Surfing the Cycle: Cyclical Investment Opportunities and Firms' Risky Financial Assets*

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Abstract

This paper studies why non-financial firms invest in risky financial assets. Within a dynamic corporate finance model with macroeconomic fluctuations, I show that firms can use risky financial assets to transfer liquidity from states with low aggregate investment opportunities to states with high aggregate investment opportunities. Specifically, when investment funding demand is more pro-cyclical than profits and external financing is costly, risky financial assets with pro-cyclical returns can increase firm value by improving the match bet en internal cash flows and investment opportunities. Therefore, investing in risky financial assets can be naturally optimal for the firm from a macro perspective. Based on U.S. firm data scraped from the SEC 10-K filings using a machine learning algorithm, I find empirical evidence consistent with this mechanism: (1) time-serially, the value of risky financial assets is positively correlated with the corporate investment rate; (2) cross-sectionally, firms with more pro-cyclical investment funding demand in excess of profits hold more risky financial assets. The empirical results are robust to adding variables to control for the poor corporate governance, CEO risk-seeking and overconfidence channels.

JEL Classifications: E32, G11, G32

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1 Introduction

Why do non-financial firms invest in risky financial assets? A recent study by Duchin, Gilbert, Harford, and Hrdlicka (2017) shows that risky financial assets represent more than 40% of S&P 500 firms' financial assets, or 6% of their total book assets. This finding is puzzling because in the absence of positive abnormal returns, as documented by the literature on mutual fund performance (e.g., Fama & French, 2010), holding risky financial assets does not generate value for the firms' shareholders once the cost of capital is properly adjusted for the risk (see Duchin et al., 2017). Moreover, holding cash has a tax disadvantage (e.g., Opler, Pinkowitz, Stulz, & Williamson, 1999), and firms seem to be aware of the tax costs associated with cash holdings. For example, Foley, Hartzell, Titman, and Twite (2007) document that high repatriation taxes create incentive for firms to retain earnings overseas and result in high cash holdings, and De Simone, Piotroski, and Tomy (2018) find that expected reduction in repatriation taxes stimulates overseas cash holdings. Finally, these investments in risky financial assets also cast doubt on whether firm savings are precautionary or not.

In this paper, complimentary to the channels explored in the existing literature from the micro-perspective, I provide a rational explanation for firms' risky financial asset holdings from a macro-perspective. In a dynamic corporate finance model, I show that when investment funding demand is pro-cyclical and external financing is costly, risky financial assets can increase firm value by improving the match between internal cash flows and investment opportunities. Based on U.S. firm data scraped from the SEC 10-K filings using a machine learning algorithm, I find empirical evidence consistent with the model's predictions: the value of risky financial assets is positively correlated with the corporate investment rate, and one unit increase in the funding gap beta, the sensitivity of firm's investment funding demand in excess of profits to the aggregate bond market returns, is positively associated with 3%-6% increase in risky financial asset holdings.

In Figure 1 and Figure 2, I show that both the aggregate investment and financing activities exhibit pro-cyclical patterns, as in Covas and Den Haan (2011) and Begenau and Salomao (2018). The pro-cyclical investment and financing activities suggest that the shortage of funding, or the mismatch between investment opportunities and internal cash flows, can be pro-cyclical as well. When external financing is costly, the pro-cyclical shortage of funding creates a natural incentive to invest in risky financial assets, simply because risky financial assets provide pro-cyclical returns.

To formalize the above intuition, I study the optimal allocation of corporate cash holdings through the lens of a dynamic corporate investment and financing model. A dynamic model has the advantage of generating macroeconomic fluctuations in investment opportunities, and it simultaneously provides a relative simple way to design risky securities with stochastic returns. More specifically, I build upon the model by Riddick and Whited (2009), where the optimal cash holding is mainly determined by the trade-off between the tax costs associated with savings, and the benefits from reducing expected costs of external financing in case of good investment opportunities or negative profitability shocks. I introduce a risky security into this framework to study the role of risky financial assets as a saving option.

The model delivers several theoretical predictions. First, due to costly external financing, the marginal cost of investment is cheaper through internal funding than through external financing. As a result, the investment rate is positively correlated with risky financial asset holdings, controlling for investment opportunities. Second, even though the dividend policy is counter-cyclical in the model, it mirrors pro-cyclical investment opportunities. Therefore, controlling for investment opportunities, the dividend payout ratio is also positively correlated with risky financial asset holdings.

Moreover, the model shows that the cyclicality of investment funding demand and external financing costs form the key determinants of saving behavior. Specifically, over business cycles, at any period t, firms know that investment opportunities are state-contingent in period $t+1$, which translates to state-contingent investment funding demand. Furthermore, firms also know that the profits generated from operations are state-contingent in period

$t+1$. Since both investment funding demand and profits are state-contingent, the mismatch between investment funding demand and profits, which I define as the "funding gap", is also state-contingent. Given the feature that returns on risky financial assets are mostly pro-cyclical, investing in risky financial assets can be valuable if the funding gap is also pro-cyclical. Finally, for any given cyclical intensity of the funding gap, higher external financing costs provide stronger incentives to invest in risky financial assets, as they reduce the need for costly external financing when investment opportunities are good.

To test the key empirical predictions from the model, I scrape the fair value of firms' risky financial assets disclosed in the footnotes of the SEC 10-K filings through a machine learning algorithm, which generates firm-year observations of the fair value of risky financial assets.[1] In particular, the algorithm targets tables with a specific type of format, which covers around 80% of firm-years disclosing fair value information, and exploits text information associated with different tables to detect whether the table contains relevant information.[2] The final sample contains 20,873 observations from 2009 to 2018 for 3,077 U.S. firms. The sample starts in 2009 when compulsory disclosure is required.

I use panel regressions to test the relationship between the fair value of risky financial assets and investment/dividend policies. Consistent with the model's predictions, I find that the investment rate is positively correlated with the fair value of risky financial assets, controlling for Tobin's q. A one percent increase in the value of risky financial assets is positively associated with a 0.0081% to 0.0120% increase in capital expenditure and a 0.0861% to 0.0942% increase in R&D expenditure. I also find that dividend rate is positively correlated with the fair value of risky financial assets, controlling for Tobin's q. A one percent increase in the value of risky financial assets is positively associated with a 0.0621% to 0.0715% increase in dividend rate.

I use Fama and MacBeth (1973) regressions to test the cross-sectional relationship be-

[1] The information regarding the fair value of financial instruments is usually disclosed in the 10-K filing footnote named "Fair Value Measurements", but the name of the footnote is not standard.

[2] A detailed description of the algorithm and an out-of-sample accuracy test of the algorithm is provided in Appendix D.

tween the cyclical intensity of the funding gap, external financing costs, and risky financial asset holdings. More specifically, I first estimate the "funding gap beta", the cyclical intensity of the funding gap, by time-series regressions of several measures of the funding gap on the bond market returns for each firm. I use bond market returns to estimate funding gap beta instead of equity market returns as most of the risky financial assets on the firms' balance sheets are bond securities, therefore funding gap beta estimated from bond market returns should be a better measure than funding gap beta estimated from equity market returns as the measure of incentive to invest in those risky financial assets. Then I conduct cross-sectional regressions to test the relationship between the funding gap beta, external financing costs and risky financial asset holdings. Consistent with the model's predictions, I find that a one unit increase in the funding gap beta is positively associated with a 3% to 6% increase in risky financial asset holdings. I find mixed evidence regarding the relationship between external financing costs and risky financial asset holdings. Firms classified as financially constrained hold more risky financial assets than their unconstrained counterparts when either dividend payment, credit rating, or the Hadlock and Pierce (2010) index is used as the financing constraint index; however, firms classified as financially unconstrained hold more risky financial assets than their constrained counterparts when the Kaplan and Zingales (1997) index or the Whited and Wu (2006) index is used as the financing constraint index. The difference in estimation results between the KZ index and other indices of financing constraints is not surprising. As noted out by Whited and Wu (2006) and Farre-Mensa and Ljungqvist (2016), firms classified as financially constrained by the KZ index are different from firms classified as financially constrained by the other four indices in almost every dimension they consider. Dividend payment, credit rating, WW index and HP index classify young, small, less tangible and less levered firms with more investment opportunity and R&D expenditure as financially constrained, while the KZ index does the opposite.

Taken together, this evidence suggests that corporate investment in risky financial assets can be driven by both financing frictions and the mismatch between investment funding demand and internal cash flows caused by macroeconomic fluctuations.

This paper fits into both the theoretical and empirical literature on corporate savings. As far as I know, this is the first study of corporate saving composition from a macro-perspective. The model is most similar to Riddick and Whited (2009) and Eisfeldt and Muir (2016). I extend their models by embedding a risky security as another saving option besides the risk-free security. This extension creates new economic forces to sketch complicated corporate saving behavior, which is absent from the traditional corporate saving theories where savings are always assumed to be safe. The mechanism in this paper is similar to Acharya, Almeida, Ippolito, and Perez (2014) and Nikolov, Schmid, and Steri (2019), where credit lines are used as state-contingent liquidity, in my model, risky financial assets is used as state-contingent liquidity. The model also shares similarities with Duchin et al. (2017), who also incorporate risky financial assets as a saving option. However, in contrast to their model, I assume that both the profits and investment opportunities can fluctuate over business cycles to allow richer dynamic interactions between investment, dividend, and saving behavior. This setup highlights that there is in fact a rational incentive for firms to invest in risky financial assets, in addition to the behavioral and agency explanations for firms' investment in risky financial assets described by Duchin et al. (2017).

Empirically, most of the literature on corporate cash holdings focuses on the relationship between corporate savings and firm-specific characteristics, such as cash flow volatility, growth opportunity, and CEO compensation (e.g., Bates, Kahle, & Stulz, 2009; Liu & Mauer, 2011; Opler et al., 1999). Another strand of literature documents the relationship between cash holdings and cost incentives such as tax costs or interest rate (e.g., Azar, Kagy, & Schmalz, 2016; Bates et al., 2009; De Simone et al., 2018; M. W. Faulkender, Hankins, & Petersen, 2019; Foley et al., 2007). This paper is most closely related to studies on corporate saving compositions. Brown (2014) studies the difference between marketable security investment and actual cash holdings; Cardella, Fairhurst, and Klasa (2015) analyze the determinants of illiquid financial asset holdings; Duchin et al. (2017) investigate the determinants of illiquid financial asset holdings and risky financial asset holdings through behavior and agency perspectives. The contribution of this paper is the analysis of coporate saving behavior from a macroeconomic/asset-pricing perspective, which highlights the role of macroeconomic fluctuations in shaping corporate saving policies.

This paper is also related to the risk-management literature. The mechanism in this paper can be traced back to both Smith and Stulz (1985) and Froot, Scharfstein, and Stein (1993), who develop models in which firms choose risk management policies to smooth cash flows to reduce either expected financial distress costs or expected external financing costs. The model in this paper extends Froot et al. (1993) by introducing stochastic investment opportunities, this extension allows firms to be financially constrained induced by good investment opportunities besides negative liquidity shocks. The empirical results in this paper are related to M. Faulkender (2005). Using data for the chemical industry, M. Faulkender (2005) finds that the sensitivity of firms' cash flows to interest rates is not significantly correlated with firms' floating-versus-fixed rate choice when issuing debt, but also finds that downward macroeconomic and industry risk is positively correlated with fixed rate choice when issuing debt, suggesting corporate interest rate policies are responsive to macroeconomic and industry risk. Building on these findings, I find that the risk-management incentive can indeed help to explain firms' investment behavior in risky financial assets.

The paper is organized as follows. Section 2 outlines the model and illustrates the key intuition. Section 3 develops empirical hypotheses from simulations and numerical experiments from the model. Section 4 describes the data. Section 5 presents the empirical evidence and Section 6 concludes.

2 Model

In this section I embed a risky security into a dynamic investment-saving model similar to Riddick and Whited (2009) and Eisfeldt and Muir (2016). Specifically, I allow firms to invest in a risky security as another saving option on top of a risk-free security. First I describe technology and investment, then I introduce a risk-free security and a market-security as saving options, after that I define the firm's cash flow and optimization problem, and I develop the key intuition behind the model to close this section.

2.1 Technology and Investment

Firms are indexed by j and time is indexed by t. For firm j in period t, profits generated by physical capital k_{jt} are assumed to be

$$\pi_{jt} = \exp(\beta_\pi x_t + z_{jt})k_{jt}^{\alpha} - fk_{jt}, \tag{1}$$

where x_t denotes the aggregate productivity shock; z_{jt} denotes the idiosyncratic productivity shock; k_{jt} is the book value of the firm's physical capital; β_π captures the cyclical intensity of the profits; α captures the curvature of the profit function; and f captures the operating costs of the firm. For simplicity of the numerical solution, I assume $\alpha = 1$ to reduce dimension of the optimization problem.[3]

Both x_t and z_{jt} are assumed to be $AR(1)$ processes

$$x_t = \rho_x x_{t-1} + \sigma_x \varepsilon_t^x$$

$$z_{jt} = \rho_z z_{jt-1} + \sigma_z \varepsilon_{jt}^z,$$

where both ε_t^x and ε_{jt}^z are IID truncated standard normal shocks; ε_t^x is independent of ε_{jt}^z; ε_{jt}^z and ε_{lt}^z are independent for $j \neq l$; ρ_x and ρ_z capture the persistence of the aggregate and idiosyncratic productivities respectively; and σ_x and σ_z capture the conditional standard deviations of the aggregate and idiosyncratic productivities respectively.

