Investor Demand, Firm Investment, and Capital Misallocation*

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Abstract

Fluctuations in investor demand dramatically affect firms' valuation and access to capital. To quantify their real impacts, we develop a dynamic investment model that endogenizes the demand- and supply-side of equity capital. Strong demand dampens price impacts of issuance, facilitating investment and financing, while weak demand encourages opportunistic repurchases, crowding out investment. We estimate the model using indirect inference by matching the endogenous relationship between investor demand and firm policies. Our estimation suggests that investor demand is an important driver of misallocation, compared with financial and real frictions and heterogeneous risk premia. Eliminating excess demand reduces dispersion in the marginal product of capital by 23.8% and productivity losses by 22.3%. With demand fluctuations, firms hold higher cash savings and tend to be larger—excess demand allows firms with financial market power to profit from financial market transactions, contributing to the emergence of superstar firms.

Keywords: investor demand, capital misallocation, investor sentiment, demand estimation, firm investment, financial market power.

JEL Classification: G30, G10, G20, E22.

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1 Introduction

The history of the U.S. stock market has seen striking events of booms and busts in valuations. During the Nasdaq bubble of the 1990s, for example, internet stocks were traded at price levels that would defy any rational pricing explanations. In the recent "meme stock" episode of 2021, prices of GameStop and multiple other stocks skyrocketed, creating financing opportunities that would have otherwise been unavailable to these companies. These dramatic valuation episodes are often attributed to sentiment-driven demand from investors who favor those stocks despite the mismatch between valuations and fundamentals. How does such demand affect capital allocation across firms? Does it foster capital investments in firms with greater financing needs? If not, how large is distortion in capital allocation arising from investor demand? These questions speak directly to the central thesis of financial economics on the role of financial markets in efficient capital allocation.

In this paper, we tackle these questions by developing and estimating a dynamic model, wherein firms make optimal investment and financing decisions facing capital provision that arises from investor demand for firms' equity. The key feature of this setting that is distinct from standard models is the direct incorporation of time-varying demand from investors, which we tightly discipline using detailed data on investor holdings. Our model also embeds the endogenous relationship between firms' investment and financing decisions and investor demand. Using this joint modeling of the demand and supply side of capital, we estimate firms' optimal financial responses—share issuance and repurchases, dividend payout, and cash holdings—as well as investing policies, which we then investigate to assess how sentiment-driven demand affects capital allocations.

To separate demand components associated with investor sentiment, we follow the setup of Koijen and Yogo (2019) and first model investor demand using firm fundamentals that proxy for expected returns and risk of firms. In their approach, the latent component of demand in excess of the demand component represented by firm fundamentals is a firm-level measure of sentiment, which we also adopt in our paper. We exploit this separation of demand to quantify the misallocation of capital in a panel of firms with differing degrees of productivity. The effects of sentiment-driven demand on firm policies, firm size distributions, and capital allocations are substantial in our estimation. In the counterfactual case in which we remove latent excess demand, firms on average hold lower cash savings and tend to be smaller with fewer mega-sized firms, and their average marginal product of capital is approximately 10.1% higher. Removing excess demand also alleviates the misallocation of capital across firms by reducing the dispersion in the marginal product of capital by 23.8%, which reduces productivity losses by 22.3%.

Let us first explain the economic forces that operate behind the interplay between investors and firms in our dynamic model. The novel feature is that firms make financing and investment decisions while taking into account the equilibrium prices shaped by demand from investors. When investor demand is high, it incentives firms to issue additional stocks, whereas firms optimally repurchase shares at a favorable price when investor demand is weak. Accompanying these issuance and repurchase decisions are firms' investment and other financial policies, which change firm characteristics, including market capitalizations, capital expenditures, and dividends, and should in turn affect investors' demand for the firms' stocks, as prescribed by the characteristic-based demand system. Our model captures this feedback effect of firm decisions on investor demand, not only through stock prices but also through the dynamics of firm characteristics, thus incorporating the endogenous supply of capital from investors in a standard neoclassical investment model.

Investor demand should also influence firms' real investment decisions. There are two opposing channels at work. First, fluctuations in investor demand allow firms to profit from financial transactions, helping alleviate financial constraints and facilitate investments. Second, when weak investor demand realizes, firms might find it more profitable to spend cash reserves on share purchases, thus crowding out investments and exacerbating inefficient investment. The effects of these two channels vary across firms, making it easier for some firms to finance their investments while leaving others more financially constrained and passing on good investment opportunities. This cross-firm heterogeneity created by investor demand generates additional frictions in investment for more productive firms and can harm capital allocation efficiency in the economy.

We quantify these effects of investor demand by estimating the parameters of our dynamic model with the simulated method of moments (SMM). We divide the model parameters into two groups: one for the demand system and the other for firm dynamics. In demand system estimation, it is crucial to consider the feedback effects of firm decisions. We thus identify the key parameters of the demand system by employing an indirect inference approach with an auxiliary model that approximates the endogenous relationship between firm characteristics and latent excess demand, without resorting to an instrumental variable approach as in Koijen and Yogo (2019). In estimating firm dynamics, we match model-generated moments to real-data moments and obtain a set of parameters that describe firm dynamics and policies. Our estimated model parameters help generate simulated data that can fit the key features of the data fairly well.

With our estimation of the model in hand, we can now identify latent excess demand for each firm and can also explore how firms respond to it. We first examine firm value, financing, and investment. An interesting finding is that firm value is U-shaped with respect to excess demand because of firms' market timing incentives. While positive excess demand clearly increases firm values and relaxes financial constraints, negative excess demand is also beneficial to firms because firms can make cash redistributions at a favorable price. Facing negative excess demand, firms cut investment as it might be more profitable for firms to engage in equity market transactions than real investments. This effect can further create a wedge between investment and cash holdings among firms with varying degrees of financial standings, generating over- and under-allocations of capital in the cross-section of firms.

We then proceed to quantify the magnitude of demand-driven capital misallocation in the economy. To this end, we compare the allocation of physical capital under our baseline model to that under a counterfactual benchmark where excess demand from investors is absent. Note that in our baseline model we use the estimated parameters that yield a close match between the model-predicted distribution of investor demand and that in the data, which ensures that the resulting quantitative predictions from our counterfactual are also highly empirically relevant. We measure capital misallocation using the variance of the marginal product of capital (MPK) in the cross-section of firms and the average level of loss in the total factor productivity (TFP) in the economy, which capture deviations from the efficient capital allocation across firms (Hsieh and Klenow, 2009). We find that excess demand leads to substantial increases in measured capital misallocation among firms— dispersion in the MPK would decrease by 23.8% and TFP loss will be reduced by 22.3% in a counterfactual economy where we shut down investors' excess demand. These results suggest that sentiment-driven investor demand can impose significant barriers to the efficient allocation of capital in the real economy. Firms prefer to engage in financial market transactions, generating conflicting incentives for firms as to how they allocate capital resources.

Our counterfactual analysis provides several further interesting results. First, investor excess demand results in greater dispersion in firms' cash holding and size distributions. In particular, large firms can benefit more from their financial transactions than small firms, contributing to the emergence of mega-size firms. Second, sentiment-driven demand is an important driver of misallocation, compared with the other sources of misallocation examined in the previous studies (Midrigan and Xu, 2014; Moll, 2014; David, Schmid, and Zeke, 2022). Its impact on misallocation is much stronger than that of debt market frictions, while comparable to that of real investment frictions and time-varying heterogeneous risk premia. Third, latent excess demand estimated from our demand system is strongly and positively associated with sentiment fluctuation and the household share of stock ownership, providing a tight link between excess demand and investor sentiment. Accordingly, capital allocation and investment efficiency are distorted even more in the subsample of firms with greater sentiment fluctuation and household ownership.

Our paper contributes to several strands of literature. First, it adds to the growing literature on the allocation of capital in the real and financial markets. Hsieh and Klenow (2009) document substantial gaps in TFP across Chinese and Indian firms. Midrigan and Xu (2014) develop a model with debt constraints to study its impact of capital misallocation. Bai, Lu, and Tian (2018) use firm-level data to identify financial frictions in China and find they can explain aggregate firms' savings and investments and around 50% of the dispersion in the MPK within private firms, which translates into a TFP loss as high as 12%. David and Venkateswaran (2019) quantify the contributions of capital adjustment cost, technology dispersion, and information friction on capital misallocation. Bau and Matray (2020) show that foreign capital liberalization reduces capital misallocation and increases aggregate productivity in India. David et al. (2022) develop a theory linking misallocation to macroeconomic risk and show that risk considerations explain about 30% of observed MPK dispersion among US firms and rationalize a large persistent component in firm-level MPK. Using model-based estimation, Zhao and Whited (2021) show that significant misallocation of debt and equity exists in China but not in the U.S. Unlike these studies, we examine the extent to which investor demand drives the allocation of capital in the economy, which none of the papers in the existing literature have studied yet.

Our paper also contributes to the large literature on how mispricing and investor demand affect corporate policies. Using survey data from corporate managers, Graham and Harvey (2001) report that managers consider equity market valuation for share issuance. Baker and Wurgler (2002) show that managers actively exploit relative misvaluation and engage in market timing. Edmans, Goldstein, and Jiang (2012) and Khan, Kogan, and Serafeim (2012) show that equity mispricing driven by investor flows affects managers' financing and investment decisions.[1] Warusawitharana and Whited (2016) study a dynamic investment model to examine the extent to which mispricing drives investment and financing. Dessaint, Foucault, Frésard, and Matray (2019) find that firm investment is sensitive to nonfundamental shocks in stock prices and stock market inefficiencies can affect the real economy, even in the absence of financing or agency frictions. Binsbergen and Opp (2019) investigate the implications of cross-sectional asset pricing anomalies for the real economy using a dynamic framework to link distortions in agents' subjective beliefs to these mispricings (or alphas) and capital misallocation. Our study is distinct from these studies in two dimensions. First, we provide a micro-foundation for the sources of mispricing by estimating investor demand from institutional holdings data. Our focus constitutes a significant departure from existing work by endogenizing both the demand- and supply-side of equity capital. Second, we examine the extent to which excess demand from investors can influence the allocation of finance and capital, and quantify the magnitude of the resulting misallocation effects.

