm investment during economic expansions than during economic recessions.

These results suggest that central banks should implement QE-like policies and that regulators should implement pension fund portfolio regulations *before* the occurrence of recessions.

6 Conclusion

In this paper, I quantify the real effects of investors' asset demand in the stock market. To achieve this, I first develop a supply-demand framework in the stock market that extends the demand system asset pricing models by incorporating firms' decisions. In this respect, this paper is the first to link production asset pricing with demand system asset pricing. Adding the supply side allows us to go beyond the price impact to quantify the real impact of investor flows. This supply-demand framework yields closed-form relationships between investor flows and corporate decisions such as financing and investment in equilibrium, facilitating the estimation of the financing and investment multipliers in simple regressions. Both the financing and investment multipliers depend on four elasticities as opposed to only two as was previously believed. This framework revises the intuitive approach to quantifying the real impact of investor flows of dividing the supply elasticity by the demand elasticity of stock price. Two additional elasticity factors are required to sufficiently quantify the real impact of investor flows.

I apply the GIV method to estimate the multipliers. The GIV method subtracts investors' idiosyncratic demand shocks as the source of aggregate investor flows to the firm. My estimation indicates that firms immediately respond to demand shocks by issuing additional shares to the market. They continue share issuance and investment growth up to two years after investor flows. In the long horizon, the firm is an important share supplier that absorbs 24% of demand shocks. The firm also increases its investment by 19% in the long horizon for a 100% demand shock. Firm responses are asymmetric, with the firm responding more strongly to investor inflows than to outflows. This asymmetric impact reflects the supply side story: the firm's decisions are mainly dependent on its own objective function, not on the financial frictions in the stock market. Additionally, this also indicates that the stock market is quite efficient. I also demonstrate that during economic recessions, investor flows have a weaker impact on firm share issuance and investment growth compared to during expansions.

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

This table shows the regression results of the GIVs on demand shocks induced by mutual fund flows and dividend reinvestment. Standard errors are clustered by quarter in Columns (1)–(2) and (4)–(5), and by firm and quarter in Columns (3) and (6). Standard errors are reported in parentheses. $^{*}p < .1$;$^{**} p < .05$;$^{***} p < .01$.

Panel A: Mutual Fund Flows

	(1)	(2)	(3)	(4)	(5)	(6)
MFFlow	0.001**	0.002***	0.002***			
	(0.000)	(0.001)	(0.001)			
MFFlow5%				0.001**	0.002***	0.002***
				(0.000)	(0.001)	(0.001)
Obs.	372044	372044	372044	360003	360003	360003
R^2	0.000	0.004	0.004	0.000	0.004	0.004
Quarter FEs		Yes	Yes		Yes	Yes

Panel B: Dividend Reinvestment

	(1)	(2)	(3)	(4)	(5)	(6)
DivFlow	8.949***	15.779***	15.779***			
	(1.443)	(1.857)	(2.075)			
DivxFlow				9.007***	16.002***	16.002***
				(1.464)	(1.904)	(2.124)
Obs.	399635	399635	399635	399635	399635	399635
R^2	0.004	0.012	0.012	0.004	0.012	0.012
Quarter FEs		Yes	Yes		Yes	Yes

Panel C: Mutual Fund Flows vs Dividend Reinvestment

	(1)	(2)	(3)	(4)	(5)	(6)
MFFlow	0.000	0.001***	0.001***			
	(0.000)	(0.000)	(0.000)			
DivxFlow	9.854***	17.807***	17.807***	10.014***	18.572***	18.572***
	(1.653)	(2.125)	(2.322)	(1.703)	(2.209)	(2.396)
MFFlow5%				0.000	0.001***	0.001***
				(0.000)	(0.000)	(0.000)
Obs.	372019	372019	372019	359979	359979	359979
R^2	0.005	0.014	0.014	0.006	0.015	0.015
Quarter FEs		Yes	Yes		Yes	Yes

Table 2. Share Issuances in the Short Horizon

This table shows the regression results of share issuance on GIV in the quarter of investor flows. Standard errors are clustered by firm and by 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. Share Issuances in the Long Horizon

This table shows the regression results of share issuance and net stock sales on GIV over eight quarters after investor flows. 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 Share Issuances in the Long Horizon