The firm accumulates capital according to

$$k_{jt+1} = (1-\delta)k_{jt} + i_{jt+1}k_{jt}, \tag{2}$$

where i_{jt+1} is the investment rate and δ is the depreciation rate. By investing $i_{jt+1}k_{jt}$, the

[3] This assumption is also exploited in other studies to simplify solutions to the optimization problems (e.g., Bazdresch, Kahn, & Whited, 2017; J. Gomes, Jermann, & Schmid, 2016).

firm incurs quadratic capital adjustment costs defined as

$$Adj(i_{jt+1}, k_{jt}) = \frac{\psi_i}{2} i_{jt+1}^2 k_{jt}. \tag{3}$$

In many investment models, capital adjustment costs also incorporate non-convex part.[4] Since investment behavior is not the focus of this study, for straightforward illustration of the key economic forces determining saving behavior and simplicity of the numerical solution, I assume away non-convex adjustment costs.

2.2 Stochastic Discount Factor and Financial Securities

Following Clementi and Palazzo (2019), I assume the stochastic discount factor to be

$$M(x_t, x_{t+1}) = \eta \exp(\gamma_0 x_t + \gamma_1 x_{t+1}), \tag{4}$$

where $\eta \in (0, 1)$ is the time preference parameter, and γ_0 and γ_1 are the risk-averse parameters.[5]

There are two types of securities in the market, one risk-free security and one market-security. Return on the risk-free security is denoted by r_f. I assume the risk-free security has maturity of one and price of one. Using no arbitrage condition, r_f is determined by

$$1 = \mathbf{E}\big[M(x_t, x_{t+1})\big(1 + r_f\big)|x_t\big]. \tag{5}$$

Return on the market-security is denoted by r_M. As for the risk-free security, I assume the market-security has maturity of one and price of one. On top of that, the market-security has beta of one.[6] So r_M is determined by

$$\begin{aligned} 1 &= \mathbf{E}\big[M(x_t, x_{t+1})\big(1 + r_M\big)|x_t\big] \\ 1 &= -\mathbf{Cov}\big[M(x_t, x_{t+1}), \big(1 + r_M\big)|x_t\big]/\mathbf{Var}\big[M(x_t, x_{t+1})|x_t\big]. \end{aligned} \tag{6}$$

[4]See Cooper and Haltiwanger (2006) for a detailed discussion.

[5]Stochastic discount factors similar to this specification are widely used in the asset-pricing literature (e.g., J. F. Gomes & Schmid, 2010; Livdan, Sapriza, & Zhang, 2009; Zhang, 2005).

[6]Applying covariance decomposition $\mathbf{E}\big[XY\big] = \mathbf{Cov}\big[X, Y\big] + \mathbf{E}\big[X\big]\mathbf{E}[Y]$ and the pricing equation for the risk-free rate $1 = \mathbf{E}\big[M(x_t, x_{t+1})(1 + r_f)|x_t\big]$ to the pricing equation $1 = \mathbf{E}\big[M(x_t, x_{t+1})\big(1 + r_M\big)|x_t\big]$ to get the beta representation of the pricing equation

Further, I assume the gross return on the market-security to be linear in the stochastic discount factor

$$1 + r_M = U + VM(x_t, x_{t+1}), \tag{7}$$

where U and V are coefficients to be determined. Combining equation (5), (6) and (7), returns on the risk-free security and the market-security can be solved as

$$\begin{aligned}
r_f(x_t) &= \frac{1}{\mathbf{E}\big[M(x_t, x_{t+1})|x_t\big]} - 1 \\
\lambda(x_t) &= \mathbf{Var}\big[M(x_t, x_{t+1})|x_t\big] / \mathbf{E}\big[M(x_t, x_{t+1})|x_t\big] \\
r_M(x_t, x_{t+1}) &= r_f(x_t) + \lambda(x_t) + \frac{1}{1 + r_f(x_t)} - M(x_t, x_{t+1}) \\
\mathbf{E}\big[r_M(x_t, x_{t+1})|x_t\big] &= r_f(x_t) + \lambda(x_t),
\end{aligned} \tag{8}$$

where $\lambda(x_t)$ is the risk-premium.[7]

$$\begin{aligned}
\mathbf{E}\big[r_M\big] &= r_f + \Big(- \frac{\mathbf{Cov}\big[M(x_t, x_{t+1})(1 + r_M)|x_t\big]}{\mathbf{Var}\big[M(x_t, x_{t+1})|x_t\big]} \Big) \frac{\mathbf{Var}\big[M(x_t, x_{t+1})|x_t\big]}{\mathbf{E}\big[M(x_t, x_{t+1})|x_t\big]} \\
\beta_M &= - \frac{\mathbf{Cov}\big[M(x_t, x_{t+1})(1 + r_M)|x_t\big]}{\mathbf{Var}\big[M(x_t, x_{t+1})|x_t\big]} \\
\lambda(x_t) &= \frac{\mathbf{Var}\big[M(x_t, x_{t+1})|x_t\big]}{\mathbf{E}\big[M(x_t, x_{t+1})|x_t\big]},
\end{aligned}$$

where r_f is the risk-free rate, β_M is the beta of the stochastic return $1 + r_M$, and $\lambda(x_t)$ is the risk-premium. See Cochrane (2009) for a detailed discussion.

[7]Theoretically, the risk-premium implied by the stochastic discount factor has following closed form solution:

$$\lambda(x_t) = \eta \exp((\gamma_0 + \gamma_1 \rho_x x_t))\big(\exp(\gamma_1^2 \sigma_x^2) - 1\big) \exp(\gamma_1^2 \sigma_x^2 / 2).$$

When γ_1 is set to $-\gamma_0/\rho_x$, which is the parameter I choose for the model, the stochastic discount factor reduces to

$$M(x_t, x_{t+1}) = \eta \exp(\gamma_0 x_t - \gamma_0/\rho_x(\rho_x x_t + \sigma_x \varepsilon_{t+1}^x)) = \eta \exp(\gamma_1 \sigma_x \varepsilon_{t+1}^x) = M(\varepsilon_{t+1}^x),$$

and the risk-free rate reduces to a constant $r_f = 1/\big(\eta \exp(\gamma_1^2 \sigma_x^2/2)\big) - 1$ and the risk-premium reduces to a constant $\lambda = \eta\big(\exp(\gamma_1^2 \sigma_x^2) - 1\big) \exp(\gamma_1^2 \sigma_x^2/2)$. However, the numerical solution of the model is based on discretization of the process x_t onto a bounded limited number of grid points. Therefore, the innovation ε_t^x, which is a necessary state variable to describe the state-contingent return on the market-security, is approximated by $\varepsilon_t^x = (x_t - \rho_x x_{t-1})/\sigma_x$ in the numerical solution, and this approximation of ε_t^x introduces x_{t-1} as another state variable and makes the risk-free rate and the risk-premium dependent on x_{t-1}.

2.3 Cash Flow

The firm can invest in both the risk-free security and the market-security. If the firm has invested $(1-s_{jt})c_{jt}k_{jt}$ dollars in the risk-free security and $s_{jt}c_{jt}k_{jt}$ dollars in the market-security in period $t-1$, where s_{jt} is the fraction of dollars invested in the market-security, the value of this financial portfolio in period t is

$$c_{jt}k_{jt}\big[1+(1-s_{jt})r_f(x_{t-1})+s_{jt}r_M(x_{t-1},x_t)\big],$$

where $(1-s_{jt})r_f(x_{t-1})$ is the return from investment in the risk-free security, and $s_{jt}r_M(x_{t-1},x_t)$ is the return from investment in the market-security. Returns on financial assets are assumed to be taxable, so the taxable income for the firm in period t is

$$TI_{jt}=\exp(\beta_\pi x_t+z_{jt})k_{jt}^{\alpha}-fk_{jt}-\delta k_{jt}+c_{jt}k_{jt}\big[(1-s_{jt})r_f(x_{t-1})+s_{jt}r_M(x_{t-1},x_t)\big].$$

Motivated by Duchin et al. (2017), who argue that the marginal value risky financial assets is less than the marginal value of risk-free assets for the firm, I add a penalty parameter $\psi_a>0$ to make sure that it is more costly for the firm to hold the market-security than the risk-free security. More specifically, I assume the "price" of a portfolio with $(1-s_{jt+1})c_{jt+1}k_{jt+1}$ dollars invested in the risk-free security and $s_{jt+1}c_{jt+1}k_{jt+1}$ dollars invested in the market-security is $\exp(\psi_a s_{jt+1})c_{jt+1}k_{jt+1}$ for the firm. This functional form features zero costs of holding the risk-free security, and the costs of holding this portfolio are approximately $\psi_a s_{jt+1}(c_{jt+1}k_{jt+1})$ for the firm when ψ_a is close to zero. This assumption is also consistent with the fact that risky financial assets usually involve higher transaction costs and management fees.

The sum of investment in physical capital, capital adjustment costs, gross investment in financial assets and equity payout must equal the cash flow generated by capital and financial asset holdings, as described by the following cash flow identity

$$i_{jt+1}k_{jt} + Adj(i_{jt+1}, k_{jt}) + \exp(\psi_a s_{jt+1})c_{jt+1}k_{jt+1} + E_{jt} = (1-\tau)TI_{jt} + \delta k_{jt} + c_{jt}k_{jt}, \quad (9)$$

where E_{jt} is the equity payout. When $E_{jt} \geq 0$, the firm makes distributions to shareholders, and when $E_{jt} < 0$, the firm issues equity. Issuing equity incurs external financing costs proportional to the issuing amount, and the distributions to shareholders net of external financing costs are

$$D_{jt} = \left[1 + \lambda_1 \mathbf{1}[E_{jt} < 0]\right] E_{jt}. \quad (10)$$

2.4 The Firm's Problem

The equity value of the firm, V_{jt}, is defined as the present value of all the future cash flows to shareholders, D_{jt}, discounted by the stochastic discount factor. For simplicity of notation, I omit firm index j. I also omit time index t, and use superscript $'$ to denote state variables for period $t+1$ and superscript $^-$ to denote state variables from period $t-1$. Each period the firm chooses (s', c', k') for the next period to maximize the equity value of the firm. I simplify the firm's problem by exploiting the constant return to scale assumption and redefining all the variables as fraction of physical capital k as follows

$$v = \frac{V}{k}, \quad e = \frac{E}{k}, \quad d = \frac{D}{k},$$

and the Bellman equation for the firm's problem is

$$
\begin{aligned}
v(x^-, x, z, s, c) &= \max_{s', c', i'} \; d + (1-\delta+i')\mathbf{E}\big[M(x,x')v(x,x',z',s',c')|x,z\big] \\
d(x^-, x, z, s, c, s', c', i') =&\big[1+\lambda_1 \mathbf{1}[e<0]\big]e \\
e(x^-, x, z, s, c, s', c', i') =&(1-\tau)\big[\exp(\beta_\pi x + z) - f\big] + \tau\delta - i' - \frac{\psi_i}{2}i'^2 + c \\
&+(1-\tau)c\big[(1-s)r_f(x^-) + s r_M(x^-, x)\big] - \exp(\psi_a s')c'(1-\delta+i') \\
s.t. \quad i' \geq& -(1-\delta) \\
s' \leq& 1.
\end{aligned} \tag{11}
$$

2.5 Key Intuition Illustration

In this section I develop the key intuition behind the model by analyzing how savings in the market-security can affect optimal investment decisions. Conditional on current state (x^-, x, z, s, c) and arbitrary saving policy (s', c'), the optimality condition for investment is

$$
\big[1+\lambda_1\mathbf{1}[e<0]\big](1+\exp(\psi_a s')c' + \psi_i i'^*) + \mu^* = \mathbf{E}\big[M(x,x')v(x,x',z',s',c')|x,z\big], \tag{12}
$$

where μ^* is the shadow price associated with the financing constraints. The left hand side of equation (12) is the shadow price of investment and the right hand side of equation (12) is the marginal value of investment. When $\mu^* > 0$, optimal investment is constrained by internal funding, which means the marginal cost of investment through internal funding is lower than the marginal value of investment, but the marginal cost of investment through external financing is higher than the marginal value of investment. The marginal cost of investment jumps at the point $e = 0$, and the internal funding which can be used to finance investment is given by

$$
(1-\tau)\big[\exp(\beta_\pi x + z) - f\big] + \tau\delta - \exp(\psi_a s')c'(1-\delta) + c\big[1 + (1-\tau)\big((1-s)r_f(x^-) + s r_M(x^-, x)\big)\big].
$$

Notice that the internal funding is increasing in the aggregate productivity x through two parts. The first part is $\exp(\beta_\pi x + z) - f$, the profits generated by capital, and the second part is $sr_M(x^-, x)$, the return on investment in the market-security. Investment in the market-security decreases the internal funding when x is low but increases the internal funding when x is high. Intuitively, the firm can be better off by investing in the market-security when two conditions are satisfied:

(1) the firm has internal funding more than investment funding demand when x is low.

(2) investment is constrained when x is high.