Our paper also pertains to the growing literature on the demand-based approach

[1] Baker (2009) and Bond, Edmans, and Goldstein (2012) provide an extensive review of the literature.

in asset pricing, *à la* Koijen and Yogo (2019) and Koijen, Richmond, and Yogo (2020). Using a dynamic model of firm investment and financing, we provide a more general equilibrium perspective to these studies using the demand-based approach. We contribute to this literature by showing how investor demand can influence corporate investment and financing policies and thus close the loop in the demand system approach in these studies. Methodologically, our paper belongs to the growing literature that employs structural model calibration or estimation to answer corporate finance questions in capital investment, leverage choice, mergers and acquisitions, market competition and valuation (e.g., Hennessy and Whited, 2005; Rampini and Viswanathan, 2010; Korteweg, 2010; Taylor, 2010; Morellec, Nikolov, and Schurhoff, 2012; Glover and Levine, 2017; Terry, 2017; Corhay, Kung, and Schmid, 2020; David et al., 2022).

Lastly, our paper also adds to the literature on the rise of superstar firms. We show that financial market power also, to some extent, contributes to the emergence of superstar firms. This finding complements the previous studies (e.g., Autor, Dorn, Katz, Patterson, and Van Reenen, 2020; Akcigit and Ates, 2019, 2021; Kehrig and Vincent, 2017), which largely focus on the role of product market power in explaining the emergence of superstar firms.

The paper is organized as follows. In Section 2, we develop a dynamic investment model with financial frictions and time-varying demand from investors. Section 3 discusses how we estimate the model and present our estimation results. Section 4 presents the model solution and demonstrates its main mechanisms. We use the estimated model to evaluate the effects of excess demand on capital misallocation and aggregate productivity. In Section 5, we estimate the model based on different subsamples to examine whether our estimated parameters can pick up variations in investor demand and firm characteristics across subsamples. Concluding remarks are offered in Section 6.

2 Model

In this section, we construct a dynamic model in which firms face capital provision that arises from investor demand for firms' equity. Our model endogenizes both the demand- and supply-side of capital. In response to productivity and time-varying investor demand, firms make optimal decisions on share issuance and repurchase, dividend payout, leverage, cash holding, and investment. Figure 1 summarizes the model's timeline.

2.1 Firm's cash flows

We consider a model of heterogeneous firms, indexed by n, that face a decreasing return-to-scale technology and use capital, $K_{n,t}$, as the input to generate per period pre-tax profit:

$$Y_{n,t} = a_t^{\zeta_n} z_{n,t} K_{n,t}^{\alpha}. \tag{1}$$

Firm productivity (in logs) equals $\zeta_n \log(a_t) + \log(z_{n,t})$, where $\log(a_t)$ captures an aggregate component of productivity that is common across firms, and $\log(z_{n,t})$ denotes an idiosyncratic component of productivity. ζ_n captures the exposure of the productivity of firm n to aggregate conditions. We assume ζ_n is heterogeneously distributed as $\zeta_n \sim \mathcal{N}\left(1, \sigma_{\zeta}^2\right)$ across firms. Both the macro- and firm-level components of productivity follow AR(1) processes:

$$\log(a_{t+1}) = \rho_a \ \log(a_t) + \nu_{t+1}^a, \quad \text{with} \quad \nu_t^a \sim \mathcal{N}\left(0, \sigma_a^2\right). \tag{2}$$

$$\log(z_{n,t+1}) = \rho_z \ \log(z_{n,t}) + \nu_{n,t+1}^z, \quad \text{with} \quad \nu_{n,t}^z \sim \mathcal{N}\left(0, \sigma_z^2\right). \tag{3}$$

For the ease of notation, we drop subscript n when the meaning is clear. The law of motion for K_t is given by:

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

where I_t is the capital investment at time t and δ is the capital depreciation rate.

A firm making investment I_t incurs a quadratic capital adjustment cost:

$$\Xi(I_t, K_t) \equiv \xi \frac{I_t^2}{K_t}, \tag{5}$$

where ξ denotes the capital adjustment parameter.

We use C_t to denote a firm's net cash: $C_t > 0$ means the firm is holding more cash than its debt outstanding and hence it is earning the risk-free interest rate, r, on the net cash balance, while $C_t < 0$ means that the firm carries net debt on its balance sheet. The firm's debt is subject to a collateral constraint:

$$-C_t \leq \theta K_t, \tag{6}$$

where θ is the pledgeability parameter and can be interpreted as the fraction of tangible assets that the firm can pledge to the lender. The firm can finance its investments via internal cash or by issuing new debt:

$$I_t + \Xi(I_t, K_t) = (1-\tau_c)a_t^{\zeta} z_t K_t^{\alpha} + \delta\tau_c K_t + C_t\left[1 + r(1-\tau_c)\right] - \mathring{C}_t - f, \tag{7}$$

where $\mathring{C}_t$ denotes the company's cash reserve before any equity issuance or payout, and f represents the fixed operating costs. The firm can draw down its cash reserve by making payments to equity holders or increase it by floating new shares:

$$C_{t+1} = \mathring{C}_t + E_t - \Psi(E_t) - D_t, \tag{8}$$

where we allow the dollar amount of equity flow, E_t, to be both positive and negative, with a *positive* number indicating equity *issuance* and a *negative* number indicating share *repurchase*, and D_t represents dividend payments. When the firm issues new equity ($E > 0$), it incurs an equity issuance cost:

$$\Psi(E_t) = \phi|E_t| \times \mathbb{1}_{\{E_t>0\}}, \tag{9}$$

where ϕ is the equity issuance cost parameter.

The equity issuance costs are motivated by underwriting fees and adverse selection costs. To keep the model tractable, we do not model costs of external equity as the outcome of an asymmetric information problem. As in Cooley and Quadrini (2001), we capture adverse selection costs and underwriting fees in a reduced form. We adopt a simple formulation by choosing a linear equity payout cost, ϕ, as in Gomes and Schmid (2021) and Begenau and Salomao (2019).

2.2 Investors' portfolio choice

We follow the characteristics-based demand system of Koijen and Yogo (2019) for investors' portfolio choice in firms' equities. There are I investors index by $i = 1, \ldots, I$, each endowed with wealth $A_{i,t}$ at date t. Assets are indexed by $n = 0, 1, \ldots, N$, with asset $n \geq 1$ corresponding to firm n's stock and $n = 0$ corresponding to the outside asset (i.e., assets other than stocks). Each investor allocates wealth $A_{i,t}$ across the assets in her investment universe $\mathcal{N}_{i,t} \subseteq \{1, \ldots, N\}$. The portfolio weight of investor i in asset n is denoted by $w_{i,t}(n)$ with $\sum_{n \in \mathcal{N}^i} w_{i,t}(n) = 1$.

We model investor i's demand for asset n as a logit function of the asset's K observed characteristics $x_{k\in\{1,\ldots K\},t}(n)$ (with $x_{1,t}(n)$ being the log market equity) and $\epsilon_{i,t}(n)$ that represents excess demand, which is the unobserved latent component in our demand system as in Koijen and Yogo (2019):[2]

$$w_{i,t}(n) = \frac{\exp\left\{\sum_{k=1}^{K} \beta_{k,i,t}\, x_{k,t}(n) + \beta_{0,i,t}\right\} \cdot \epsilon_{i,t}(n)}{1 + \sum_{m \in \mathcal{N}^i} \exp\left\{\sum_{k=1}^{K} \beta_{k,i,t}\, x_{k,t}(m) + \beta_{0,i,t}\right\} \cdot \epsilon_{i,t}(m)}. \tag{10}$$

Demand parameter $\beta_{k,i,t}$ captures how investor i' demand varies with respect to firm characteristic k, including log market equity, log book equity, investment, profitability, dividends, and market beta. Note that the investor's demand for stock n depends not only on stock n's own characteristics but also those of all other stocks in investor i's investment universe, reflected by the denominator in Equation (10).

2.3 Firm-level latent demand, issuance decisions, and price impacts

In this section, we discuss a firm's decisions to issue and repurchase stocks and how such decisions interact with investors' demand for the firm's equity.

We assume that investors share the same demand parameter (β_k) but differ in their investment wealth ($A_{i,t}$) and stock-level excess demand that they receive every period ($\epsilon_{i,t}(n)$). The setting can be extended to accommodate investors with heterogeneous demand parameters drawn from a common distribution. Let $\boldsymbol{x_t}$ denote a K-dimensional vector of characteristics that influence demand, including log market equity, size, profitability, investment, dividend, and market beta. We further assume that the demand parameters are time-invariant, and $\boldsymbol{\beta}$ denotes a $K+1$ vector for the demand parameters, with the last element being the constant term.

We follow Koijen and Yogo (2019) to construct a firm-level measure of investor senti-

[2] The latent demand for the outside asset is normalized to one, and hence investor i's portfolio weight on the outside asset, $w_{i,t}(0)$, equals one divided by the denominator in Equation (10).

ment by aggregating excess demand across investors. Excess demand for firm n is defined as follows:

$$\frac{\epsilon_t(n)}{\epsilon_t(0)} \equiv \left\{ \frac{\int_{i \in I} w_{i,t}(n) \cdot A_{i,t} \, di}{A_t(n)} \right\} \cdot \left\{ \frac{\int_{i \in I} w_{i,t}(0) \cdot A_{i,t} \, di}{A_t(0)} \right\}^{-1} \cdot \exp\left[-\boldsymbol{\beta}\, \boldsymbol{x}_t(n) \right], \tag{11}$$

where $\epsilon_t(n)$ captures aggregate excess demand for firm n at time t, and $\epsilon_t(0)$ is the aggregate excess demand for the outside asset, which is normalized to 1. $A_t(n) \equiv \int_{i \in I} A_{i,t} \cdot \mathbb{1}_{n \in \mathcal{N}_i} \, di$ is the aggregate dollar amount of investable wealth on firm n. $\mathcal{N}^n \equiv \bigcup_{n \in \mathcal{N}_i} \mathcal{N}_i$ includes all other securities that firm n's investors are also holding, which forms the universe of competing securities from firm n's perspective. We can express the aggregate portfolio weight in firm n as $W_t(n)$, where

$$W_t(n) \equiv W\left(\boldsymbol{x}_t(n), \epsilon_t(n)\right) = \frac{\exp\left\{\boldsymbol{\beta}\, \boldsymbol{x}_t(n)\right\} \cdot \epsilon_t(n)}{1 + \sum_{m \in \mathcal{N}^n} \exp\left\{\boldsymbol{\beta}\, \boldsymbol{x}_t(m)\right\} \cdot \epsilon_t(m)}. \tag{12}$$

Using Equations (11) and (12), we can verify that:

$$\frac{W_t(n) \cdot A_t(n)}{W_t(0) \cdot A_t(0)} = \frac{\int_{i \in I} w_{i,t}(n) \cdot A_{i,t}}{\int_{i \in I} w_{i,t}(0) \cdot A_{i,t}}, \tag{13}$$

which allows us to write down the market clearing condition similar to that in Koijen and Yogo (2019) using variables at the firm level:

$$\log\left[W_t(n) \cdot A_t(n)\right] - p_t(n) - s_t(n) = 0, \tag{14}$$

where $p_t(n)$ and $s_t(n)$ denote the logarithm of stock price and shares outstanding, respectively.