This table shows the regression results of share issuance and net stock sales on positive and negative GIVs over eight quarters after investor flows. Standard errors are clustered by firm and by 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. Firm Investment in the Short Horizon

This table shows the regression results of firm investment growth on GIV in the quarter of investor flows. 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. Firm Investment in the Long Horizon

This table shows the regression results of firm investment growth on the GIV over eight quarters after investor flows. 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 Firm Investment in the Long Horizon

This table shows the regression results of firm investment growth on positive and negative GIV over eight quarters after investor flows. 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. The Impact of Investor Flows during Recessions vs. Expansions

This table shows the regression results of firm share issuance and investment growth on the GIV during economic recessions and expansions in the long horizon. Standard errors are clustered by firm and quarter, and reported in parentheses. $^*p < .1$;$^{**}\, p < .05$;$^{***}\, p < .01$.

Panel A: Share Issuance in the Long Run

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t(n)$	0.250***	0.248***	0.248***	0.273***	0.271***	0.271***
	(0.031)	(0.031)	(0.031)	(0.033)	(0.034)	(0.034)
Recession	-0.119***	-0.119***	-0.119***			
	(0.030)	(0.030)	(0.030)			
$z_t(n)\times$Recession	-0.110	-0.111	-0.111	-0.129	-0.131	-0.131
	(0.079)	(0.081)	(0.081)	(0.081)	(0.084)	(0.084)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.298	0.300	0.300	0.306	0.308	0.308
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm$\times\eta_1$		Yes	Yes		Yes	Yes
Firm$\times\eta_2$			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Panel B: Investment in the Long Run

	(1)	(2)	(3)	(4)	(5)	(6)
$z_t(n)$	0.187***	0.183***	0.183***	0.131***	0.125***	0.125***
	(0.044)	(0.045)	(0.045)	(0.035)	(0.035)	(0.035)
Recession	-0.300***	-0.297***	-0.297***			
	(0.096)	(0.095)	(0.095)			
$z_t(n)\times$Recession	-0.093*	-0.095*	-0.095*	-0.101**	-0.106**	-0.106**
	(0.047)	(0.050)	(0.050)	(0.047)	(0.050)	(0.050)
Obs.	38172	38172	38172	38172	38172	38172
R^2	0.123	0.131	0.131	0.157	0.165	0.165
Firm FEs	Yes	Yes	Yes	Yes	Yes	Yes
Firm$\times\eta_1$		Yes	Yes		Yes	Yes
Firm$\times\eta_2$			Yes			Yes
Quarter FEs				Yes	Yes	Yes

Figure 1. The Distribution of GIV $z_t(n)$

This figure shows the distribution of the GIV.