Figure 3 illustrates the key intuition. For simplicity, I assume that the aggregate state can only be Low or High. The marginal value of investment is assumed to be a function of the aggregate state. The blue line and red line stand for the marginal value of investment in the Low state and High state respectively. The marginal cost of investment is $\psi_i i'$ through internal funding and $(1 + \lambda_1)\psi_i i'$ through external financing. External financing costs create a jump in the marginal cost at the point where investment exceeds internal funding. Sub-figure A plots the optimality condition for investment assuming the firm has not invested in the market-security. The green line is the marginal cost of investment in the Low state and the purple line is the marginal cost of investment in the High state. In this scenario, the firm has sufficient internal funding to finance optimal investment in the Low state but optimal investment is capped by internal funding in the High state. If the firm has invested in the market-security in the previous period, in the current period the firm would have less internal funding in the Low state but more internal funding in the High state, and the optimality condition for investment may switch to sub-figure B. In sub-figure B, the dashed green line represents the marginal cost of investment in the Low state and the dashed purple line represents the marginal cost of investment in the High state. In this scenario, optimal investment can be financed through internal funding in both the Low and High states.

To conclude this section, when investment funding demand is more pro-cyclical than the profits generated by capital, by investing in the market-security, the firm can transfer extra funding from states with low aggregate investment opportunities to states with high aggregate investment opportunities to alleviate financing constraints. Therefore, investing in risky financial assets can be optimal when external financing is costly and investment opportunities fluctuate along business cycles.

3 Numerical Experiments

In this section I use the model to conduct numerical experiments to develop empirical hypotheses.

3.1 Calibration

The values of the model's parameters are summarized in Table 1. Most values are either directly taken or calculated based on existing literature. The persistence of the aggregate productivity ρ_x, is annualized from Kydland and Prescott (1982), which is also widely used in the asset-pricing literature.[8] The conditional standard deviation of the aggregate productivity σ_x, is calculated based on Savov (2011).[9] The time preference parameter η and the risk-averse parameter γ_0 are directly taken from Savov (2011). The risk-averse parameter γ_1 is set to generate a constant risk-free rate and a constant risk-premium, which also generates a risk-premium of 7.2%, which is close to 6.9% reported by J. Y. Campbell (2008) and 7.43% produced by the average stock return reported by Fama and French (2002). The cyclical

[8] E.g., J. F. Gomes and Schmid (2010); Livdan et al. (2009); Zhang (2005).

[9] In the standard Consumption-CAPM with power utility, the stochastic discount factor is

$$M(c_t, c_{t+1}) = \eta\Big(\frac{c_{t+1}}{c_t}\Big)^{-\gamma},$$

where c_{t+1} is the consumption in period $t+1$, c_t is the consumption in period t, η is the time preference parameter, and γ is the risk-averse parameter. Applying log transformation to the stochastic discount factor to get

$$\log\big(M(c_t, c_{t+1})\big) = \log\eta - \gamma\log\Big(\frac{c_{t+1}}{c_t}\Big),$$

where $\log\big(\frac{c_{t+1}}{c_t}\big)$ approximately equals the consumption growth rate. In Table 1 of Savov (2011), the standard deviation of the annual growth of consumption per capita, measured by total garbage, is 2.48%. Based on this value, I assume

$$0.0248 = \mathbf{STD}\big[\log\big(\frac{c_{t+1}}{c_t}\big)\big] = \mathbf{STD}\big[x_{t+1} - x_t\big].$$

Combining this assumption with $x_t = \rho_x x_{t-1} + \sigma_x \varepsilon_t^x$, σ_x can be calculated as $0.0248\sqrt{\frac{1+\rho_x}{2}}$.

intensity of the profits β_π is standardized to 1. The tax rate τ, the depreciation rate δ, the persistence of the idiosyncratic productivity ρ_z, and the conditional standard deviation of the idiosyncratic productivity σ_z are directly taken from either Riddick and Whited (2009) or Nikolov and Whited (2014). The linear external financing cost is set to 0.1, which is also used in Belo, Lin, and Yang (2018). The cost of holding the market-security ψ_a is set to 0.0015, which is chosen to match the fraction of risky financial assets, 40% as reported in Duchin et al. (2017) and is equivalent to 15bps annual costs to hold a market portfolio.

3.2 Investment, Dividends and Savings

Since the focus of this study is the interaction between macroeconomic fluctuations, investment and saving behavior, I focus on the role of the aggregate productivity shock in shaping the firm's investment, dividend, and saving policies. Figure 4 plots policy functions against the aggregate productivity shock. In this figure, investment is defined as i', savings in the market-security are defined as $s'c'$, savings in the risk-free security are defined as $(1-s')c'$, and equity payout is defined as e. Due to the constant return to scale assumption, all variables can be directly interpreted as ratios over physical capital k. Intuitively, investment rate is monotonically increasing in the aggregate productivity shock. A negative aggregate productivity shock $x < 0$ reduces the marginal value of investment, which directly reduces investment funding demand. On top of that, since the aggregate productivity shock is persistent ($\rho_x > 0$), a negative aggregate productivity shock today also implies low investment opportunities in the near future, which translates to low saving demand. Shrinkage in the investment funding demand and saving demand unlocks financing constraints, so negative aggregate productivity shocks increase equity payout. Unlocking financing constraints also implies low opportunity cost of internal funding, and now the firm can switch from savings in the market-security to savings in the risk-free security to avoid the costs of holding the market-security. When a positive aggregate productivity shock hits the firm $x > 0$, the marginal value of investment is pushed up and the shadow price of financing constraints μ^*

increases. So the firm is always constrained ($e \leq 0$) when $x > 0$. Again, since the aggregate productivity shock is persistent, high shadow price of financing constraints today implies high shadow price of financing constraints in the near future, which increases the value of the market-security since the market-security serves the role of expanding investment and alleviating financing constraints when the aggregate productivity shock is high. So the firm increases savings in the market-security and reduces savings in the risk-free security when the aggregate productivity shock is high. However, as the aggregate productivity shock keeps increasing, investment becomes very valuable today, and due to the fact that the aggregate productivity shock is mean-reverting, the opportunity cost of savings keeps increasing with the aggregate productivity shock since a dollar in savings reduces a dollar in investment. When the aggregate productivity shock exceeds some threshold, the substitute effect is activated and leads to a decrease in savings.

To further understand how investment and dividend policies are linked with saving behavior, I simulate an artificial panel data to analyze the relationship between investment, dividend and financial asset holdings. Since I can only observe the fair value of financial assets at the end of each period in the real data, to make the simulation analysis more relevant as guidance for empirical design, I also investigate the relationship between investment, equity payout, and the fair value of financial assets in the simulated data. I simulate the model for 3,000 firms over 100 years, keep the last 50 years, and estimate the following regressions

$$\begin{aligned} i_{jt} &= \theta_1^i risky\ assets_{jt-1} + \theta_2^i safe\ assets_{jt-1} + \theta_3^i q_{jt-1} + \mu_j + \mu_t + \varepsilon_{jt} \\ e_{jt} &= \theta_1^e risky\ assets_{jt-1} + \theta_2^e safe\ assets_{jt-1} + \theta_3^e q_{jt-1} + \mu_j + \mu_t + \varepsilon_{jt}, \end{aligned} \tag{13}$$

where j indexes firms and t indexes time; i_{jt} is the investment rate; e_{jt} is the equity payout rate; $risky\ assets_{jt}$ is defined as $sc[1+r_M(x^-,x)]$ (the fair value of investment in the market-security); $safe\ assets_{jt}$ is defined as $(1-s)c[1+r_f(x^-)]$ (the fair value of investment in the risk-free security); q_{jt} is defined as $v - c\big[1+(1-\tau)\big((1-s)r_f(x^-) + sr_M(x^-,x)\big)\big]$ (the fair value of total assets minus the after-tax fair value of financial assets, which is the fair value of physical capital); μ_j represents firm fixed effects; and μ_t represents year fixed effects. Due to the constant return to scale assumption, all variables can be interpreted as ratios over physical capital k, and Tobin's q can be interpreted as the marginal value of investment. The estimation results are presented in Table 2. The estimated coefficient on q is positive in the investment model and negative in the equity payout model, which indicates good investment opportunities drive up investment and deplete dividends. The estimated coefficient on *risky assets* is positive in both the investment model and the equity payout model. Based on the estimation results from the simulated data, I develop the following two hypotheses that will be tested in the empirical analysis:

Hypothesis I: The fair value of risky financial assets is positively correlated with investment rate ($\theta_1^i > 0$), controlling for the value of safe financial assets and the marginal value of investment.

Hypothesis II: The fair value of risky financial assets is positively correlated with equity payout rate ($\theta_1^e > 0$), controlling for the value of safe financial assets and the marginal value of investment.

The positive correlation between investment rate and the fair value of risky financial assets is intuitively straightforward. Since external financing is costly, the marginal cost of investment is lower through internal funding than through external financing. Therefore, fixing the marginal value of investment, more internal funding translates to lower marginal cost of investment and higher investment rate. This mechanism implies the coefficient on measures of internal funding is positive, controlling for the marginal value of investment. Since risky financial assets are part of internal funding, the coefficient on the fair value of risky financial assets should be positive, controlling for the marginal value of investment. The positive correlation between equity payout rate and the fair value of risky financial assets seems counter-intuitive at first glance, since the policy functions imply that optimal equity payout policy is counter-cyclical. However, in the model equity payout is the residual of internal funding, investment and saving decisions, and the counter-cyclical equity payout policy mechanically mirrors pro-cyclical investment funding demand driven by pro-cyclical investment opportunities. So after controlling for investment funding demand, the fair value of risky financial assets, which is part of internal funding, is also positively correlated with equity payout rate.

3.3 Firm Heterogeneity and Saving Behavior

Matching investment funding demand with internal funding to avoid external financing costs is the key mechanism behind the model. Since the cyclical intensity of investment funding demand and external financing costs are the two key economic forces determining saving behavior in the model, I conduct comparative statics along β_π (the cyclical intensity of the profits) and λ_1 (external financing costs) to explore how saving behavior is related to firm attributes. Notice that β_π itself is not enough to describe the incentive to invest in the market-security for the firm. Since β_π increases the sensitivity of investment opportunities and profits to the aggregate productivity shock at the same time, β_π may not measure the incentive to hold the market-security properly. The same applies to λ_1, even though high external financing costs intuitively increase the value of holding the market-security to alleviate financing constraints in the good states, external financing costs also affect q and the cyclical intensity of optimal investment policy at the same time.

In order to capture the incentive to hold the market-security properly, I follow the intuition sketched in Figure 5 to construct measures. In Figure 5 the blue lines are profits generated by capital as functions of the aggregate productivity shock and the red lines are investment funding demand as functions of the aggregate productivity shock. Sub-figure A shows a firm with weak incentive to hold the market-security. This firm has weak incentive to hold the market-security since the firm's "funding gap", defined as the difference between investment funding demand and profits, is not very sensitive to the aggregate productivity shock. Sub-figure B shows a firm with strong incentive to hold the market-security. Intuitively, this firm has strong incentive to hold the market-security since the firm faces large shortage of funding for investment, representing strong desire for liquidity, in the good states, but has extra liquidity, representing weak desire for liquidity, in the bad states. Therefore, this firm has strong incentive to transfer liquidity from the bad states to the good states to alleviate financing constraints in the good states, and the market-security makes it possible to transfer liquidity from the bad states to the good states.

Based on the above intuition, the sensitivity of the funding gap to the aggregate state may be a good candidate measure of the incentive to hold the market-security. In order to construct this measure empirically, I first need to know the investment funding demand. I use $\frac{1}{1+\psi_i} q_{jt-1}$ as the measure of investment funding demand in period $t-1$. This measure is derived from the model as follows. In the absence of external financing costs, the firm never saves and the optimal investment rate is approximated by $\frac{1}{1+\psi_i} q_{jt-1}$.[10] Since external financing costs also affect Tobin's q, $\frac{1}{1+\psi_i} q_{jt-1}$ measures the optimal investment rate conditional on the firm receiving an unexpected one period exemption (with probability 0, otherwise optimal investment policy will also be affected) of financing frictions, but expecting the financing frictions to be in place for all the future periods. Therefore, it is a measure of counter-factual optimal investment rate, which fits the definition of investment funding demand as the target investment rate the firm wants to achieve without altering the cyclical intensity of optimal investment policy. With a measure of investment funding demand, the funding gap is defined as the difference between investment funding demand and profits generated by capital as

$$funding\ gap_{jt} = \frac{1}{1+\psi_i} q_{jt-1} - (1-\tau)\pi_{jt-1},$$

which reflects the desirability for liquidity as illustrated in Figure 5. Then I estimate the following regression equation

[10]Based on the Bellman equation of the firm's problem, without external financing costs, the optimal saving is always 0, and the optimality condition of investment in period $t-1$ is given by

$$i_t^* = \frac{1}{1+\psi_i} \mathbf{E}\big[M(x_{t-1}, x_t) v(x_{t-1}, x_t, z_t, s_t, c_t) | x_{t-1}, z_{t-1}\big],$$

where $\mathbf{E}\big[M(x_{t-1}, x_t) v(x_{t-1}, x_t, z_t, s_t, c_t) | x_{t-1}, z_{t-1}\big]$ is the ex-dividend market-to-book ratio at the end of period $t-1$, which is also the marginal value of investment at the end of period $t-1$, and I use Tobin's q at the end of period $t-1$ as a proxy. See Hayashi (1982) for a detailed discussion.

$$funding\ gap_{jt} = \beta_j^F r_{Mt-1} + \mu_j + \varepsilon_{jt}, \tag{14}$$

where r_{Mt-1} is the return on the market-security from period $t-2$ to period $t-1$ and μ_j represents firm fixed effects, and I use $\hat{\beta}_j^F$, which I call "funding gap beta", as an empirical measure of the incentive to hold the market-security. $funding\ gap_{jt}$ captures the shortage of liquidity at period $t-1$, which the firm can purchase the market-security or the risk-free security in period $t-2$ to alleviate, and β_j^F measures the sensitivity of the funding gap on the ex-post market return. Intuitively, if the funding gap is very sensitive to the ex-post market return, which means the ex-post funding gap is highly correlated with the ex-post market return, the firm has strong incentive to purchase the market-security ex-ante.