The market clearing condition in Equation (14) is the key to examining how changes in firm-level excess demand and the firm's decisions to issue or repurchase shares would influence the equilibrium price. Taking derivatives of Equation (14) with respect to log firm-level excess demand and log shares outstanding, we can define price impacts from excess demand, Υ^{ϵ}, and equity issuance, Υ^{s}:

$$\begin{aligned}\Upsilon^{\epsilon}\left(\boldsymbol{x}_t(n), \epsilon_t(n)\right) \equiv \frac{\partial p_t(n)}{\partial \log\left[\epsilon_t(n)\right]} &= -\left\{\frac{\partial \log\left[W_t(n)\, A_t(n)\right]}{\partial \log\left[\epsilon_t(n)\right]}\right\} \cdot \left\{\frac{\partial \log\left[W_t(n)\, A_t(n)\right]}{\partial p_t(n)} - 1\right\}^{-1} \\ &= -\left\{1 - W_t(n)\right\} \cdot \left\{\beta^{me}\left[1 - W_t(n)\right] - 1\right\}^{-1}, \end{aligned} \tag{15}$$

$$\begin{aligned}\Upsilon^{s}\left(\boldsymbol{x}_t(n), \epsilon_t(n)\right) \equiv \frac{\partial p_t(n)}{\partial s_t(n)} &= -\left\{\frac{\partial \log\left[W_t(n)\, A_t(n)\right]}{\partial s_t(n)} - 1\right\} \cdot \left\{\frac{\partial \log\left[W_t(n)\, A_t(n)\right]}{\partial p_t(n)} - 1\right\}^{-1} \\ &= -\left\{\left(\beta^{me} + \beta^{be} \cdot mebe\right)\left[1 - W_t(n)\right] - 1\right\} \cdot \left\{\beta^{me}\left[1 - W_t(n)\right] - 1\right\}^{-1}, \end{aligned} \tag{16}$$

where β^{me} and β^{be} are coefficients associated with log market and book equity, respectively, in Equation (10) and $mebe$ is the market to book ratio.

These two quantities for price impacts in Equations (15) and (16) capture the investor-firm interface. The first one in Equation (15) quantifies the percent change in stock price when underlying excess demand changes by one percent, which is positive (i.e., excess demand increases the stock price of the firm) when $\beta^{me} < 1$ (i.e., the demand curve is downward-sloping). The second quantity in Equation (16) represents the percentage change in stock price when the firm issues one percent of new equity, i.e., the price impact of net share issuance. This quantity will be in general negative when $\beta^{me} + \beta^{be} \cdot mebe$ is less than one. When investors' demand for high book-equity stocks is weak (i.e., low β^{be}) and book equity does not increase much with new share issuance (which happens when the market-to-book is low), the stock price will respond more negatively to net issuance.

2.4 Firm's optimization problem

Figure 1 illustrates the timeline of the model.

FIGURE 1 ABOUT HERE

Following Zhang (2005) and David et al. (2022), we directly specify the stochastic discount factor without explicitly modeling consumers' problem. The stochastic discount factor (SDF) is given by:

$$\log(m_{t+1}) = \log\beta - \gamma_t \nu^a_{t+1} - \frac{1}{2}\gamma_t^2\sigma_a^2, \tag{17}$$

$$\gamma_t = \gamma_0 + \gamma_1 \log(a_t), \tag{18}$$

where a_t is the aggregate productivity, ν^a_{t+1} is the time $t+1$ innovation to the aggregate shock, and σ_a^2 captures the variance of the innovation, as defined in Equation (2). $0 < \beta < 1$, $\gamma_0 > 0$, and $\gamma_1 \leq 0$ are constant parameters that govern the relationship between the SDF and aggregate productivity. This formulation allows us to capture in a simple manner a time-varying and countercyclical price of risk as observed in the data.

At the beginning of each period, firms observe their idiosyncratic productivity (z), aggregate productivity (a), and excess demand (ϵ) shocks. Firms approximate the evolution of their log excess demand $\{\epsilon_t\}$ using an AR(1) process:

$$\log(\epsilon_{t+1}) = \rho_\epsilon \log(\epsilon_t) + \nu^\epsilon_t, \quad \text{with} \quad \nu^\epsilon_t \sim \mathcal{N}\left(0, \sigma^2_\epsilon\right). \tag{19}$$

Firms then produce and simultaneously announce their current-period investment and dividend policies. They can also tap the capital market to issue or repurchase additional shares; the price at which these transactions take place is determined in equilibrium by both firms' actions and investors' demand. Firms optimize their investment and financing polices to maximize the value of their controlling shareholders, whose Bellman equation can be written *recursively* as the following (here, we drop the time subscript and firm indexing for simplicity):

$$V(K, C, z, \epsilon; a) = \max_{\{\Delta s, E, D, I, C'\}} (1-\tau_d)D + \frac{1}{1+\Delta s}\mathbb{E}_{z,\epsilon,a}\left[m(a,a')V(K',C',z',\epsilon';a')\right], \quad (20)$$

where any variable with a prime denotes value in the next period. K and C represent the existing level of physical capital and cash balance, I represents investments, Δs and E are the fraction and dollar amount of equity issuance, respectively, D is the dividend payment, and τ_d denotes the dividend tax. We have $\frac{1}{1+\Delta s}$ multiplied by the continuation value of the firm to capture the dilution effect after new equity issuance. The firm optimizes Equation (20) subject to the laws of motions and constraints in Equations (1), (3), (4), (5), (6), (7), (8), and (9). In addition, the firm's dollar amount of equity issuance (E) and the fraction of new shares issued (Δs) satisfy the following condition:

$$E = \Delta s\left\{1 + \left[\int_{\log(\tilde{\epsilon})=0}^{\log(\epsilon)} \Upsilon^{\epsilon}(\boldsymbol{x}_{\Delta s=0}, \epsilon) + \int_{\tilde{s}=0}^{\Delta s} \Upsilon^{s}(\boldsymbol{x}, \epsilon)\right]\right\} \cdot \left[V(K, C, z, \epsilon; a) - (1-\tau_d)D\right], \quad (21)$$

which states that the dollar amount of equity issuance should be equal to the fraction of shares issued, multiplied by the market price. Functions $\Upsilon^{\epsilon}(\cdot)$ and $\Upsilon^{s}(\cdot)$ in Equation (21) capture price pressure from excess demand and firm equity issuance, respectively.[3] The market value of the firm equals the forward-looking intrinsic value, adjusted for any price pressure as a result of either investor demand or the firm's equity issuance.

[3]Note that price pressure function $\Upsilon^{\epsilon}(\cdot)$ is evaluated at the point where no equity is issued ($\Delta s = 0$).

2.5 Recursive competitive equilibrium

Let Γ_t denote the distribution of firms in the economy. This distribution is central to firms' decision-making because, according to Equation (12), firms' portfolio weights depend not only on their own characteristics but also on the joint distribution of characteristics for other firms held by investors. Therefore, Γ_t will significantly influence prices at which firms can issue or repurchase shares through the investor demand channel detailed in Section 2.3.

Given an initial firm distribution, a recursive competitive equilibrium consist of (i) the value function $V(K, C, z, \epsilon; a)$; (ii) firm policy functions $K'(K, C, z, \epsilon; a)$, $C'(K, C, z, \epsilon; a)$, $\Delta s(K, C, z, \epsilon; a)$, $E(K, C, z, \epsilon; a)$, and $D(K, C, z, \epsilon; a)$; (iii) investors' policy function for the portfolio choices $w_{i,t}(a)$; (iv) a bounded sequence of firm measures $\{\Gamma_t\}_{t=1}^{\infty}$, such that for all $t \geq 0$:

1. Firm policy functions $K'(K, C, z, \epsilon; a)$, $C'(K, C, z, \epsilon; a)$, $\Delta s(K, C, z, \epsilon; a)$, $E(K, C, z, \epsilon; a)$, $D(K, C, z, \epsilon; a)$, and value function $V(K, C, z, \epsilon; a)$ solve the firm' optimization problem (Equation (20));
2. All investors choose their portfolio weights $w_{i,t}(n)$ following the demand function specified in Equation (10);
3. Asset market clears as specified in Equation (14);
4. For all Borel sets $\mathcal{K} \times \mathcal{C} \times \mathcal{Z} \times \mathcal{E} \subset \mathcal{R}^{+} \times \mathcal{R} \times \mathcal{R}^{+} \times \mathcal{R}^{+}$ and $\forall\, t \geq 0$,

$$\Gamma_{t+1}(\mathcal{K} \times \mathcal{C} \times \mathcal{Z} \times \mathcal{E}) = \int_{\mathcal{Z}} \int_{\mathcal{E}} \int_{\mathcal{B}(\mathcal{K}, \mathcal{C}, \mathcal{A})} d\Gamma_t(K, C, z, \epsilon) dG(\epsilon'|\epsilon) dH(z'|z), \tag{22}$$

where $\mathcal{B}(\mathcal{K}, \mathcal{C}, \mathcal{A}) = \{(K, C, z, \epsilon) \;\; s.t. \;\; K'(K, C, z, \epsilon; a) \in \mathcal{K}, C'(K, C, z, \epsilon; a) \in \mathcal{C}\}$, and $G(\epsilon)$ and $H(z)$ denote the distribution of excess demand and productivity shocks, respectively.

3 Estimation

3.1 Data

Our analysis of firm-level dynamics requires stock price and accounting data from CRSP-Compustat database. We remove from the data utility (SIC 4900-4999) and financial firms (SIC 6000-6999) and also exclude firms with missing total assets and sales, following the standard practice in the literature. Using the data from the CRSP-Compustat database, we construct the key variables used in our estimation, and we detail the definitions of these variables in Table 1. Our sample period is from 1980 to 2019. The beginning point of the sample period is determined by the sample availability of the institutional holdings data that we describe below.