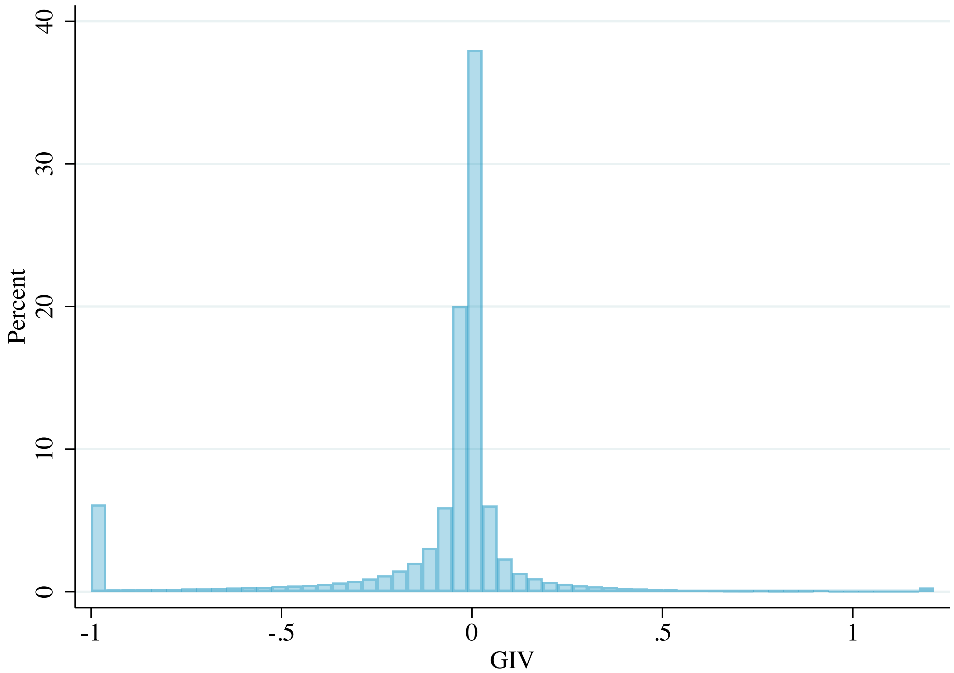


Figure 2. The Long Term Impact of Investor Flows on Share Issuance

This figure shows the quarterly share issuance multipliers on the investor flow that occurs in quarter 0.

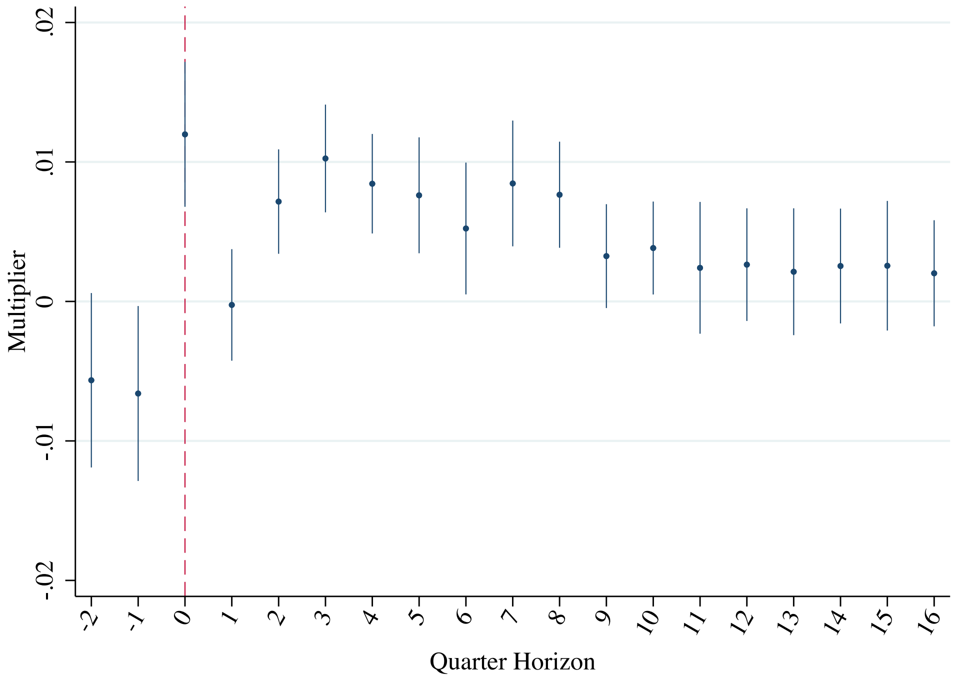
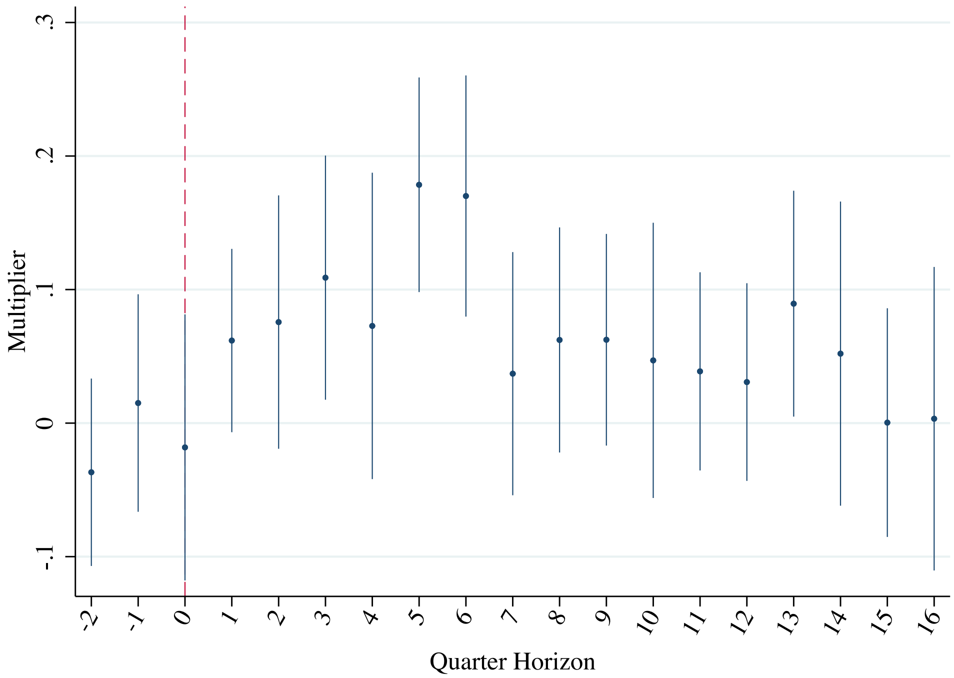