I conduct comparative statics experiments for the parameter $\beta_\pi \in [1.0, 1.1]$ and $\lambda_1 \in [0.1, 0.2]$ following the above procedures. Figure 6 plots the results, including construction of funding gap beta $\hat{\beta}_j^F$ as functions of β_π and λ_1, the average fair value of investment in the market-security as functions of β_π and λ_1, and the average fair value of investment in the market-security as functions of $\hat{\beta}_j^F(\beta_\pi)$ and $\hat{\beta}_j^F(\lambda_1)$ respectively.

Regarding β_π, the cyclical intensity of the profits, we can see that the funding gap beta $\hat{\beta}_j^F$ exhibits decreasing pattern in β_π, indicating that the cyclical intensity of the funding gap is negatively correlated with the cyclical intensity of the profits. On the other hand, the fair value of investment in the market-security exhibits decreasing pattern in β_π. And consistent with the intuition behind the measure construction, the fair value of investment in the market-security exhibits increasing pattern in $\hat{\beta}_j^F$.

As for λ_1, external financing costs, the results are qualitatively similar to the results for β_π. The funding gap beta $\hat{\beta}_j^F$ exhibits decreasing pattern in λ_1, and the fair value of investment in the market-security exhibits decreasing pattern in λ_1 and increasing pattern in $\hat{\beta}_j^F$. Even though the fair value of investment in the market-security exhibits increasing pattern in $\hat{\beta}_j^F$, the relationship shows larger variance than the relationship generated by varying β_π. The reason is that both the funding gap beta and external financing costs are important determinants of saving behavior. Variation in β_π mainly influences saving behavior through the funding gap beta channel, so the relationship is more evident. Different from β_π, external financing costs play a more complicated role. On one hand, the funding gap beta exhibits decreasing pattern in λ_1, indicating that external financing costs reduce the cyclical intensity of the funding gap, and equivalently reduce the incentive to invest in the market-security through the funding gap beta channel. However, fixing the funding gap beta, high external financing costs intuitively should increase the incentive to invest in the market-security since more external financing costs can be saved in case of good investment opportunities. So external financing costs can effectively influence the incentive to invest in the market-security through two channels with opposite effects, which makes the net effects ambiguous and renders the relationship between the fair value of investment in the market-security and $\hat{\beta}_j^F$ more noisy. Based on the numerical experiments and the above arguments, I develop the following two hypotheses:

Hypothesis III: Firms with high funding gap beta (large β_j^F) hold more risky financial assets, controlling for external financing costs.

Hypothesis IV: Firms with high external financing costs (large λ_1) hold more risky financial assets, controlling for funding gap beta.

4 Data

This section describes the sample selection process, risky financial assets classification, and detailed construction of the funding gap beta.

4.1 Sample Selection

The data used in this study mainly comes from Compustat annual data from 1980 to 2018. Following the literature, I drop firms in regulated utility industry (SIC 4900-4999) and firms in financial industry (SIC 6000-6999), and observations with missing or negative total assets (Compustat item AT) or property, plant and equipment (Compustat item $PPEGT$). I then merge this sample with the fair value of risky financial assets data scraped from the SEC 10-K filings by CIK and fiscal year.[11] Then this data is merged with macroeconomic time-series data including producer price index from Bureau of Labor Statistics[12] and real GDP of chained 2009 dollars from Bureau of Economic Analysis.[13] The detailed definitions of main variables are presented in Table A.1 in Appendix C. In Table A.1, aggregate variables are defined following Covas and Den Haan (2011) except aggregate external financing and aggregate net external financing. Tobin's q and investment measures are defined following Fazzari, Hubbard, and Petersen (1988), Erickson and Whited (2012) and many others, which is found to perform best by Erickson and Whited (2006). Other firm level financial variables are defined following Bates et al. (2009) and Duchin et al. (2017). Finally I drop observations with more risky financial assets than total assets, which are almost surely caused by algorithm errors, and observations with $PPEGT$ less than 5 millions. Then for each fiscal year, I winsorize all variables in ratios at 1st and 99th percentiles, and I also winsorize estimated funding gap beta $\hat{\beta}_j^F$ at 1st and 99th percentiles. Estimation of funding gap beta and construction of financing constraint indices are discussed in section 4.3. In the key variable definitions, risky financial assets is scale by lagged $PPEGT$ when used as the dependent variable (corresponding to the control variable in the Bellman equation), and is scaled by current period $PPEGT$ when used as the right hand side variable in regressions (corresponding to the state variable in the Bellman equation). These definitions are more closely related to the theoretical model, and the results do not hinge on these definitions.

Table 3 presents summary statistics of key variables used in this study. The mean of risky financial assets is 35.3% of capital. For comparison, the mean of safe assets (Compustat item CH) is 97.0% of capital.

[11] A detailed description of the algorithm used to scrape the fair value of risky financial assets, and an out of sample accuracy test of the algorithm are presented in Appendix D.

[12] https://beta.bls.gov/dataViewer/view/timeseries/WPU03THRU15.

[13] https://www.bea.gov/national/xls/gdplev.xls.

4.2 Risky Financial Assets Classification

The classification of risky financial assets is different from Duchin et al. (2017). In Duchin et al. (2017), safe assets comprise money-like securities labeled as M4 (and L) by the Federal Reserve: cash, cash equivalents, time deposits, bank deposits, money market funds, commercial paper, and U.S. Treasury securities. But this cash equivalents defined by the Federal Reserve is not the cash equivalents on the firms' accounts, as noticed by Duchin et al. (2017):

> Contrary to the common view, firms may hold risky or illiquid assets in the balance sheet accounts "cash and cash equivalents" and "short-term investments." Therefore, the traditional measure of corporate cash holding may be overstated by including non-money-like financial assets.

Since the data used in Duchin et al. (2017) is manually collected, securities can be accurately classified as safe securities and risky securities based on the Federal Reserve's classification, and omitted items or other kind of complicated reporting structures can be detected manually.[14] These rules are hard to be implemented in the algorithm, and detecting all the anomalies implies that all the anomalies without systematic patterns need to be collected before programmed into the algorithm, which means all the filings need to be read manually. Therefore, I follow an easier to implement approach to determine whether a security is risky or not. When the reporting table is incomplete, the omitted items are more likely to be safe assets.[15] So I only scrape the fair value of risky financial assets from the disclosing tables by detecting risky securities. On the other hand, the names of safe securities are

[14]Some firms do not disclose all of their financial asset holdings in the disclosing table. See Appendices of Duchin et al. (2017) for an example, they find that Intel (INTC) does not report the actual cash in the table disclosing fair value information of financial assets. They detect this omitted item by comparing total value reported in the table and cash and cash equivalents accounts reported on the balance sheet. Some firms report the fair value of their financial assets in text instead of tables.

[15]As noted by Duchin et al. (2017), "SFAS No. 157 and the related SFAS No. 115 stipulate that firms must report the aggregate fair value, gross unrealized gains or losses, and amortized cost basis for at least the following major security types: equity securities, U.S. government and agency debt securities, U.S. municipal debt securities, foreign government debt securities, corporate debt securities, mortgage-backed securities, and other debt securities." This disclosing requirement means that safe assets like cash are less likely to be subject to the disclosure requirement.

more standardized than the names of risky securities, which makes them easier to detect than risky securities, so I classify a security as risky if it is not safe. This classification rule requires a set of safe securities, and I go through the definitions of Compustat item CH and $IVST$ to construct the set of safe securities. Following the spirit of Duchin et al. (2017), I classify all securities in Compustat item CH as safe, which include cash, bank receivables, bank drafts, bank acceptances, deposits, checks, letters of credit, and money orders. For securities in $IVST$, I classify commercial papers, treasuries, and money market funds as safe. After construction of the set of safe securities, I classify all securities not belong to the set of safe securities as risky. Besides, I also exclude any financial assets related to restricted cash, pension plan assets, any liabilities, assets held for compensation, and hedging activities.

4.3 Funding Gap Beta and Financing Constraint Indices

Funding gap beta β_j^F and external financing costs λ_1 are the two key economic forces determining the saving behavior based on the model predictions. Since both of these variables are not directly observable, I use Compustat quarterly data to estimate the funding gap beta β_j^F and construct five widely used financing constraint indices (non-dividend payer, unrated, Kaplan and Zingales (1997) index, Whited and Wu (2006) index, and Hadlock and Pierce (2010) index) as proxies for external financing costs λ_1.

To estimate funding gap beta, I first need to construct measures of funding gap. I start from Compustat quarterly data and restrict the sample to 20 years from 1999 to 2018. I drop firms in regulated utility industry (SIC 4900-4999) and firms in financial industry (SIC 6000-6999), and observations with missing or negative total assets (Compustat item ATQ) or property, plant and equipment (Compustat item $PPEGTQ$). I only keep firms with at least 20 quarters of data for either investment rate, R&D expenditure rate or total expenditure rate. Then I construct following 6 measures of funding gap:

$$
\begin{aligned}
theoretical\ gap\ i_{jt} &= \hat{\alpha}_j^i + \hat{\delta}_j^i q_{jt-1} - profits_{jt-1} \\
theoretical\ gap\ rd_{jt} &= \hat{\alpha}_j^{rd} + \hat{\delta}_j^{rd} q_{jt-1} - profits_{jt-1} \\
theoretical\ gap\ tex_{jt} &= \hat{\alpha}_j^{tex} + \hat{\delta}_j^{tex} q_{jt-1} - profits_{jt-1} \\
realized\ gap\ i_{jt} &= i_{jt} - profits_{jt-1} \\
realized\ gap\ rd_{jt} &= rd_{jt} - profits_{jt-1} \\
realized\ gap\ tex_{jt} &= tex_{jt} - profits_{jt-1},
\end{aligned}
\tag{15}
$$

where j indexes firms and t indexes fiscal quarter; q_{jt} is Tobin's q at the end of fiscal quarter t; $profits_{jt}$ is defined as operating income before depreciation (Compustat item $OIBDP$) over physical capital at the end of fiscal quarter t; i_{jt}, rd_{jt} and tex_{jt} are investment rate, R&D expenditure rate and total expenditure rate respectively. Total expenditure rate is defined as investment rate plus R&D expenditure rate. Coefficients $(\hat{\alpha}_j^i, \hat{\delta}_j^i)$, $(\hat{\alpha}_j^{rd}, \hat{\delta}_j^{rd})$ and $(\hat{\alpha}_j^{tex}, \hat{\delta}_j^{tex})$ are estimated from the following q-theory investment models for each firm j individually

$$
\begin{aligned}
i_{jt} &= \alpha_j^i + \delta_j^i q_{jt-1} + \varepsilon_{jt} \\
rd_{jt} &= \alpha_j^{rd} + \delta_j^{rd} q_{jt-1} + \varepsilon_{jt} \\
tex_{jt} &= \alpha_j^{tex} + \delta_j^{tex} q_{jt-1} + \varepsilon_{jt}.
\end{aligned}
\tag{16}
$$

where all the investment measures and Tobin's q are winsorized at 1st and 99th percentiles for each fiscal year. After construction of funding gap measures, I winsorize all the funding gap measures at 1st and 99th percentiles for each fiscal year.

The theoretical constructions of the funding gap exactly follow section 3.3 and use a q-theory investment model to predict unobserved counter-factual optimal investment rate.[16]

[16] Based on the Bellman equation of the firm's problem, without external financing costs, the optimal saving is always 0, and the optimality condition of investment in period $t-1$ is given by

$$
i_t^* = \frac{1}{1+\psi_i}\mathbf{E}\big[M(x_{t-1}, x_t)v(x_{t-1}, x_t, z_t, s_t, c_t)|x_{t-1}, z_{t-1}\big],
$$

where $\mathbf{E}\big[M(x_{t-1}, x_t)v(x_{t-1}, x_t, z_t, s_t, c_t)|x_{t-1}, z_{t-1}\big]$ is the ex-dividend market-to-book ratio at the end of period $t-1$, which is also the marginal value of investment and a sufficient statistic for optimal investment decision. The empirical counterpart of this optimality condition is

$$
i_{jt} = \alpha + \delta q_{jt-1} + \varepsilon_{jt},
$$

The theoretical constructions of the funding gap have the appealing advantage of capturing the unobservable target investment rate the firms try to achieve through available saving technologies, but due to the poor empirical performance of the q-theory and the measurement error problems rooted in using average q as a proxy for marginal q, the observed investment rate may be a better empirical measure of the unobservable counter-factual optimal investment rate than the investment rate predicted by the q-theory, so I also construct funding gap measures using observed investment rate directly.

After construction of funding gap measures, the data is merged with U.S. aggregate bond market index data from Bloomberg by calendar year-month for each firm to estimate funding gap beta. I use bond market index returns to estimate funding gap beta instead of equity market returns as most of the risky financial assets on firms' balance sheets are bond securities. If hedging investment funding demand is the key motivation behind the investment in those risky financial assets, then funding gap beta estimated from bond market returns is a better measure than funding gap beta estimated from equity market returns as the incentive to invest in those risky financial assets (mainly bond securities). I estimate the funding gap beta β_j^F using the following time-series regressions for each firm j

$$funding\ gap_{jt} = \beta_j^F r_{Mt-1} + \varepsilon_{jt} \tag{17}$$

where the funding gap can be each of the funding gap measures defined in equation (15), and r_{Mt-1} is the U.S. bond market return from fiscal quarter $t-2$ to $t-1$.