TABLE 1 ABOUT HERE

To estimate investor demand, we draw institutional stock holdings data from the Thompson Reuters Institutional Holdings Database, which are based on Form 13F filings. All U.S.-based institutions with assets under management exceeding $100 millions dollars should report their long side holdings in the 13F filings if their holding in a publicly listed stock is greater than 10,000 shares or $200,000. We merge these institutional holdings data with the CRSP-Compustat data and filter out any holdings data that do not match with the CRSP-Compustat database. We compute portfolio weights of the 13F institutions as the ratio of dollar amounts held to the total sum of dollar amounts of all stocks held by the institutions.

3.2 Identification

We estimate the key model parameters using the SMM, the objective of which is to pick the set of parameter values that makes the simulated data track the actual data as closely as possible. The success of SMM estimation depends critically on choosing the moments that are sensitive to variations of underlying structural parameters. At the same time, it is also crucial that we avoid "cherry-picking," by focusing on the moments that reflect important characteristics of the data. We explain below how we choose those moments in our SMM estimation.

The demand-side parameters are estimated using the indirect inference approach, with their empirical counterparts as the moments to match. These parameters include $\{\beta_{me}, \beta_{be}, \beta_{inv}, \beta_{prof}, \beta_{div}, \beta_{mktbeta}\}$, which capture how investors' demand responds to observed firm characteristics, such as log market equity, log book equity, investment, profitability, dividends, and market beta, respectively. The indirect inference procedure involves first running the following regression in the data:

$$\log w_{i,t}(n) \sim \gamma_{me} \cdot me_{n,t} + \gamma_{be} \cdot be_{n,t} + \gamma_{inv} \cdot inv_{n,t} + \gamma_{prof} \cdot prof_{n,t} + \gamma_{div} \cdot div_{n,t} + \gamma_{\beta} \cdot mktbeta_{n,t} + \epsilon_{n,t}. \tag{23}$$

If latent demand is exogenous, i.e., $\{\epsilon_{n,t}\}$ is uncorrelated with the regressors in Equation (23), then the estimates, $\{\hat{\gamma}\}$, should be unbiased and equal the true structural demand parameters, $\{\boldsymbol{\beta}\}$. This condition, however, is likely to be violated because of inherent endogeneity in market equity and other supply-side policies. Nevertheless, the main idea of our indirect inference approach is that we can still use these biased estimates as moments to match because they contain useful information on the underlying structural parameters that we are interested in.

To match with the regression coefficients from the data, $\{\hat{\gamma}\}$, we run the same regression of investor portfolio holdings $w_{i,t}$ on firm characteristics, using the simulated data from the model. For the ease of notation, we drop index i in Equation (23) when we describe the model counterpart. Note first that the estimated regression coefficients from the actual data, $\{\hat{\gamma}\}$, of Equation (23) can be viewed as the true parameter, $\{\boldsymbol{\beta}\}$, plus a feedback effect that captures how supply-side policies respond to latent demand shocks. Therefore, the regression coefficients are informative of the underlying preference parameters and can serve as effective identifying moments. In addition, our model endogenizes firms' investment and financing decisions based on their information set including their knowledge of the latent demand, as specified in Equation (20). Therefore, the regression coefficients obtained using our simulated data also capture similar endogenous relationships between the latent demand, ϵ, and the observed firm characteristics that should be present in the data, leading to a consistent mapping between the model and data moments. By matching these regression coefficients, $\{\hat{\gamma}\}$, that capture feedback from the supply-side effects, we can effectively back out the underlying structural demand parameters, $\{\boldsymbol{\beta}\}$. This identification strategy follows the indirect inference approach employed in the large body of literature, wherein the complexity of the setup rules out a direct inference approach to match the deep structural parameters (Gourieroux, Monfort, and Renault, 1993; Cooper and Haltiwanger, 2006).

Next, we identify the autocorrelation and standard deviation of latent demand that firms face, $\{\rho_\epsilon, \sigma_\epsilon\}$, using the autocorrelation and standard deviation of residual in the auxiliary Equation (23). We use the autocorrelation and standard deviation of firms' profitability to identify the law of motion that captures the TFP process, $\{\rho_z, \sigma_z\}$. We include the mean of investment to determine the depreciation rate, δ, and the standard deviation of investment to determine the cost of capital adjustment, ξ. We include the mean and standard deviation of firms' percentage of equity issuance to identify the equity issuance cost parameter, ϕ. We include the mean and standard deviation of firms' share repurchase to ensure that we can also match the net changes in firms' shares outstanding over time. Firms' equity issuance and share repurchase decisions reflect how they react to investors' excess demand, which is the key focus of our model. Our estimation aims to match the levels and volatilities of these decisions at the firm level. Next, we use firms' average leverage to pin down the collateral constraint, θ. We use firms' average profitability and market-to-book ratio to identify the fixed operating cost parameter, f, and the curvature of firms' production function, α. Lastly, we include firms' average dividend payout because firms can view dividends and share repurchases as substitutable ways of redistributing cash. Therefore, it is important for us to also match firms' tendency to pay dividends to ensure that our model can capture the substitution pattern.

3.3 Parameter estimates

Table 2 presents the moment conditions used in our SMM estimation. The first eight moment conditions involve the regression coefficients and the residuals from the auxiliary demand equation in (23), and the remaining 12 moment conditions involve the moments from the firm-side variables. We find that all the simulated moments stay reasonably close to their real data counterparts. Given that we are matching more moment conditions than the parameters, our model fits the data surprisingly well.

Table 2 About Here

Table 3 About Here

Table 3 shows the parameter estimates of our model. Panel A presents the calibrated parameters, which are less model-specific, so we calibrate them outside of the SMM estimation to ensure that our choices are consistent with the observed data characteristics. The corporate tax rate, τ_c, is set to 35%; the dividend tax rate, τ_d, is set to 15%; and J is set to 1000, indicating that an average investor in our simulated data holds 1000 firms simultaneously in her investment portfolio. Turning to the parameters of the SDF in Equations (17)-(18), we set $\beta = 0.98$ to approximate an average risk free rate of 2%, and we calibrate γ_0 and γ_1 in Equation (18) to match the average annual excess return and Sharpe ratio of the market portfolio. The annual autocorrelation and standard deviation of aggregate productivity shocks, ρ_a and σ_a, are set to 0.8145 and 0.014, respectively, corresponding to the quarterly values of 0.95 and 0.007, as in Cooley and Prescott (1995). The standard deviation of exposure to aggregate shocks, σ_ζ, is calibrated to match dispersion in expected stock returns.

In Panel B of Table 3, we report the structural model parameters that we estimate by matching the coefficients and the moments of residuals in the demand auxiliary equation in (23). We can see that the investor-firm feedback interface is operating in our model by comparing these deep structural parameter estimates for investors' demand system, $\{\boldsymbol{\beta}, \rho_\epsilon, \sigma_\epsilon\}$, with the regression coefficients for the auxiliary equation, i.e., the simulated moments in rows (1) to (7) in Table 2. In principle, if latent demand $\epsilon(n)$ is orthogonal to all firm characteristics, then the two sets of parameter estimates should be equal. This would be true if observed firm characteristics $x(n)$, including log market equity, are exogenous. As illustrated in Figure 3, however, firms' optimal polices in a given period depend on latent demand, investor demand in turn depends on firm policies, and the market prices of firms will be eventually determined in equilibrium by the market clearing condition.

Thus, the characteristics in the demand system are endogenous to realized latent demand, which creates a wedge between the structural parameters and the regression coefficients from the auxiliary equation. We are thus addressing the challenge in identifying demand parameters by embedding in our model the endogenous relationship between firms characteristics and the underlying latent demand. To the extent that the simulated data from the model and the actual data are subject to the same types of endogeneity, we are able to back out the structural parameters.

In Panel C, we report the parameters that we estimate for the firm-side model. For example, the curvature of the production function is close to two thirds, physical capital deprecates at a rate of approximately 16% per year, and firms can collateralize about 80% of their assets. These estimates are consistent largely with those that are documented in the literature (see Nikolov, Schmid, and Steri, 2021 among others). Interestingly, we find that the persistence and standard deviation of firms' productivity shock process, 0.8561 and 0.0861, respectively, are comparable in magnitudes with those of latent investor demand, 0.7317 and 0.0913. These results suggest that firms may find it as profitable to time their issuance decisions in the financial market as it is to manage their real investments.

4 Model Implications

Using the parameter estimates from our model, we first explore the implications of the model to provide the intuitions of the economic mechanisms. We then examine how fluctuations in latent demand influence firms' investment decisions and financing policies. Finally, we perform counterfactual exercises and examine the extent to which investor demand affects firm cash holdings, size distributions, and efficiency in capital allocation across firms by comparing the baseline case with the counterfactual case without latent demand.

4.1 Firm policies and valuations

Figure 2 shows an intuitive, monotonic relationship between investors' demand and price impacts, the latter of which represent the premium/discount in market prices over firms' intrinsic values that arises from latent demand and share issuance. Thus, stocks that experience positive latent demand shocks are traded at higher prices than their fundamental values, which facilitate firms to issue additional equity shares, while firms that face negative latent demand experiences price discounts.

FIGURE 2 ABOUT HERE

Next, we examine how price impacts induced by latent excess demand affect firms' intrinsic value, as defined in Bellman Equation (10), and firms' optimal investment and financing policies. Panel A of Figure 3 shows that a firm's intrinsic value is U-shaped with respect to excess demand, suggesting that large excess demand, regardless its sign, is beneficial from the firm's perspective. Specifically, large and negative excess demand allows firms to make cash redistributions at favorable prices, and, as ϵ increases to zero, the benefit of redistribution transactions slowly diminishes. When ϵ further increases and becomes positive, firms will have an incentive to "time the market" by issuing more shares instead of making cash redistribution. Firms' optimal issuance and stock repurchase decisions (i.e., net issuance decisions) are reported in Panel B of Figure 3, which are consistent with the intuition outlined above.

FIGURE 3 ABOUT HERE

Latent excess demand also influences firms' cash holdings. Panel C of Figure 3 shows a positive monotonic relationship between cash holdings and latent excess demand. When excess demand is positive, firms issue more equity as firms want to exploit positive price impacts, leading to higher cash holdings from the proceeds of equity issuance. When excess demand is negative, firms resort to internal cash savings instead of costly external financing to fund their investment. In addition, firms engage in share repurchases to take advantage of negative excess demand, leading to a further decrease in cash holdings.