Figure 3. The Long Term Impact of Investor Flows on Investment

This figure shows the quarterly investment multipliers on the investor flow that occurs in quarter 0.



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

IA.1 Proofs

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

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

$$\Delta Q_t^F = \frac{\partial Q_t^F}{\partial V_t} \Delta V_t \tag{IA.2}$$

$$\Delta P_t = \frac{\partial P_t}{\partial V_t} \Delta V_t \tag{IA.3}$$

$$\Delta X_t = \frac{\partial X_t}{\partial V_t} \Delta V_t \tag{IA.4}$$

where all the left hand variables are vectors with length N. Take derivatives of Equation 1 with respect to the unobservable V_t on both sides,

$$\frac{\partial Q_t^F}{\partial V_t} = \sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial V_t} + \left(\sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial P_t}\right) \frac{\partial P_t}{\partial V_t} + \left(\sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial X_t}\right) \frac{\partial X_t}{\partial V_t} \tag{IA.5}$$

After a shock ΔV_t, we get

$$\frac{\partial Q_t^F}{\partial V_t} \Delta V_t = \sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial V_t} \Delta V_t + \left(\sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial P_t}\right) \frac{\partial P_t}{\partial V_t} \Delta V_t + \left(\sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial X_t}\right) \frac{\partial X_t}{\partial V_t} \Delta V_t \tag{IA.6}$$

$$= \Delta D_t + \left(\sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial P_t}\right) \Delta P_t + \left(\sum_{i=1}^{I} \frac{\partial Q_{i,t}}{\partial X_t}\right) \Delta X_t \tag{IA.7}$$

$$= \Delta D_t - \left(\sum_{i=1}^{I} \text{diag}(Q_{i,t}) \boldsymbol{\zeta}_{i,t}^{P} \text{diag}(P_t)^{-1}\right) \Delta P_t + \left(\sum_{i=1}^{I} \text{diag}(Q_{i,t}) \boldsymbol{\zeta}_{i,t}^{X} \text{diag}(X_t)^{-1}\right) \Delta X_t \tag{IA.8}$$

$$= \Delta D_t - \boldsymbol{\zeta}_t^{P} \text{diag}(P_t)^{-1} \Delta P_t + \boldsymbol{\zeta}_t^{X} \text{diag}(X_t)^{-1} \Delta X_t \tag{IA.9}$$

Note the left hand side equals ΔQ_t^F. Re-arrange the above equation, we get Lemma 1.

$$\Delta D_t = \boldsymbol{\zeta}_t^P \mathrm{diag}(P_t)\Delta P_t + \Delta Q_t^F - \boldsymbol{\zeta}_t^X \mathrm{diag}(X_t)\Delta X_t. \tag{IA.10}$$