I follow Farre-Mensa and Ljungqvist (2016) and use Compustat annual data to construct financing constraint indices. Detailed construction of financing constraint indices are presented in Appendix E. A firm is classified as non-dividend payer if the firm does not pay any cash dividend between 1999 and 2018. A firm is classified as unrated if the firm does not

where q_{jt-1} is Tobin's q at the end of period $t-1$. Based on the arguments in section 3.3, different from observed investment rate i_{jt}, which is the observed optimal investment rate with financing constraints, estimated $\hat{i}_{jt}$ is the counter-factual target investment rate conditional on the firm receiving one-period exemption of financing frictions, therefore the optimal investment rate without altering the cyclical intensity of optimal investment policy.

have Standard and Poor's credit rating for long term issuer credit rating (Compustat item *SPLTICRM*). When I use either KZ index, WW index, or HP index as the financing constraint index, following convention firms are sorted into terciles based on their index values in the previous year. Firms in the top tercile are coded as financially constrained and firms in the bottom tercile are coded as financially unconstrained.

5 Results

In this section I present empirical evidence regarding the cyclical pattern of aggregate investment and financing activities, the relationship between the value of risky financial assets and investment/dividends policies, and the relationship between firm heterogeneity and saving behavior.

5.1 Cyclical Behavior of Investment and Financing

In this section, I document the cyclical behavior of aggregate investment and financing activities following Covas and Den Haan (2011). Hodrick and Prescott (1997) filter is used to compute the cyclical component of all the aggregate series.

Figure 1 shows the cyclical behavior of aggregate investment, and Figure 2 shows the cyclical behavior of aggregate financing activities. Table 4 presents correlations between aggregate investment and financing activities and real GDP and lagged real GDP. Consistent with the model predictions, all the correlations between investment measures (aggregate investment, R&D expenditure and total expenditure) and real GDP series are positive and significant at the 5% level, suggesting investment opportunities and investment funding demand exhibit systematically pro-cyclical patterns. The correlations between debt financing measures (aggregate debt issuance and net debt issuance) and real GDP series are all positive and statistically significant at the 5% level. The correlations between equity financing measures (aggregate sales of equity and change in book equity) and real GDP series are all positive but less evident, with the only correlation between sales of equity and real GDP significant at the 5% level. The correlations between aggregate financing activities and real GDP series are both qualitatively and quantitatively similar to those in Covas and Den Haan (2011) and Begenau and Salomao (2018), and these positive correlations are consistent with the model mechanism that investment opportunities drive up investment funding demand and push firms to tap external financing. Since I do not differentiate debt financing and equity financing in the model, neither debt financing nor equity financing fits well the external financing in the model, and I construct two other measures of external financing more inline with the spirit of the model. One measure is aggregate external financing, defined as sales of equity plus debt issuance, and the other measure is aggregate net external financing, defined as change in book equity plus net debt issuance. From Table 4 we can see that these external financing measures also exhibit pro-cyclical patterns.

5.2 Investment, Dividends and Savings

To test the hypothesis regarding investment, dividend and the fair value of risky financial assets, I specify the regression equation as follows

$$y_{jt} = \theta_1 risky\ assets_{jt-1} + \theta_2 safe\ assets_{jt-1} + \theta_3 q_{jt-1} + \mu_j + \mu_t + \varepsilon_{jt}, \tag{18}$$

where j indexes firms and t indexes fiscal year; the dependent variable y_{jt} can be either investment rate i_{jt}, R&D expenditure rate rd_{jt}, dividend rate div_{jt}, or total expenditure rate tex_{jt}; $risky\ assets_{jt}$ is defined as the fair value of risky financial assets over property, plant and equipment at the end of fiscal year t; $safe\ assets_{jt}$ is defined as cash over property, plant and equipment at the end of fiscal year t; q_{jt} is Tobin's q at the end of fiscal year t; μ_j represents firm fixed effects; and μ_t represents year fixed effects.

Table 5 presents the OLS estimation results of equation (18). First of all, the estimated coefficient on q is positive when either the investment rate, R&D expenditure rate or total expenditure rate is used as the dependent variable, and the coefficient on q is negative when the dividend rate is used as the dependent variable. These values indicate that investment opportunities drive up investment funding demand and deplete dividend, as suggested by the model. The variable of interest is *lagged risky assets*. Based on the model predictions, when external financing is costly, internal funding is positively correlated with both the investment rate and the dividend rate once the marginal value of investment is fixed. Since risky financial assets are part of internal funding, coefficient on *lagged risky assets* should be positive when either the investment rate or the dividend rate is used as the dependent variable. The same arguments apply to *lagged safe assets*. Consistent with **Hypothesis I**, the estimated coefficient on *lagged risky assets* is positive and statistically significant at the 5% level when either the investment rate, R&D expenditure rate or total expenditure rate is used as the dependent variable. The estimated coefficient on *lagged safe assets* is also positive and statistically significant at the 5% level when either the investment rate, R&D expenditure rate or total expenditure rate is used as the dependent variable, which is also consistent with the model predictions. These values imply that a one percent increase in the fair value of risky financial assets as percentage of capital is associated with 0.0081% increase in the investment, 0.0861% increase in the R&D expenditure, and 0.0951% increase in the total expenditure. Consistent with **Hypothesis II**, the estimated coefficient on *lagged risky assets* is positive and statistically significant at the 10% level and the estimated coefficient on *lagged safe assets* is also positive and statistically significant at the 5% level when dividend rate is used as the dependent variable. The results indicate that a one percent increase in the fair value of risky financial assets is associated with 0.0621% increase in dividend rate.

5.3 Firm Heterogeneity and Saving Behavior

I use Fama-MacBeth cross-sectional regressions to test the hypotheses regarding firm heterogeneity and saving behavior. I specify the regression equation as

$$risky\ assets_{jt} = \gamma_t^{\beta}\hat{\beta}_j^F + \gamma_t^{FCH} FCH_{jt-1} + \gamma_t^{FCL}(FCL_{jt-1} + FCH_{jt-1}) + \mu_{sic} + \varepsilon_{jt} \quad (19)$$

where j indexes firms and t indexes fiscal year; the dependent variable $risky\ assets_{jt}$ is the fair value of risky financial assets over property, plant and equipment at the end of fiscal year t; $\hat{\beta}_j^F$ is funding gap beta estimated from time-series regressions for each firm j; FCH_{jt} is financing constraint dummy; FCL_{jt} is financing unconstraint dummy; and μ_{sic} represents industry fixed effects. A firm is classified as financially constrained if the firm does not pay any dividend between 1999 and 2018 and unconstrained otherwise when dividend is used to construct the financing constraint dummy. A firm is classified as financially constrained if the firm does not have credit rating for long term debt issuance from Standard and Poor's and unconstrained otherwise when credit rating is used to construct the financing constraint dummy. When either KZ index, WW index, or HP index is used to construct the financing constraint dummy, firms are sorted into terciles based on financing constraint index used. Firms in the top tercile are classified as financially constrained and firms in the bottom tercile are classified as financially unconstrained based on the corresponding index value. The coefficient γ_t^{FCH} captures the difference of risky financial asset holdings between financially constrained and financially unconstrained firms.

The variables of interest are funding gap beta $\hat{\beta}_j^F$ and financing constraint dummy FCH_{jt-1}. These two variables are designed to capture the major economic forces determining saving behavior based on the model predictions. Funding gap beta captures the sensitivity of investment funding demand in excess of profits to returns of risky financial assets. Ceteris paribus, firms with high funding gap beta should have strong incentive to transfer liquidity from states with low aggregate investment opportunities to states with high aggregate investment opportunities by investing in risky financial assets. On the other hand, fixing funding gap beta, firms with high external financing costs should have strong incentive to invest in risky financial assets since more external financing costs can be saved by investing in risky financial assets to exploit good investment opportunities. Based on the model predictions, both γ^{β} and γ^{FCH} should be positive.

Table 6 presents the estimation results of Fama-MacBeth cross-sectional regressions of risky financial assets on various measures of funding gap beta and financing constraints, using dividend payer as the financing constraint index. Specifically, six measures of funding gap beta are used to estimate equation (19), investment measure stands for the investment measure (either one of investment rate i_{jt}, R&D expenditure rate rd_{jt}, or total expenditure rate tex_{jt}) used to construct the funding gap measure and estimate the funding gap beta in the first stage time-series regressions, and q-theory investment measure indicates whether or not the q-theory predicted investment rate is used as the counter-factual optimal investment rate to construct funding gaps before estimating the funding gap beta. I report coefficients on funding gap beta in panel A and coefficients on financing constraint dummy in panel B, together with time-series average and standard errors of these coefficients at the end. Table 7 presents the estimation results using other four financing constraint indices. In this table I do not present the estimated coefficients for each period. In each panel, I only report the time-series average of coefficient $\hat{\gamma}_t^{\beta}$ and $\hat{\gamma}_t^{FCH}$ with their respective standard errors.

Table 6 and Table 7 present results showing that funding gap beta is positively correlated with the fair value of risky financial assets, which are consistent with **Hypothesis III**. $\hat{\gamma}^{\beta}$'s are all positive, statistically significant at the 5% level, and quantitatively similar across various measures of funding gap beta and financing constraint index I used. The value of $\hat{\gamma}^{\beta}$ varies between 0.03 and 0.06. This implies a one unit increase in funding gap beta is positively associated with a 3% to 6% (as percentage of capital book value) increase in risky financial asset holdings. This is economically meaningful considering the median of safe asset holdings (Compustat item CH) is about 28.8% of capital book value.

I find mixed evidence regarding **Hypotheis IV**. Fixing funding gap beta, Table 6 and Table 7 show that financing constraint dummy is positively correlated with risky financial asset holdings when either dividend, credit rating, or the HP index is used as the financing constraint index, and the value of $\hat{\gamma}^{FCH}$ varies between 0.07 and 0.4, which implies financially constrained firms hold 7% to 40% (as percentage of capital book value) more risky financial assets than their unconstrained counterparts with same capital. These estimation results are consistent with the view that firms facing greater financing frictions hold more cash.[17] But the financing constraint dummy is negatively correlated with risky financial asset holdings when the WW index or the KZ index is used as the financing constraint index, and the value of $\hat{\gamma}^{FCH}$ varies between -0.45 to -0.15, which implies financially unconstrained firms hold 15% to 45% (as percentage of capital book value) more risky financial assets than their constrained counterparts with same capital. The evidence regarding the relationship between financing constraint indices and risky financial asset holdings should be interpreted more cautiously, as pointed out by Farre-Mensa and Ljungqvist (2016) that the five widely used financing constraint indices can not identify firms that behave as if they were in fact constrained.

5.4 Robustness Checks

5.4.1 Control Variables

The model parsimoniously demonstrates the motivation and trade-off determining corporate investment in risky financial assets, and the empirical analysis is based on variables mapped from the model. In order to alleviate the concern that the empirical results may be driven by other omitted variables not modeled explicitly, in this section I repeat the empirical analysis with control variables defined following Bates et al. (2009) and Duchin et al. (2017).

Table 8 presents the estimation results of equation (18) by including control variables. The results are both qualitatively and quantitatively similar to the results in Table 5. The estimated coefficients on *lagged risky assets* are all positive and statistically significant at the 5% level. A one percent increase in the fair value of risky financial assets is positively associated with 0.0120% increase in investment rate, 0.0942% increase in R&D expenditure rate, 0.1074% increase in total expenditure rate, and 0.0715% increase in dividend rate.

[17] Almeida, Campello, and Weisbach (2004) argue that firms facing greater financing frictions save a larger portion of their cash flow as cash reserves. Denis and Sibilkov (2009); M. Faulkender and Wang (2006); Pinkowitz and Williamson (2002) argue that cash holdings are more valuable for financially constrained firms.

Table 9 presents the estimation results of equation (19) by including control variables. The results are both qualitatively and quantitatively similar to the results in Table 6 and Table 7. The estimated coefficient on funding gap beta varies between 0.03 to 0.05, which implies that a one unit increase in funding gap beta is positively associated with 3% to 5% increase in risky financial assets. The estimated coefficient on financing constraint dummy is positive when either dividend payment, credit rating, or HP index is used as the financing constraint index, and negative when KZ index or WW index is used as the financing constraint index.