Panel D of Figure 3 uncovers a positive and monotonic relation between excess demand and firm investment. Negative excess demand induces firms to cut investments and sacrifice investment efficiency to exploit profitable financial transactions in the equity market. As excess demand increases and becomes more positive, there is no longer competition in the uses of funds between share repurchases and capital investments. Firms can enjoy relaxed financial conditions by issuing more shares and making more investments. Thus, the graph in Panel D shows that the effect of investors' demand not only influences firms' financial policy but it also passes on to their real investments. This pass-through effect can further create a wedge in returns to investments in the cross section of firms with differing levels of cash condition and cost to excess equity capital.

4.2 Investor demand, financial constraints, and flows of funds

Building on the model implications as depicted in Figure 3, we now examine how capital flows that originate from investor demand help alleviate (or exacerbate) financial constraints by focusing on firms' uses of investor capital. To this end, Table 4 reports the sources and uses of funds for two-by-two subgroups of simulated firms, split by latent demand ϵ that firms experience in the current period and the degree of firms' financial constraints. The sources and uses of funds are calculated for each firm as the share of their relative contributions to the total funds, and we report their average values that are calculated using the simulated data. Firms are classified as financially constrained if their dividend-to-asset ratios are below the median. This measure based on low dividend payments is not only widely used in the empirical literature (e.g., DeAngelo and DeAngelo, 1990; Moyen, 2004) but also has the advantage that it can be directly calculated for our simulated firms. In our model, unconstrained firms face a low opportunity cost of retaining a marginal dollar and are thus more willing to pay dividends. This strong association between firms' dividend payments and underlying financial constraints is an important feature in a broad class of dynamic investment models, including Hennessy and Whited (2005).

TABLE 4 ABOUT HERE

Table 4 reports the results. We make several interesting observations. First, we find that low latent demand (low ϵ) incentivizes firms to repurchase shares while high ϵ encourages equity issuance, consistent with the findings in Figure 3. In our simulations for constrained firms (Columns 2 and 3), for example, equity issuance and share repurchase represent 1.8% and 11.0%, respectively, for low ϵ firms versus 12.4% and 0.7% for high ϵ firms. We find similar patterns in unconstrained firms (Columns 4 and 5) while equity issuance for high ϵ firms is much higher at 20.4%, indicating that positive price impacts from investors provide a nice opportunity for unconstrained firms to issue more shares at a favorable price point and use the proceeds to pay dividends to existing shareholders.

Second, we find that the incentives to engage in financial transactions can crowd out firms' investments, and this crowding-out effect varies with financial constraints. Among financially constrained firms in Columns (2) and (3), investments account for 35.5% and

40.6% of the uses of funds for low and high ϵ firms, respectively. These results show that investor demand can crowd out investment substantially among financially constrained firms—these firms not only face lower levels of cash flows, but they also spend a smaller fraction of the cash flows on investments. For financially unconstrained firms, however, the fraction of uses of funds spent on investment does not increase with ϵ. Rather, high ϵ firms spend a smaller fraction of their cash flows on investments: investments account for 36.4% of the uses of funds for high ϵ firms, lower than 38.6% for low ϵ firms. This result is because, for financially unconstrained firms, latent demand does not matter much for their optimal investment decisions as their investment tends to be at the optimal level already. Instead, these firms will focus on generating extra cash flows from financial market transactions. Therefore, the effect of latent demand tends to manifest itself only in dividend and cash retention decisions for financially unconstrained firms, and optimal investment will account for a smaller fraction of total cash inflows among these firms.

Finally, it is worth noting that latent demand not only interacts with firms' financial constraints in the current period but can also influence the level of constraints in future periods. Such an effect mainly operates through firms' net cash savings decisions. Low ϵ firms also draw down their cash reserves more aggressively, while high ϵ firms can issue more equity and use the proceeds to replenish their cash pool. These results imply that constrained, low ϵ firms are likely to stay constrained for an extended period of time due to their investment and cash management strategies. In contrast, high ϵ firms are likely to save out of their constraints more quickly, thanks to misvaluation shocks.

4.3 Cash holding and firm size distributions

Using counterfactual exercises, we now examine how firms' cash holdings and capital accumulations would vary when switching on and off the excess demand channel. Let us first outline the economic intuition on how demand fluctuation from investors would influence firms' cash policies. In a static setting, the presence of latent demand will lead to greater variation in financial constraints across firms. On the one hand, high latent demand serves to relax firms' financial constraints by making equity financing essentially cheaper, facilitating cash accumulation and investment. On the other hand, low latent demand exacerbates firms' financial constraints because it introduces conflicting incentives for firms—they would want to use cash to buy back shares and optimally time the market, driving out investments in physical capital. Such incentives will exacerbate the financial constraints of those firms and further limit their ability to invest.

In a dynamic setting, investor demand influences firm policies through an additional channel—decisions on precautionary savings that will facilitate future financial transactions. Facing with fluctuation in future demand shocks, firms will retain a larger share of cash flows that they generate. Higher cash buffers ensure that firms have enough liquidity to repurchase shares at favorable prices when a negative demand shock materializes in the future. When firms do not engage in large-scale share repurchases, they can also use the cash buffer to finance investment. Fluctuation in investor demand essentially provides firms with an additional source of profits, which makes internal cash more valuable for firms as external financing is costly.

Figure 4 illustrates how the abovementioned effects of excess demand on individual firm policies can aggregate and shape the cross-sectional distribution of firm capital and cash holdings. Compared with a counterfactual case in which excess demand is absent, firms in the baseline model facing time-varying excess demand will choose a greater fraction of their assets in cash. High cash holdings provide the firms with abundant funds to expand their operation when growth opportunities arise. The materialization of growth opportunities creates more cash flows, allowing firms to further benefit from financial transactions as further excess demand shocks arrive. Panel B of Figure 4 shows that this feedback loop also creates a heavier right tail in the firm size distribution under the benchmark economy. Our results imply that financial market power significantly contributes to firms' cash stockpiling (Begenau and Palazzo, 2021; Denis and McKeon, 2021; Lyandres and Palazzo, 2016) and, to a certain extent, the emergence of superstar firms. Our findings also complement the previous literature, which largely focuses on the role of product market power in explaining the emergence of superstar firms (see e.g., Autor et al., 2020; Akcigit and Ates, 2021, 2019; Kehrig and Vincent, 2017).

FIGURE 4 ABOUT HERE

4.4 Investor demand and capital misallocation

Using the equilibrium distribution of firms based on our model estimation, we now proceed to examine how the presence of excess investor demand across firms affects the allocation of capital across firms in the economy. We focus on two measures of capital allocation efficiency: the variance of MPK and the TFP loss. Consider our model economy populated by heterogeneous firms with production function $Y_n = a^{\zeta_n} z_n K_n^{\alpha}$. From the definition of MPK, we have:

$$K_n = \left(\frac{\text{MPK}_n}{\alpha a^{\zeta_n} z_n} \right)^{\frac{1}{\alpha - 1}}. \tag{24}$$

We sum over K_n across firms to define the aggregate capital, K. Similarly, we sum over firm-level output Y_n to calculate the aggregate output, Y. With these quantities defined, we can calculate the aggregate TFP in our baseline model as:

$$\mathrm{TFP} = \frac{Y}{K^{\alpha}} = \frac{\int_n a^{\zeta_n} z_n \left(\frac{\mathrm{MPK}_n}{\alpha a^{\zeta_n} z_n}\right)^{\frac{\alpha}{\alpha-1}} dn}{\left[\int_n \left(\frac{\mathrm{MPK}_n}{\alpha a^{\zeta_n} z_n}\right)^{\frac{1}{\alpha-1}} dn\right]^{\alpha}}. \tag{25}$$

In an efficient allocations without aggregate risk, capital can flow freely to its most productive use without any frictions, which maximizes static production. The marginal product of capital is equalized across firms. Denote the aggregate TFP in efficient allocations as TFP^e. We can then define TFP loss as the difference between aggregate TFP in the efficient allocations and the baseline model:

$$\mathrm{TFP}_{loss} = \log\left(\mathrm{TFP}^e\right) - \log\left(\mathrm{TFP}\right). \tag{26}$$

Hsieh and Klenow (2009) show that when z_n and MPK_n are jointly log-normally distributed with zero correlations, TFP_{loss} will be linear in $\mathrm{var}\left(\log \mathrm{MPK}_n\right)$, which implies that TFP loss only depends on the dispersion of MPK. However, when z and MPK are correlated with each other, given a fixed level of MPK dispersion, distortion in MPK for large versus small firms will have different implications for TFP losses. In such cases the variance of MPK might not be a sufficient statistic for capital misallocation. Therefore, we employ both measures, the variance of MPK and the TFP loss, to study the degree of misallocation.

Panel A in Table 5 reports the mean and variance of MPK and TFP losses for the benchmark model and also for the counterfactual case without excess demand. In this counterfactual experiment, we shut down excess demand shocks while keeping the value of other parameters the same as the baseline estimation. Shutting down excess demand shocks increases the average MPK in the economy by 10.08%. The result is consistent with our prior finding that excess demand leads to stronger precautionary saving behavior, so firms can invest more on average, and their MPK decreases.

The results in Table 5 also show that excess demand exacerbates capital misallocation across firms. Without excess demand, for example, firms' MPK becomes less dispersed by 23.82% compared with the baseline case. Intuitively, excess demand incentivizes firms to engage in financial transactions by issuing equity or buying back shares. Such financing decisions can make the firm more cash-constrained when excess demand is low and less cash-constrained when excess demand is high, thus crowding out firms' ability to pursue investments and introducing additional variations in MPK. Finally, we find that TFP loss in the counterfactual case is 22.30% lower than the baseline case, which also shows higher misallocation driven by excess demand. These findings, taken together, indicate that investors' excess demand imposes another friction in efficient capital allocation across firms. Facing with fluctuation in excess demand from investors, firms are provided with profit opportunities through financial transactions, which can create a conflicting incentive regarding how firms, especially the financially constrained ones, allocate their resources.