Further assume that $\Delta Q_t^F = \boldsymbol{\Lambda}^F \mathrm{diag}(P_t)\Delta P_t$ and $\mathrm{diag}(X_t)\Delta X_t = \boldsymbol{\Lambda}^X \mathrm{diag}(P_t)\Delta P_t$, the above equation becomes

$$\Delta D_t = \boldsymbol{\zeta}_t^P \mathrm{diag}(P_t)\Delta P_t + \boldsymbol{\Lambda}^F \mathrm{diag}(P_t)\Delta P_t - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}^X \mathrm{diag}(P_t)\Delta P_t. \tag{IA.11}$$

Solve this equation, we can get the price impact of the demand shock ΔD_t. We can also get the financing and investment effects after we know the price impact of the demand shock.

$$\mathrm{diag}(P_t)\Delta P_t = (\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}^F - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}^X)^{-1}\Delta D_t \tag{IA.12}$$

$$\Delta Q_t^F = \boldsymbol{\Lambda}^F (\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}^F - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}^X)^{-1}\Delta D_t \tag{IA.13}$$

$$\mathrm{diag}(X_t)\Delta X_t = \boldsymbol{\Lambda}^X (\boldsymbol{\zeta}_t^P + \boldsymbol{\Lambda}^F - \boldsymbol{\zeta}_t^X \boldsymbol{\Lambda}^X)^{-1}\Delta D_t \tag{IA.14}$$

□

Proof of Proposition 2. I start from estimating the following demand-supply system,

$$\Delta q_{i,t}(n) = -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \gamma_i(n)\eta_t + \varepsilon_{i,t}(n) \tag{IA.15}$$

$$\Delta Q_t^F(n) = \lambda^F(n)R_t(n) + \mu_t(n) \tag{IA.16}$$

$$\Delta x_t(n) = \lambda^X(n)R_t(n) + \nu_t(n) \tag{IA.17}$$

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

$$\sum_{i=1}^I S_{i,t}(n)\Delta q_{i,t}(n) = -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \left(\sum_{i=1}^I S_{i,t}(n)\gamma_i(n)\right)\eta_t + \left(\sum_{i=1}^I S_{i,t}(n)\varepsilon_{i,t}(n)\right) \tag{IA.18}$$

$$= -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \widetilde{\gamma(n)}\eta_t + \widetilde{\varepsilon_t(n)} \tag{IA.19}$$

$$= -\zeta^P(n)R_t(n) + \zeta^X(n)\Delta x_t(n) + \widetilde{\gamma(n)}\eta_t + \overline{\varepsilon_t(n)} + z_t(n) \tag{IA.20}$$

Note that the left hand side, the aggregate demand shock, must equal the supply $\Delta Q_t^F(n)$

in equilibrium. Put Equation (13) and (14) into the above, we get

$$R_t(n) = [\zeta^P(n) + \lambda^F(n) - \zeta^X(n)\lambda^X(n)]^{-1} z_t(n) + \widetilde{\gamma(n)}\eta_t + \overline{\varepsilon_t(n)} + \zeta^X(n)\nu_t(n) - \mu_t(n) \tag{IA.21}$$

Then we get the equations for share issuance and fundamentals:

$$\Delta Q_t^F(n) = \underbrace{\lambda^F(n)[\zeta^P(n) + \lambda^F(n) - \zeta^X(n)\lambda^X(n)]^{-1}}_{=M^F(n)} z_t(n) + \xi_t(n) \tag{IA.22}$$

$$\Delta x_t(n) = \underbrace{\lambda^X(n)[\zeta^P(n) + \lambda^F(n) - \zeta^X(n)\lambda^X(n)]^{-1}}_{=M^X(n)} z_t(n) + \upsilon_t(n) \tag{IA.23}$$

where the two error terms are

$$\xi_t(n) = \lambda^F(n)\widetilde{\gamma(n)}\eta_t + \lambda^F(n)\overline{\varepsilon_t(n)} + \lambda^F(n)\zeta^X(n)\nu_t(n) - \lambda^F(n)\mu_t(n) + \mu_t(n) \tag{IA.24}$$

$$\upsilon_t(n) = \lambda^X(n)\widetilde{\gamma(n)}\eta_t + \lambda^X(n)\overline{\varepsilon_t(n)} + \lambda^X(n)\zeta^X(n)\nu_t(n) - \lambda^X(n)\mu_t(n) + \nu_t(n) \tag{IA.25}$$

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).

□