5.4.2 Peters and Taylor (2017)'s Total q

Peters and Taylor (2017) construct a new measure of Tobin's q and conduct a series of tests to show their measure is superior than the traditional measure of Tobin's q. Following Peters and Taylor (2017) and Andrei, Mann, and Moyen (2019), in this section I repeat the analysis using their Total q as robustness checks. I do not use their total q in the main analysis for three reasons: (1) Since Peters and Taylor (2017) do not provide quarterly data for intangible capital, I have to construct quarterly intangible capital stock based on their annual data and Compustat quarterly data in order to estimate funding gap beta using their total q measure;[18] (2) Peters and Taylor (2017)'s total q do exhibit superior performance than the standard q in the investment regressions, but their total q measure does not perform

[18] I follow Appendix B in Peters and Taylor (2017) to construct quarterly intangible capital stock. Specifically, I first replace Compustat item *XSGAY, XRDY* and *RDIPY* with 0 if missing, and construct *SGAY* as *XSGAY* minus *XRDY* minus *RDIPY*. I then replace *SGAY* with *XRDY* if *XRDY* exceeds *XSGAY* but is less than *COGSY*, and replace *SGAY* with 0 if *XSGAY* is 0. Intangible capital stock k_{yq}^{int} in fiscal year-quarter yq is constructed as follows

$$k_{yq}^{int} = \begin{cases} K_y^{int}, & if\ q = 4 \\ (1 - q\dfrac{\delta^{know}}{4})K_{y-1}^{know} + XRDY_{yq} + (1 - q\dfrac{\delta^{org}}{4})K_{y-1}^{org} + 0.3SGAY_{yq}, & if\ q \neq 4 \end{cases}$$

where K_y^{int}, K_y^{know} and K_y^{org} are annual intangible capital stock, knowledge capital stock and organization capital stock from Peters and Taylor (2017); $\delta^{know} = 0.15$ is the annual depreciation rate of knowledge capital stock; and $\delta^{org} = 0.2$ is the annual depreciation rate of organization capital stock. Peters and Taylor (2017) also use more heterogeneous depreciation rate of knowledge capital for different industries, I use 15% for all industries for simplicity.

better than the standard q in the R&D investment and total investment regressions in my sample; (3) Peters and Taylor (2017)'s data is available until 2017, and their 2017 data is limited, so I also have to exclude one year's observations using their total q measure.

Table 10 presents the estimation results of equation (18) by including control variables and using Peters and Taylor (2017)'s total q. The results are qualitatively similar to the results in Table 8. The estimated coefficients on *lagged risky assets* are all positive and statistically significant at the 5% level. A one percent increase in the fair value of risky financial assets is positively associated with 0.0121% increase in investment rate, 0.0334% increase in R&D expenditure rate, 0.0562% increase in total expenditure rate, and 0.0494% increase in dividend rate.

Table 11 presents the estimation results of equation (19) by including control variables and using Peters and Taylor (2017)'s total q. The results are qualitatively similar to the results in Table 9. The estimated coefficient on funding gap beta varies between 0.01 to 0.03, which implies that a one unit increase in funding gap beta is positively associated with 1% to 3% increase in risky financial assets. The estimated coefficient on financing constraint dummy is positive when either dividend payment, credit rating, or HP index is used as the financing constraint index, and negative when KZ index or WW index is used as the financing constraint index.

5.5 Endogeneity Concerns

5.5.1 Measurement Errors

In investment regressions, it is well known that measurement error in q can cause downward bias in estimation of coefficient on q and upward bias in estimation of coefficient on cash flow measures due to positive correlation between cash flow measures and q, as shown in Erickson and Whited (2000). On the other hand, since the data of firms' risky financial asset holdings is not completely accurate either, risky financial asset measure also contains measurement errors. Therefore OLS estimations can be biased and unreliable. In this section I conduct analysis taking into account measurement errors in both q and risky financial asset holdings. As both Almeida, Campello, and Galvao Jr (2010) and Erickson and Whited (2012) report good performance of instrumental variable method in dealing with measurement errors in their simulation analysis, I choose instrumental variable regressions following Almeida et al. (2010), also Griliches and Hausman (1986) and Biorn (2000) to deal with the measurement errors in regressors. I estimate the following equation

$$y_{jt} = \theta_1 risky\ assets^*_{jt-1} + \theta_2 safe\ assets_{jt-1} + \theta_3 q^*_{jt-1} + \mu_j + \mu_t + \varepsilon_{jt}, \tag{20}$$

with

$$\begin{aligned} risky\ assets_{jt-1} =& risky\ assets^*_{jt-1} + \varepsilon^{rf}_{jt-1} \\ q_{jt-1} =& q^*_{jt-1} + \varepsilon^{q}_{jt-1}, \end{aligned}$$

where $risky\ assets^*_{jt-1}$ and q^*_{jt-1} are true values of risky financial asset holdings and q. I take difference of equation (20) and use three-period lagged variables $risky\_assets_{jt-3}$ and q_{jt-3} as instrumental variables for $\Delta risky\_assets_{jt-1}$ and Δq_{jt-1}.

Table 12 presents the estimation results of equation (20). Kleibergen-Kaap first-stage F is reported as suggested by Andrews, Stock, and Sun (2019). Although the bias caused by measurement errors is complicated to gauge with two mismeasured regressors, but we can see that the absolute values of coefficients on *lagged Tobin's q* in Table 12 are all greater than their respective counterparts in Table 5, suggesting the measurement error indeed biases estimation of coefficients on q toward zero. Also consistent with the literature, the t-values of coefficients on cash holding measures drastically decrease when investment, R&D expenditure or total expenditure is used as the dependent variable, except the coefficient on *lagged safe assets* when investment rate is used as the dependent variable. Finally, *lagged safe assets* is also positively associated with dividend rate.

Although measurement errors can cause major concerns in the investment analysis, it is less of a concern in the saving behavior analysis. In the analysis of saving behavior, risky financial asset holdings is used as the dependent variable. With classical measurement error assumptions, measurement error in risky financial assets will increase standard errors and reduce t-values of estimated coefficients. Also with classical measurement error assumptions, measurement errors in funding gap beta will attenuate estimated coefficients on funding gap beta and associated t-values toward zero.

5.5.2 Corporate Governance, Risk-Seeking and Overconfidence

Although measurement errors are not major concerns in saving behavior analysis, there are several omitted variables of particular interest that can cause biased estimation of the relationship between funding gap beta and risky financial asset holdings. As noted by Duchin et al. (2017), poor corporate governance, stock compensation and option compensations are all positively associated with risky financial asset holdings. Both poor corporate governance and high stock/option compensation can stimulate risk-seeking behavior of CEOs to exploit convex incentives, which can lead CEOs to pursue high beta investment strategy and high beta saving strategy simultaneously and potentially cause upward bias in the estimation of coefficient of interest. In order to alleviate these concerns, I add blockholder ownership, stock compensation, and option compensation as control variables for corporate governance and CEO risk-seeking incentives. Since the data used to construct the corporate governance E-index used by Dittmar and Mahrt-Smith (2007) and Bebchuk, Cohen, and Ferrell (2008) are only available until 2002 and the sample period starts from 2009 in this study, I choose blockholder ownership as the control variable for corporate governance, which is also used in Duchin et al. (2017).

Apart from corporate governance and CEO risk-seeking incentives, extrapolated beliefs can also cause CEOs to purse high beta investment strategy and high beta saving strategy, which leads upward bias in the estimation of coefficient of interest. However, there is no commonly used measure for extrapolated beliefs, as most of the literature on extrapolated beliefs use data to gauge the underlying bias by mapping extrapolated belief bias into observed variables through structural models instead of directly construction of extrapolated belief measures.[19] So I do not include direct controls for CEO extrapolated beliefs. However, CEO overconfidence may cause consequences similar to extrapolated beliefs if CEOs are risk-averse. When CEOs are risk-averse but over estimate the precision of signals due to overconfidence, overconfident CEOs will overreact to signals compared with rational CEOs, therefore overconfidence may also cause upward bias in the estimation of coefficient of interest. Duchin et al. (2017) also find that CEO overconfidence is positively associated with risky financial asset holdings. Although they interpret the results as evidence of overconfident CEOs overestimate their ability in generating positive abnormal returns, the results can also be interpreted as CEOs overreact to noisy signals induced by overconfidence. Therefore, I include control variables for CEO overconfidence. I construct *holder 67* as a control variable for CEO overconfidence following T. C. Campbell, Gallmeyer, Johnson, Rutherford, and Stanley (2011) and Hirshleifer, Low, and Teoh (2012), who construct the measure following Malmendier and Tate (2005, 2008) and Malmendier, Tate, and Yan (2011). Besides, I also include *gender* as a control variable for CEO overconfidence.

Table 13 presents estimation results of (19) by including controls for corporate governance, risk-seeking incentives and CEO overconfidence. The results in Table 13 are qualitatively similar to the results in Table 9. The estimated coefficient on funding gap beta varies from 0.08 to 0.12, which means a one unit increase in funding gap beta is positively associated with 8% to 12% increase in risky financial asset holdings. The estimated coefficient on financing constraint dummy is positive when credit rating is used as the financing constraint index, negative when KZ index is used as the financing constraint index, and insignificant when dividend payment, WW index or HP index is used as the financing constraint index.

[19] E.g. Alti and Tetlock (2014); Barberis, Greenwood, Jin, and Shleifer (2015); Bordalo, Gennaioli, Ma, and Shleifer (2018); Bordalo, Gennaioli, and Shleifer (2018).

6 Conclusion

As documented by Duchin et al. (2017), corporate saving compositions are more complicated than traditionally assumed. Since industrial firms are heavily invested in risky financial assets, it is important to understand the motivation behind those investments. Based on a dynamic investment-saving model, I show that corporate investment in risky financial assets can arise as equilibrium results of financing frictions and macroeconomic fluctuations.

Using a machine-learning algorithm, I conduct empirical tests of hypotheses developed from the model based on a comprehensive dataset regarding corporate risky financial asset holdings. I find that the value of risky financial assets is positively correlated with investment rate. More interestingly, I find that the cyclical intensity of investment funding demand in excess of profits is indeed positively correlated with risky financial asset holdings, as predicted by the model. On top of that, I find mixed evidence regarding external financing costs and risky financial asset holdings. As noted by Farre-Mensa and Ljungqvist (2016), it should be noted that the empirical evidence regarding external financing costs should be interpreted with more caution due to the fact that these indices can not identify firms behaving as if they were financially constrained.

Admittedly, the empirical evidence in this study does not fully exclude reverse causality or some other potential explanations (e.g., managerial extrapolated beliefs) and establish the causal link between risky financial asset holdings and the cyclical intensity of investment funding demand/external financing costs, which is relevant in order to identify the motivation and causal link behind this shadow fund industry, but also challenging due to the unobservable nature of both variables, and I leave it for future research.

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Figures

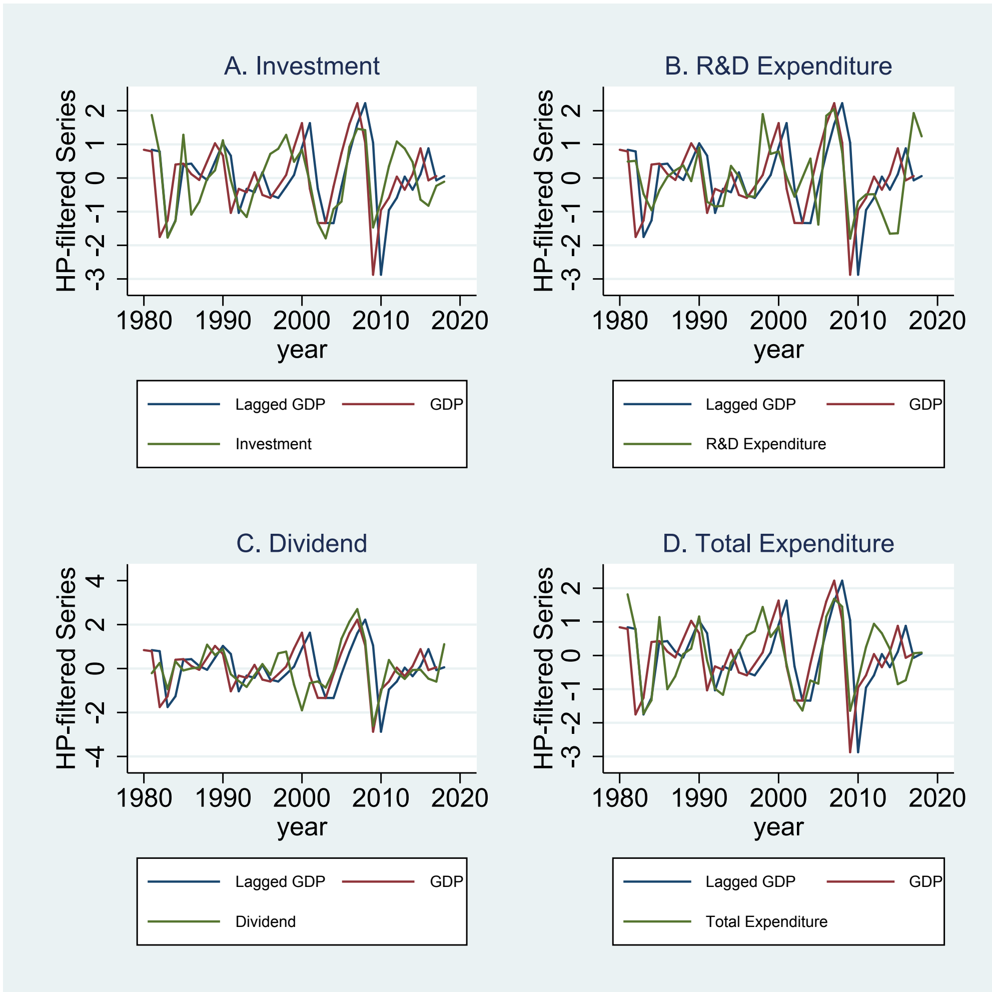

Figure 1
Aggregate Investment, R&D and Dividend
This figure shows cyclical behavior of aggregate investment, R&D expenditure, dividend and total expenditure (investment plus R&D expenditure), together with real GDP and lagged real GDP. Detailed definitions of all variables are presented in table A.1. All series are HP-filtered.