TABLE 5 ABOUT HERE

4.5 Comparison with other sources of misallocation

How big are these effects from latent demand on capital misallocation compared with other financial and real frictions previously studied in the literature? We consider three such distortions to answer this question: (1) the debt market frictions, (2) the real investment frictions, and (3) time-varying heterogeneous risk premia. To quantify the relative importance of each of these sources, we perform three additional sets of counterfactual exercises.

In Panel B of Table 5, we perform the first counterfactual exercise wherein we shut down debt market frictions by setting the collateral constraint parameter θ to one so that firms can borrow up to 100% of their physical capital. The results provided in Panel B shows that removing debt market frictions reduces the variance of MPK by 4.11% and TFP losses by 4.03%. The impact of debt market frictions on capital misallocation is much smaller than that of investor excess demand. The relatively limited impact of collateral constraint is consistent with what has been documented in prior studies (see, e.g., Midrigan and Xu, 2014; Moll, 2014). Our model shares the same mechanism as in Midrigan and Xu (2014) and Moll (2014), where firms can save to alleviate the impact of collateral constraint. One distinct feature of our model lies in that firms have heterogeneous abilities to accumulate savings due to their investors' latent demand shocks. It is more difficult for firms receiving negative investor demand shocks to accumulate savings, and firms might use accumulated savings to repurchase shares, which crowds out investments and potentially exacerbates inefficiency. Quantitatively, our counterfactual exercises show larger impacts on capital misallocation induced by firm' collateral constraints, compared with that in Midrigan and Xu (2014) and Moll (2014), where the amplified effect comes from its interaction with investors' demand shocks.

Panel C of Table 5 reports the results from the counterfactual exercise where we remove real investment frictions by setting the capital adjustment cost parameter to zero. Removing capital adjustment costs reduces the variance of MPK by 7.35% and TFP losses by 10.47%, respectively, also smaller than the impacts of investors' latent demand shocks. These results resonate with those provided in, for example, David and Venkateswaran (2019) insofar as unobservable sources of firm-level heterogeneity, which could arise from investor sentiment, are a stronger driver of misallocation in U.S. firms, although adjustment costs also play an important role.

In Panel D of Table 5, we provide the results from the counterfactual exercise wherein we shut down the exposure to aggregate risk. David et al. (2022) show that firms' heterogeneous exposure to time varying aggregate risk is an important source of firm-level MPK, explaining approximately 25% of its dispersion. In our counterfactual exercise in Panel D, we also find that time-varying aggregate risk and heterogeneous risk exposure are an important driver of MPK dispersion. For example, the variance of MPK and TFP loss fall by 14.85% and 14.48%, respectively, compared with the baseline case, although the contributions of latent demand for MPK dispersion, as reported in Panel A, tend to be larger. Overall, our findings indicate that fluctuations in latent investor demand are quantitatively significant and can impose substantial barriers to efficient capital allocation.

5 Subsample analysis

Estimation of our baseline model reveals substantial variation in latent demand faced by firms. Such heterogeneity provides a natural setting to test our model and examine whether it can generate predictions consistent with the data. The purpose of this exercise is three-fold. First, it helps examine whether our estimated parameters can pick up variations in investor demand and firm characteristics across different subsamples. By ascertaining whether the model can reconcile patterns in the data not used in its estimation, these subsample analyses serve as informal "out-of-sample" tests of the validity of our model. Second, the subsample analysis also helps us predict the heterogeneous effects of model parameters governing latent demand on firm policies. Admittedly, firms in different subsamples will face heterogeneous latent demand processes and can also differ along other unobservable dimensions, such as production technology and the ease of accessing external financing. If not properly controlled, such factors could undermine our interpretation of the heterogeneous impact of latent demand. Our subsample estimation helps address this concern as we re-estimate latent demand faced by a subgroup of firms together with supply-side parameters governing the production and financing decisions of the firms. Finally, by examining the properties of our parameter estimates across the subsamples, we can better understand the sources of latent demand shocks. In particular, we confirm the interpretation of Koijen and Yogo (2019) that latent demand represents investor sentiment by showing that the effect of latent demand increases substantially for high-sentiment subsamples.

In our first subsample analysis, we split firms based on the holding share of households. Different types of investors tend to exhibit distinct patterns in their latent demand (Koijen and Yogo, 2019), and the household sector is arguably the most sensitive to sentiment fluctuation. Thus, this subsample analysis based on household holdings would be particularly informative on how sentiment fluctuation triggers different reactions among firms. Specifically, we partition firms into deciles based on the percentage of household holdings in a given quarter. We then calculate the time-series average of a firm's household holdings decile, based on which we assign them to either high household holdings ("high HH") or low household holdings ("low HH") group.

In addition, Koijen and Yogo (2019) point out that investors' sentiment and disagreement also play an important role in shaping their latent demand. Following this idea, we perform a second subsample split by partitioning firms based on their sentiment fluctuation, or sentiment risk as coined by Dumas, Kurshev, and Uppal (2009). We obtain the investor sentiment data from RavenPack News Analytics, which offers a comprehensive news database and analytical tool by collecting information from all major newspapers, press releases, regulatory disclosures, and government updates.[4] Specifically, we use the Composite Sentiment Score (CSS) in RavenPack as the measure of sentiment for a specific news event. We calculate the firm-quarter specific investor sentiment score as the average CSS for all news events. We classify a firm as having high sentiment risk ("High SR") if the time-series volatility of its sentiment score is above the sample median, and a firm is considered to have low sentiment risk ("Low SR") if the volatility is below the sample median.

In our third subsample analysis, we split firms into "Low TG" and "High TG" groups based on the their asset tangibility.[5] The purpose of this subsample split to gauge how asset tangibility affects the variations of price elasticity, excess demand and its potential aggregate implications. Presumably, investor sentiment can fluctuate more strongly for firms with low tangibility as the true values of firms' assets are difficult to assess, which can lead to noisier investor demand.

We re-estimate the model for the six subsamples mentioned above. For each subsample, we follow the same estimation strategy as described in Section 3 and present the parameter estimates in Table 6.

TABLE 6 ABOUT HERE

The results in Table 6 suggest that firms with a higher percentage of household investors and more dispersed sentiment scores tend to have much more volatile excess demand. For example, the estimated σ_ϵ among the "High SR" firms is larger than that of among the "Low SR" firms, thus proving the former group with greater opportunities to time

[4]RavenPack has been widely used in the finance and accounting literature (see Dai, Parwada, and Zhang, 2015; Dang, Moshirian, and Zhang, 2015; Bushman, Williams, and Wittenberg-Moerman 2017 among others.).

[5]We measure firm tangibility as the sum of total receivables, inventories, and net property, plant, and equipment scaled by total assets, based on information from Compustat: tangibility = (rect + invt + ppent)/at.

investors' demand fluctuations. We also find that excess demand tend to be more volatile for "Low TG" firms. This might be due to the fact that it is more difficult for investors to assess the true value of intangible assets. The estimated pledgability parameter θ is indeed higher in "high TG" subsample, further validating our model's ability to capture the underlying frictions. The parameter estimates in Table 6 also suggest variations in the price elasticity across firms, which is defined using the market clearing condition in Equation (14) as $\frac{\partial[\log(W_t A_t)-p]}{\partial p}$—it ranges from -0.6461 (-0.6477, -0.6320) among the "Low HH" ("Low SR", "high TG") firms to $-0.0.6753$ (-0.6787,-0.6774) among the "High HH" ("High SR", "low TG") firms.

To gauge whether these cross-sample differences give rise to heterogeneous impact on investment efficiency, we repeat the exercise in Table 5 based on the estimates in each subsample, with the results reported in Panel D of Table 6. The results suggest that if all firms in the economy behave similarly to the subsample of firms with high household holdings, inventors' excess demand will create substantially higher barriers to the reallocating of capital. In such an economy, the excess demand would contribute to 40% of the dispersion in MPK and 43% of the TPF loss. Similar effects show up if the economy is assumed to behave like firms in the high sentiment risk sample, in which case, the contribution of excess demand on capital misallocation can be as higher as 29%. We also find that asset tangibility reduces financial frictions and tends to dampen the negative effect of excess demand on the efficiency of capital allocation. Note that the decreased investment efficiency, however, do not necessarily imply that investors' excess demand leads to lower values. In fact, these firms face greater opportunities to time investors' demand and profit from their financial transactions. Such transactions can distort real investments but contribute to the growth in firm value.

6 Conclusion

In this paper, we examine and quantify the extent to which excess demand from investors influences the efficient allocation of capital in the economy. To study the impact of such investor demand, we develop a dynamic model wherein firms facing capital provision from investors make optimal financing and investment decisions. The novel feature of our model is that we endogenize both the demand- and supply-side of capital. When investor demand is high, it directly induces firms to issue additional stocks and finance new investments more easily. When investor demand is weak, firms would use cash to optimally repurchase shares at a favorable price instead of making capital investment. Investor demand also facilitates firms' financing and investment by dampening the price impacts of firms' decisions to issue and repurchase shares.

In our estimation, we directly incorporate time-varying demand from investors, which we tightly discipline using detailed data on investor holdings to estimate the deep parameters governing characteristics-based demand of investors. The firm-side estimation is based on the simulated methods of moments (SMM) to examine firms' optimal responses—share issuance and repurchases, dividend payout, leverage, and cash holdings—as well as investment policies and investigate and assess how investor demand affects the efficiency of capital allocations. We show that investor demand influences firms' real investment decisions differentially across firms, making it easier for some firms to finance and invest while leaving others more financially constrained and passing on good investments. This wedge created by investor demand imposes an additional barrier that prevents capital from allocating efficiently across firms. Our parameter estimates reveal that investor excess demand has a quantitatively significant impact on the capital allocation efficiency in the economy—eliminating excess demand reduces dispersion in the marginal product of capital by 23.8% and TFP losses by 22.3%. We also find that excess demand, combined with the feedback effect generated through the investor-firm interaction, creates heavier tails in firms' cash holdings and size distributions. Our results suggest that financial market power and excess investor demand also contribute to the rise in cash stockpiling and the emergence of superstar firms in the economy.

Over the recent decades, many US industries have experienced substantial consolidation and increased concentration levels (Grullon, Larkin, and Michaely, 2019), creating greater opportunities for firms to strategically exercise their oligopolistic (Corhay et al., 2020) or oligopsonistic (Berger, Herkenhoff, and Mongey, 2022) powers. Our findings highlight another important source of market power resulting from investors' large and fairly persistent demand in the capital market. Future works could examine how these different types of market power are distributed across firms in different locations and industries, and to what degree their interaction shapes resource misallocation and inequality among firms and their employees. Another important direction is to study the optimal government policies for improving capital allocation efficiency after considering interactions between firms, workers, and investors across multiple markets.

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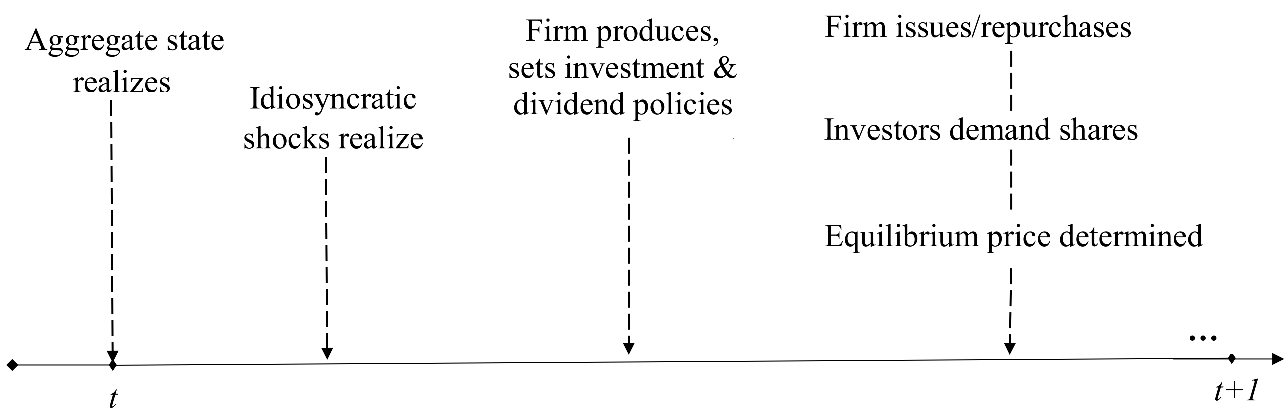

Figure 1. Model Timeline

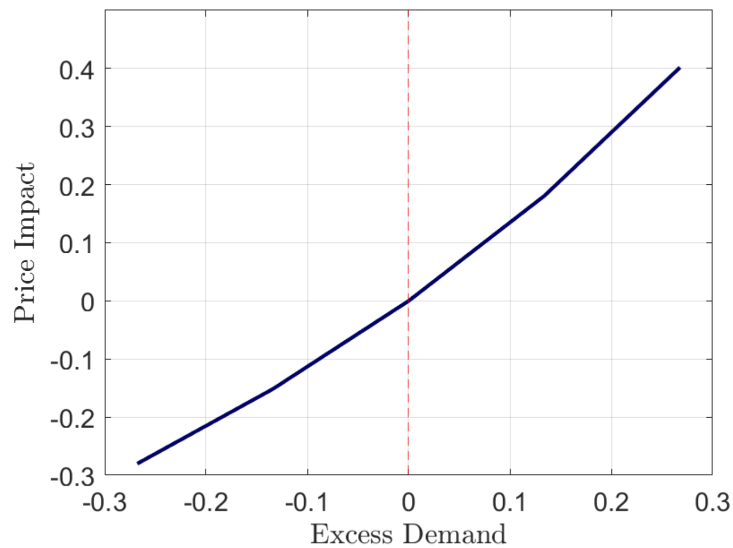

Figure 2. Excess Demand and Price Impact

This figure presents the model-predicted relationship between the excess demand that firms face and the price impact on their stocks. The solution is constructed using the parameter estimates reported in Table 3.

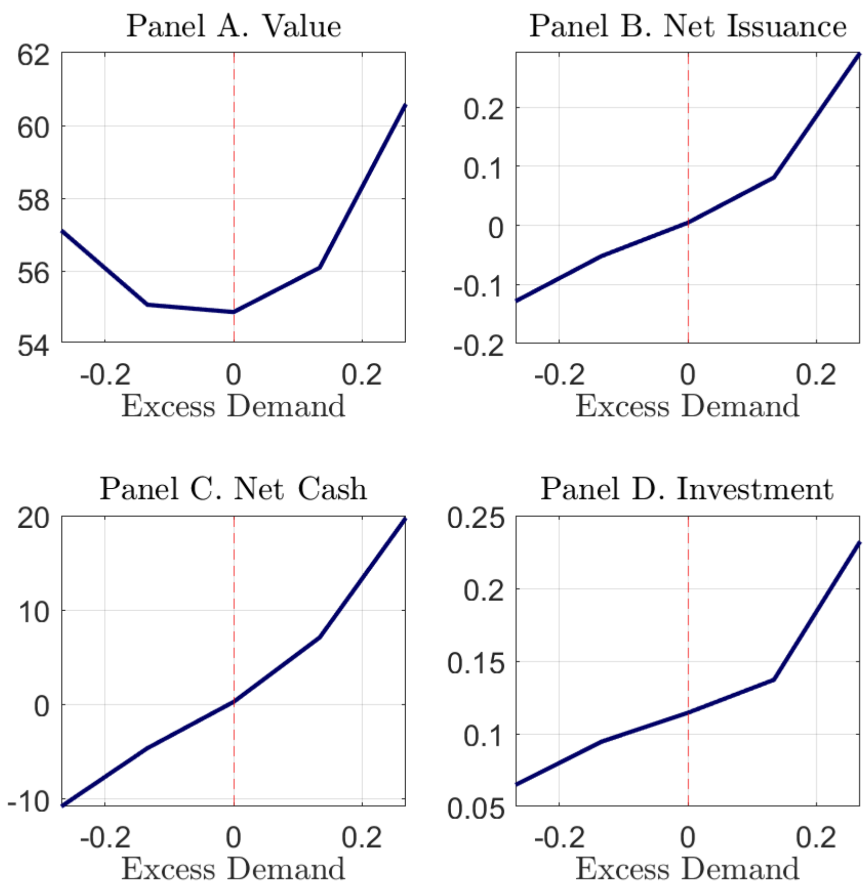

Figure 3. Excess Demand, Firm Value, and Optimal Policies

This figure presents the model-predicted relationship between the excess demand, firms' intrinsic value as defined in the Bellman Equation (10), and their optimal investment and financing policies. The solution is constructed using the parameter estimates reported in Table 3.

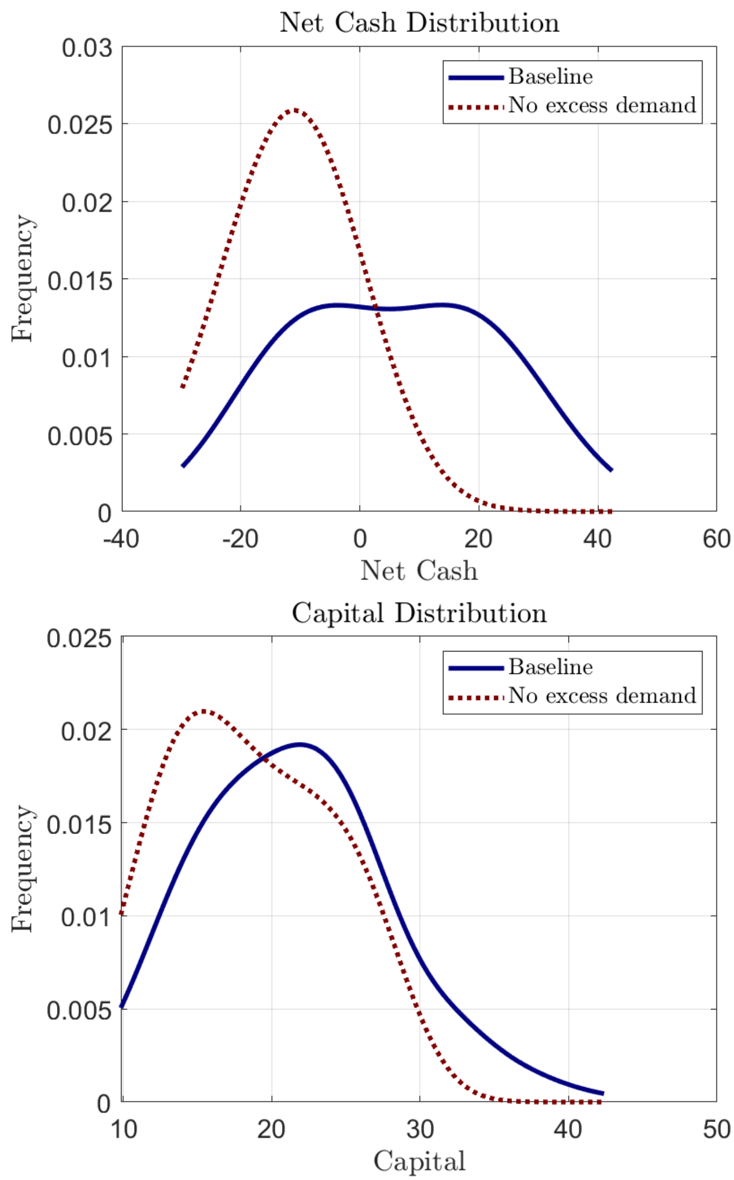

Figure 4. Excess Demand and Distribution of Firm Policies

This figure presents the distribution of net cash (cash − debt) and capital under alternative model specifications—the baseline model and a counterfactual scenario, in which firms face no excess demand ($\epsilon_{n,t} = 0, \forall n, t$).

Table 1. Variable Definition

Variable	Details of Construction
Investment	(Capital expenditure − Sale of property) / Gross plant, property and equipment
Profit	Operating income before depreciation and amortization /Assets
Leverage	Total debt / Assets
Firm Size	Log(sales)
Market-to-Book	(Assets − Book equity + Market equity) / Assets
% Equity Issuance	Sale of common and preferred stock (if larger than 2% following the algorithm in McKeon, 2015) / Market equity
% Share Repurchase	Purchase of common and preferred stock / Market equity
Dividend	Dividends on common and preferred stock / Assets

Table 2. Moment Conditions

In this table, we report the moment conditions. Moments (1)–(6) are the regression coefficients and standard deviation of residual in the following regression:

$$\log w_{i,t}(n) \sim \gamma_{me} \cdot me_{n,t} + \gamma_{be} \cdot be_{n,t} + \gamma_{inv} \cdot inv_{n,t} + \gamma_{prof} \cdot prof_{n,t} + \gamma_{div} \cdot div_{n,t} + \gamma_{\beta} \cdot mktbeta_{n,t} + \epsilon_{n,t},$$

where $w_{i,t}(n)$ stands for investor i's portfolio share in firm n at time t.