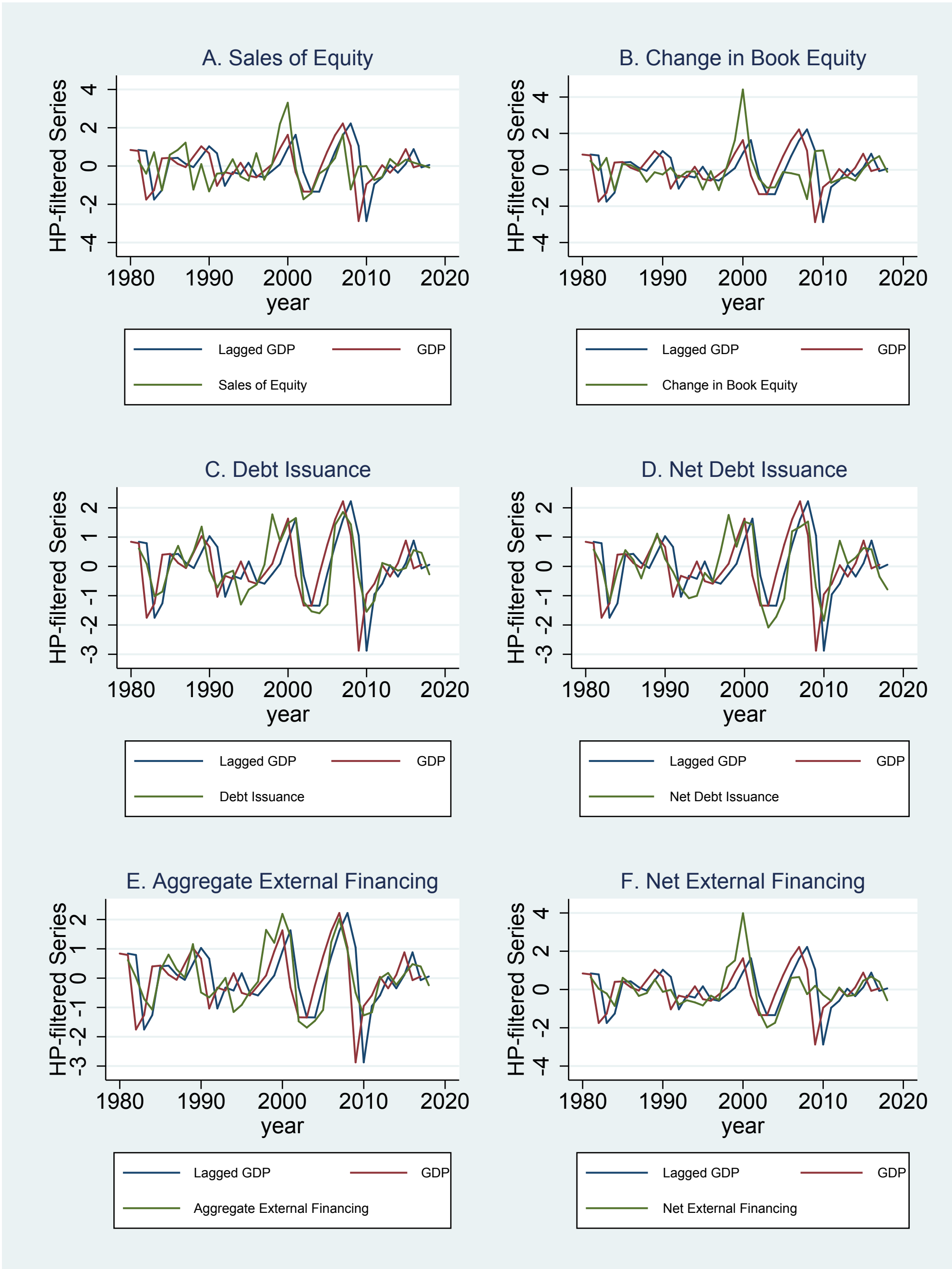

Figure 2
Aggregate External Financing
This figure shows cyclical behavior of aggregate equity financing and debt financing, together with lagged real GDP and lagged real GDP. Detailed definitions of variables are presented in table A.1. All series are HP-filtered.

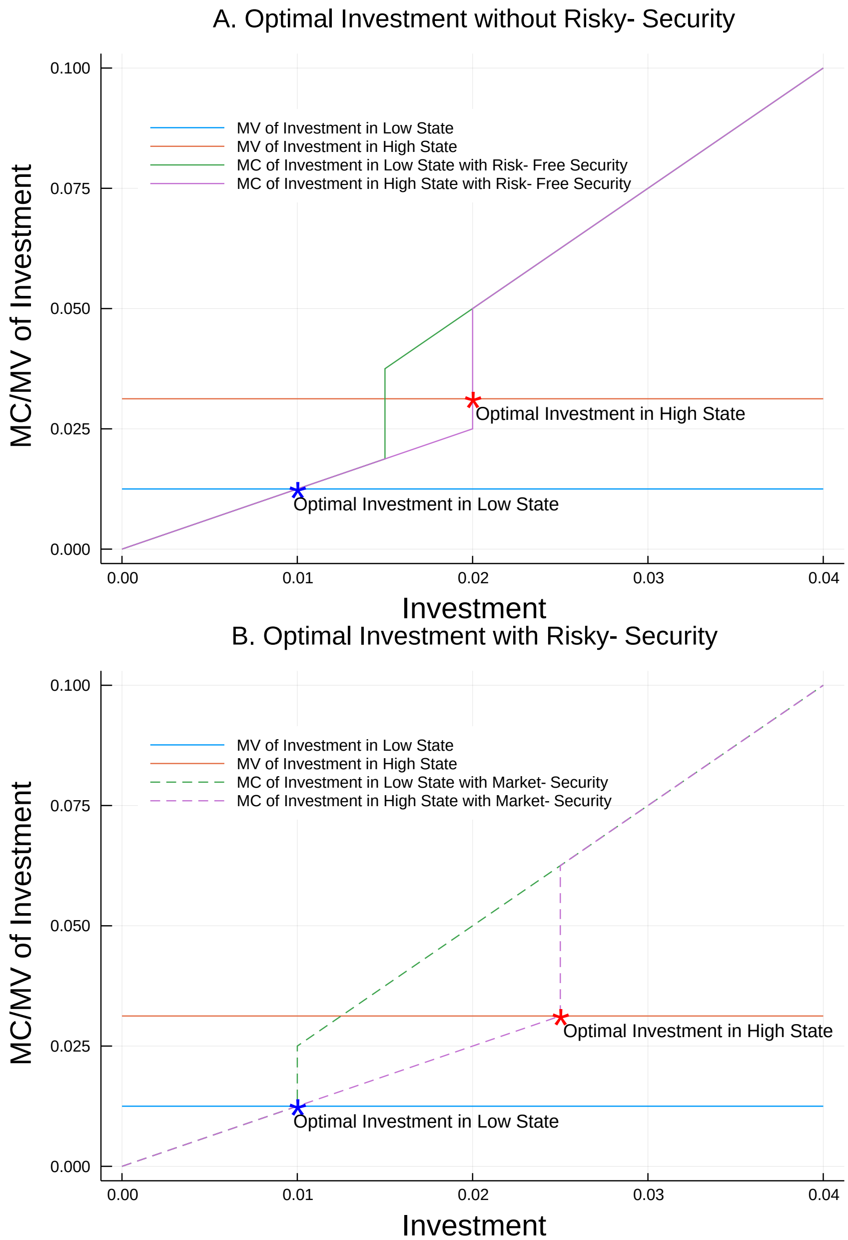

Figure 3
Intuition Illustration
This figure shows why investment in risky financial assets can be valuable by analyzing optimal investment decisions. Marginal cost of investment jumps at the point investment exceeding internal funding. Panel A shows a situation where optimal investment is not constrained in the Low state but is constrained by external financing costs in the High state. Panel B shows a situation assuming the firm has invested in risky financial assets in the previous period. In panel B, optimal investment can be financed through internal funding in both the Low and High states.

Figure 4
Policy Functions
This figure shows the optimal response of investment, savings in the market-security, savings in the risk-free security and equity payout in response to the aggregate productivity shock x.

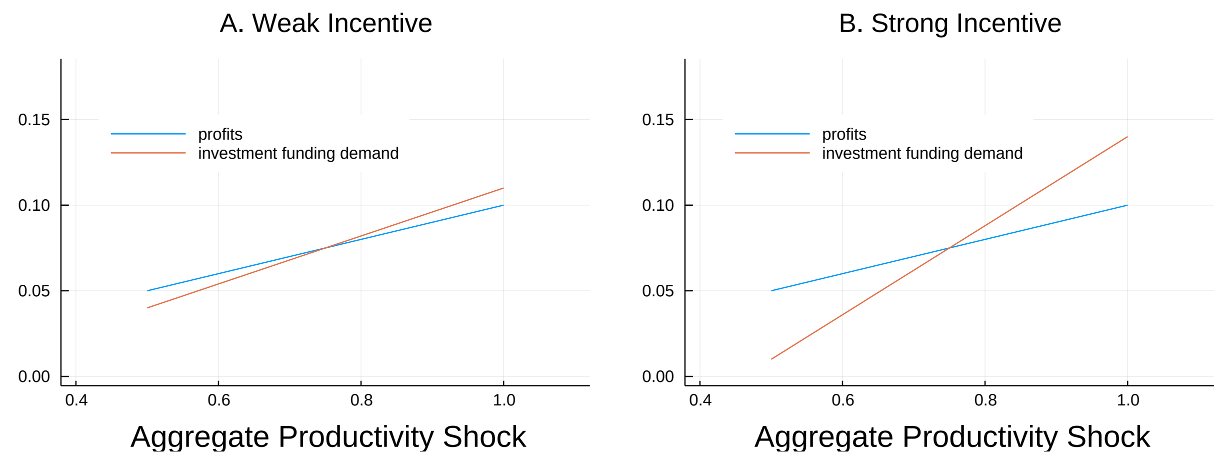

Figure 5
Intuition Behind Measure of Incentive to Hold the Market-Security
This figure shows the intuition used to guide the construction of measure to capture the incentive to hold the market-security. Panel A shows a firm with weak incentive to hold the market-security and Panel B shows a firm with strong incentive to hold the market-security.

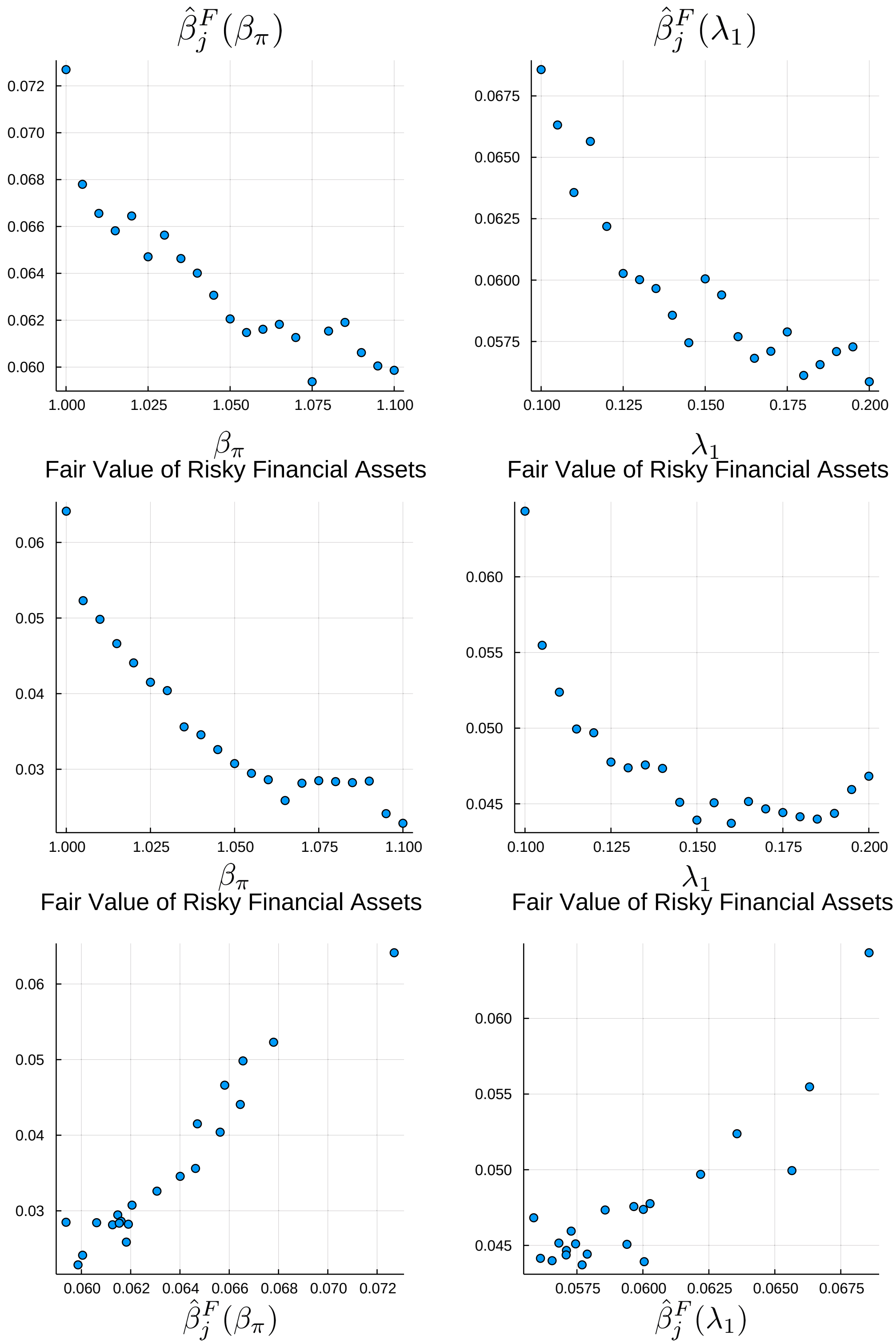

Figure 6

Firm Heterogeneity and Saving Behavior

This figure shows the relationships between parameters of interest (cyclical intensity of profits β_π and external financing costs λ_1) and moments of interest (funding gap beta and the fair value of risky financial assets over capital).