	Actual	Simulated
(1) γ_{market} in the auxiliary equation	0.8256	0.7833
(2) γ_{book} in the auxiliary equation	0.0207	0.0153
(3) γ_{prof} in the auxiliary equation	0.1161	0.0991
(4) γ_{inv} in the auxiliary equation	0.0996	0.2525
(5) γ_{div} in the auxiliary equation	0.3669	0.4334
(6) γ_{β} in the auxiliary equation	-0.0541	-0.0228
(7) Auto-correlation of residual in the auxiliary equation	0.7421	0.7270
(8) Std. of residual in the auxiliary equation	0.0925	0.0641
(9) Auto-correlation of profit	0.7880	0.8693
(10) Std of profit	0.0888	0.0681
(11) Percentage of equity issuance	0.0183	0.0216
(12) Std. of equity issuance	0.0672	0.0491
(13) Percentage of share repurchase	0.0179	0.0203
(14) Std. of share repurchase	0.0409	0.0577
(15) Mean investment	0.1303	0.1621
(16) Std of investment	0.1256	0.0887
(17) Mean leverage	0.2342	0.2582
(18) Mean profit	0.1339	0.1779
(19) Mean Market to book	2.0704	2.3120
(20) Mean dividend	0.0200	0.0364

Table 3. Parameter Estimates

In this table, we report the model parameter estimates. Panel A presents calibrated parameters, Panel B presents estimated values for parameters that capture investors' demand, and Panel C presents results for parameters that governs firms' operations. Standard errors for the estimated parameters are clustered at the firm level and reported in brackets.

Panel A: Calibrated Parameters		
τ_c	Corporate tax rate	0.35
τ_d	Dividend tax rate	0.15
J	Number of firms	1000
β	SDF parameter	0.98
γ_0	SDF parameter	0.2627
γ_1	SDF parameter	-14.196
ρ_a	Persistence of aggregate productivity shocks	0.8145
σ_a	Standard deviation of aggregate productivity shocks	0.014
σ_ζ	Standard deviation of exposure to aggregate productivity shocks	0.2148
Panel B: Parameters Governing Investors' Demand		
β_{market}	Demand coefficient on log market equity	0.3389
β_{book}	Demand coefficient on log book equity	0.1193
β_{profit}	Demand coefficient on profitability	0.8252
$\beta_{investment}$	Demand coefficient on investment rate	-0.0259
$\beta_{dividend}$	Demand coefficient on dividend yield	0.5027
$\beta_{mktbeta}$	Demand coefficient on market beta	-0.0095
ρ_v	Auto-correlation of excess demand	0.7317
σ_v	Standard deviation of excess demand	0.0913
Panel C. Parameters Governing Firms' Operation		
α	Curvature of production function	0.6210
ρ_z	Persistence of idiosyncratic productivity shocks	0.8561
σ_z	Standard deviation of idiosyncratic productivity shocks	0.0861
δ	Depreciation rate	0.1580
ξ	Capital adjustment cost	0.3478
θ	Collateral constraint	0.8025
ϕ	Linear equity issuance cost	0.0945
f	Fixed operating cost	1.4901

Table 4. Excess Demand, Financial Constraints, and the Flow of Funds

In this table, we decompose the sources and uses of funds for firms in our model. Numbers present contributions of items listed in the table rows as a fraction of the overall sources or uses of funds at the firm level. In column (1), we consider the decomposition for the full sample, and in columns (2)–(5), we break down firms in our model simulation into sub-samples based on the excess demand they face in the current period and their financial constraints. High (Low) ϵ firms corresponds to firms whose current period ϵ are above (below) zero; constrained (unconstrained) firms are those with above (below) median dividend-to-asset ratio. Model simulations are based on parameters values reported in Table 3.

	(1) Full sample	Constrained		Unconstrained	
		(2) Low ϵ	(3) High ϵ	(4) Low ϵ	(5) High ϵ
Sources					
Profit	0.723	0.800	0.802	0.786	0.681
Net cash reduction	0.129	0.162	0.037	0.179	0.079
Interest income	0.028	0.021	0.037	0.024	0.035
Equity Issuance	0.120	0.018	0.124	0.010	0.204
Uses					
Investment	0.359	0.355	0.406	0.386	0.364
Adjustment cost	0.023	0.022	0.025	0.025	0.024
Taxes	0.129	0.139	0.133	0.149	0.125
Cash increase	0.117	0.091	0.173	0.031	0.119
Interest payment	0.014	0.023	0.012	0.015	0.006
Dividends	0.110	0.036	0.041	0.138	0.206
Repurchases	0.065	0.110	0.007	0.072	0.004
Fixed operating costs	0.182	0.224	0.203	0.184	0.152

Table 5. Excess Demand and Investment Efficiency

In this table, we examine different measures of firm investment efficiency, including the mean and variance of firms' marginal product of capital (MPK) and the TFP loss relative to a benchmark case, in which there is no aggregate risk and firms do not face fictions of any kind such that the marginal products of capital are equalized across firms. We report each measure under the baseline model and several counterfactual scenarios. Panel A reports the results from the counterfactual exercise in which we shut down excess demand shocks while keeping the value of other parameters the same as the baseline estimation. In Panel B, we remove debt market frictions by setting the collateral constraint parameter θ to one so that firms can borrow up to 100% of their asset values. Panel C reports the results from the counterfactual exercise that eliminates real frictions by setting the capital adjustment cost parameter to zero. Panel D reports the results from the counterfactual exercise that removes the exposure to aggregate risk. $Percentage\ change$ captures the changes in measures from the baseline model to the counterfactual models divided by their values in the baseline model.

Panel A: Effect of latent demand

	Baseline	No excess demand	Percentage change
(1) Mean(MPK)	0.1897	0.2088	10.08%
(2) Var(log(MPK))	0.0256	0.0195	-23.82%
(3) TFP loss	2.05%	1.59%	-22.30%

Panel B: Effect of debt market frictions

	No debt frictions	Percentage change
(1) Mean(MPK)	0.1877	-1.04%
(2) Var(log(MPK))	0.0246	-4.11%
(3) TFP loss	1.97%	-4.03%

Panel C: Effect of capital adjustment cost

	No adjustment costs	Percentage change
(1) Mean(MPK)	0.1738	-8.39%
(2) Var(log(MPK))	0.0237	-7.35%
(3) TFP loss	1.84%	-10.47%

Panel D: Effect of risk premium

	No risk premium	Percentage change
(1) Mean(MPK)	0.2002	5.56%
(2) Var(log(MPK))	0.0218	-14.85%
(3) TFP loss	1.75%	-14.48%

Table 6. Subsample Estimation

In this table, we report the model parameter estimates for six subsamples: "High HH" ("Low HH") are firms with above (below) median percentage household holdings, "High SR" ("Low SR") are firms with above (below) median sentiment risk, and "High TG" ("Low TG") are firms with above (below) median tangibility. Panel A presents estimated values for parameters that capture investors' demand; Panel B presents results for parameters that governs firms' operations; Panel C reports the average demand elasticity, average elasticity of price to excess demand, and average elasticity of price to equity issuance in each subsample; Panel D reports the percentage changes in measures of capital misallocation when we remove excess demand from the baseline model following the same procedures described in Table 5.

		Low HH	High HH	Low SR	High SR	Low TG	High TG
Panel A: Parameters Governing Investors' Demand							
β_{market}	Demand coefficient on log market equity	0.3543	0.3243	0.3526	0.3217	0.3229	0.3684
β_{book}	Demand coefficient on log book equity	0.1205	0.1192	0.1204	0.1204	0.1150	0.1149
β_{profit}	Demand coefficient on profitability	0.8321	0.8332	0.8177	0.8254	0.8263	0.8101
$\beta_{investment}$	Demand coefficient on investment rate	-0.0260	-0.0260	-0.0257	-0.0259	-0.0261	-0.0263
$\beta_{dividend}$	Demand coefficient on dividend yield	0.5047	0.5064	0.4976	0.5023	0.4862	0.4862
$\beta_{mktbeta}$	Demand coefficient on market beta	-0.0095	-0.0094	-0.0094	-0.0095	-0.0093	-0.0093
ρ_v	Auto-correlation of excess demand	0.7252	0.7324	0.7244	0.7304	0.7209	0.7327
σ_v	Standard deviation of excess demand	0.0876	0.0955	0.0859	0.0950	0.0934	0.0869
Panel B. Parameters Governing Firms' Operation							
α	Curvature of production function	0.6175	0.6270	0.6148	0.6157	0.6009	0.5828
ρ_z	Persistence of idiosyncratic productivity shocks	0.8478	0.8646	0.8483	0.8483	0.8081	0.8233
σ_z	Standard deviation of idiosyncratic productivity shocks	0.0855	0.0852	0.0869	0.0859	0.0868	0.0863
δ	Depreciation rate	0.1575	0.1576	0.1568	0.1570	0.1521	0.1460
ξ	Capital adjustment cost	0.3507	0.3489	0.3443	0.3474	0.3468	0.3470
θ	Collateral constraint	0.7947	0.7872	0.8098	0.8093	0.7133	0.8421
ϕ	Linear equity issuance cost	0.0998	0.0901	0.0955	0.0926	0.0860	0.0976
f	Fixed operating cost	1.4272	1.7903	1.3178	1.4874	1.3202	1.2580
Panel C. Variations in Elasticities							
$\frac{\partial q}{\partial p}$	Average demand elasticity	-0.6461	-0.6753	-0.6477	-0.6787	-0.6774	-0.6320
$\frac{\partial p}{\partial \log \epsilon}$	Average elasticity of price to excess demand	1.5463	1.4761	1.5423	1.4720	1.4748	1.5807
$\frac{\partial p}{\partial s}$	Average elasticity of price to equity issuance	-0.4266	-0.5906	-0.3809	-0.4761	-0.4853	-0.4369
Panel D. Effect of Shutting Down Excess Demand							
Δ%Mean(MPK)		6.21%	13.69%	5.58%	8.79%	9.13%	9.25%
Δ%Var(log(MPK))		-19.06%	-40.41%	-17.16%	-28.87%	-25.63%	-24.28%
Δ%TFP loss		-20.19%	-42.90%	-17.49%	-26.56%	-24.21%	-22.45%