Tables

Table 1
Parameter Choices

Parameter	Value	Description	Note
ρ_x	0.95^4	Persistence of x	KP (1982)
σ_x	$0.0248\sqrt{\frac{1+\rho_x}{2}}$	Conditional Standard Deviation of x	Savov (2011)
η	0.95	Time Preference	Savov (2011)
γ_0	9.0	Risk Averse Parameter	Savov (2011)
γ_1	$-\gamma_0/\rho_x$	Risk Averse Parameter	
β_π	1.0	Cyclical Intensity of Profits	Standardized
τ	0.20	Tax Rate	NW (2014)
δ	0.15	Depreciation Rate	RW (2009)
ρ_z	0.66	Persistence of z	RW (2009)
σ_z	0.121	Conditional Standard Deviation of z	RW (2009)
f	0.82	Operation Costs	
ψ_i	1.281	Quadratic Capital Adjustment Costs	
ψ_a	0.0015	Costs of Holding Market-Security	
λ_1	0.10	Linear External Financing Costs	BLY (2018)

Table 2
Investment, Dividend and Savings

	Investment	Equity Payout
lagged risky assets	0.0802	0.1129
	(0.0007)	(0.0019)
lagged safe assets	0.0525	0.1370
	(0.0004)	(0.0011)
lagged Tobin's q	0.4097	-0.1356
	(0.0002)	(0.0004)
Year FEs	Yes	Yes
Firm FEs	Yes	Yes

In this table, I develop hypotheses regarding investment, dividend and the fair value of risky financial assets using simulated data. I simulate an artificial panel with 3,000 firms over 100 years, keep the last 50 years, and estimate following regressions

$$i_{jt} = \theta_1^i risky\ assets_{jt-1} + \theta_2^i safe\ assets_{jt-1} + \theta_3^i q_{jt-1} + \mu_j + \mu_t + \varepsilon_{jt}$$
$$e_{jt} = \theta_1^e risky\ assets_{jt-1} + \theta_2^e safe\ assets_{jt-1} + \theta_3^e q_{jt-1} + \mu_j + \mu_t + \varepsilon_{jt},$$

The dependent variables are investment rate and equity payout rate respectively. *risky assets* refers to the fair value of investment in the market-security over physical capital and *safe assets* refers to the fair value of investment in the risk-free security over physical capital. q is defined as the fair value of the firm's total assets minus after-tax fair value of financial portfolio, then divided by physical capital. Year and firm fixed effects are included. Standard errors in parenthesis.

Table 3
Summary Statistics

	N	mean	sd	min	max
investment	20851	.138	.16	.001	1.35
rd	20873	.398	.999	0	8.956
dividend	19287	-.168	1.402	-14.113	2.648
tex	20851	.541	1.063	.002	9.33
risky financial assets	20726	.353	1.262	0	13.656
safe assets	20728	.97	2.033	0	20.257
lagged risky assets	20719	.29	1.024	0	10.535
lagged safe assets	20742	.856	1.702	0	16.156
lagged Tobin's q	18717	6.754	14.242	-3.323	132.972
lagged size	20873	6.699	1.96	.648	13.59
lagged market-to-book ratio	19160	2.061	1.464	.476	11.626
lagged cash flow	18787	.02	.22	-1.476	.463
lagged leverage	20761	.259	.261	0	1.666
lagged net working capital	20492	.017	.182	-.923	.457
lagged CAPX over assets	20202	.06	.087	.001	.717
lagged R&D expenditure over assets	20220	.067	.132	0	.815
lagged acquisition expenditure over assets	19445	.037	.107	-.011	.935
lagged dividend payment dummy	20873	.352	.477	0	1

This table reports summary statistics of key variables used in the study. Detailed definitions of these variables are presented in table A.1. All variables in ratios are winsorized at 1st and 99th percentiles for each fiscal year.

Table 4
Cyclical Behavior of Aggregate Investment and Financing

	GDP_{t-1}	GDP_t
Aggregate Investment	**0.4822**	**0.5318**
Aggregate R&D Expenditure	**0.3399**	**0.4736**
Aggregate Dividend	0.2586	**0.6021**
Aggregate Total Expenditure	**0.4930**	**0.5633**
Aggregate Sales of Equity	0.2009	**0.3895**
Aggregate Change in Book Equity	0.1360	0.1141
Aggregate Debt Issuance	**0.7071**	**0.5839**
Aggregate Net Debt Issuance	**0.6904**	**0.6213**
Aggregate External Financing	**0.6545**	**0.6103**
Aggregate Net External Financing	**0.4945**	**0.4570**

This table reports time-series correlation between variables of interest (aggregate investment and aggregate financing activities) and real GDP using HP-filtered aggregate series. The sample period covers from 1980 to 2018. Coefficients in bold are significant at the 5% level.

Table 5
Investment, Dividend and Savings

VARIABLES	(1) investment	(2) rd	(3) dividend	(4) tex
lagged risky assets	0.0081***	0.0861***	0.0621*	0.0951***
	(0.0017)	(0.0276)	(0.0333)	(0.0268)
lagged safe assets	0.0169***	0.1060***	0.0860***	0.1265***
	(0.0038)	(0.0195)	(0.0217)	(0.0153)
lagged Tobin's q	0.0036***	0.0141***	-0.0115***	0.0174***
	(0.0003)	(0.0030)	(0.0022)	(0.0025)
lagged size	-0.0125**	0.0073	0.3207***	-0.0130
	(0.0055)	(0.0176)	(0.0591)	(0.0212)
Constant	0.1733***	0.1152	-2.2514***	0.3430**
	(0.0350)	(0.1533)	(0.3886)	(0.1700)
Observations	18,176	18,193	16,777	18,176
R-squared	0.107	0.298	0.0365	0.327
Year FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y

This table reports results for testing the relationship between investment, R&D expenditure, dividend, total expenditure, and the fair value of risky financial assets by estimating the following regression equation

$$y_{jt} = \theta_1 risky\ assets_{jt-1} + \theta_2 safe\ assets_{jt-1} + \theta_3 q_{jt-1} + \mu_j + \mu_t + \varepsilon_{jt},$$

where the dependent variable y_{jt} can be either one of the investment rate i_{jt}, R&D expenditure rate rd_{jt}, dividend rate div_{jt}, or total expenditure rate tex_{jt}; $risky\ assets$ refers to the fair value of risky financial assets over physical capital; $safe\ assets$ refers to cash over physical capital. Detailed definitions of all variables are presented in table A.1. Standard errors in parenthesis are clustered at SIC level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 6
Saving Behavior — Dividend Payments As Financing Constraints

Panel A. Coefficients on Funding Gap Beta						
Year						
2009	0.0538	0.0471	0.0473	0.0336	0.0307	0.0309
2010	0.0614	0.0588	0.0454	0.0316	0.0342	0.0313
2011	0.0725	0.0659	0.0586	0.0591	0.0598	0.0608
2012	0.0548	0.0532	0.0538	0.0573	0.0573	0.0539
2013	0.0540	0.0516	0.0429	0.0341	0.0513	0.0328
2014	0.0649	0.0637	0.0524	0.0436	0.0568	0.0413
2015	0.0781	0.0775	0.0703	0.0629	0.0722	0.0604
2016	0.0434	0.0381	0.0308	0.0306	0.0296	0.0225
2017	0.0179	0.0163	0.0125	0.0154	0.0146	0.0162
2018	0.0331	0.0264	0.0251	0.0199	0.0063	0.0057
$\hat{\gamma}^{\beta}$	0.0534	0.0498	0.0439	0.0388	0.0413	0.0356
SE($\hat{\gamma}^{\beta}$)	0.0054	0.0056	0.0051	0.0049	0.0064	0.0056
Panel B. Coefficients on Financing Constraint Dummy						
Year						
2009	0.0899	0.0867	0.0924	0.0870	0.0811	0.0844
2010	0.0512	0.0471	0.0562	0.0493	0.0411	0.0455
2011	0.0175	0.0141	0.0221	0.0094	0.0011	0.0009
2012	0.0390	0.0390	0.0406	0.0290	0.0240	0.0216
2013	0.0916	0.0864	0.0942	0.0923	0.0767	0.0897
2014	0.0786	0.0724	0.0838	0.0794	0.0702	0.0807
2015	0.0744	0.0642	0.0778	0.0725	0.0588	0.0695
2016	0.0329	0.0341	0.0383	0.0348	0.0353	0.0397
2017	0.1291	0.1235	0.1316	0.1276	0.1228	0.1260
2018	0.1566	0.1595	0.1581	0.1617	0.1740	0.1736
$\hat{\gamma}^{FCH}$	0.0761	0.0727	0.0795	0.0743	0.0685	0.0732
SE($\hat{\gamma}^{FCH}$)	0.0130	0.0131	0.0128	0.0139	0.0151	0.0152
Investment Measure	*i*	*rd*	*tex*	*i*	*rd*	*tex*
q-Theory Investment Measure	Y	Y	Y	N	N	N
Industry FEs	Y	Y	Y	Y	Y	Y

This table reports results from Fama-Macbeth cross-sectional regressions of following model

$$risky\ assets_{jt} = \gamma_t^{\beta} \hat{\beta}_j^F + \gamma_t^{FCH} FCH_{jt-1} + \gamma_t^{FCL}(FCL_{jt-1} + FCH_{jt-1}) + \mu_{sic} + \varepsilon_{jt}$$

where *risky assets* is the fair value of risky financial assets over physical capital; $\hat{\beta}_j^F$ is funding gap beta estimated from time-series regressions; FCH_{jt} is financing constrained dummy and FCL_{jt} is financing unconstrained dummy based on dividend payment.

Table 7
Saving Behavior — Other Financing Constraint Indices

Panel A. Credit Rating as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0537	0.0501	0.0441	0.0391	0.0415	0.0358
SE($\hat{\gamma}^{\beta}$)	0.0052	0.0054	0.0049	0.0047	0.0061	0.0053
$\hat{\gamma}^{FCH}$	0.1010	0.0964	0.1024	0.1013	0.0935	0.0992
SE($\hat{\gamma}^{FCH}$)	0.0143	0.0137	0.0144	0.0147	0.0137	0.0148
Panel B. KZ Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0514	0.0476	0.0416	0.0366	0.0380	0.0326
SE($\hat{\gamma}^{\beta}$)	0.0072	0.0071	0.0065	0.0063	0.0075	0.0066
$\hat{\gamma}^{FCH}$	-0.4439	-0.4449	-0.4463	-0.4451	-0.4429	-0.4425
SE($\hat{\gamma}^{FCH}$)	0.0495	0.0497	0.0495	0.0505	0.0512	0.0518
Panel C. WW Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0592	0.0541	0.0481	0.0449	0.0451	0.0401
SE($\hat{\gamma}^{\beta}$)	0.0080	0.0081	0.0073	0.0068	0.0089	0.0075
$\hat{\gamma}^{FCH}$	-0.1528	-0.1533	-0.1460	-0.1461	-0.1539	-0.1475
SE($\hat{\gamma}^{FCH}$)	0.0350	0.0353	0.0352	0.0338	0.0309	0.0315
Panel D. HP Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0536	0.0500	0.0441	0.0395	0.0412	0.0357
SE($\hat{\gamma}^{\beta}$)	0.0054	0.0056	0.0052	0.0051	0.0065	0.0057
$\hat{\gamma}^{FCH}$	0.3727	0.3695	0.3733	0.3771	0.3625	0.3698
SE($\hat{\gamma}^{FCH}$)	0.0649	0.0652	0.0656	0.0669	0.0676	0.0677
Investment Measure	i	rd	tex	i	rd	tex
q-Theory Investment Measure	Y	Y	Y	N	N	N
Industry FEs	Y	Y	Y	Y	Y	Y

This table reports results from Fama-Macbeth cross-sectional regressions of following model

$$risky\ assets_{jt} = \gamma_t^{\beta}\hat{\beta}_j^F + \gamma_t^{FCH} FCH_{jt-1} + \gamma_t^{FCL}(FCL_{jt-1} + FCH_{jt-1}) + \mu_{sic} + \varepsilon_{jt}$$

where $risky\ assets$ is the fair value of risky financial assets over physical capital; $\hat{\beta}_j^F$ is funding gap beta estimated from time-series regressions; FCH_{jt} is financing constraint dummy and FCL_{jt} is financing unconstraint dummy based on respective financing constraint index.

Table 8
Investment, Dividend and Savings — Control Variables

VARIABLES	(1) investment	(2) rd	(3) dividend	(4) tex
lagged risky assets	0.0120***	0.0942***	0.0715**	0.1074***
	(0.0018)	(0.0297)	(0.0313)	(0.0294)
lagged safe assets	0.0187***	0.0929***	0.1112***	0.1155***
	(0.0039)	(0.0139)	(0.0207)	(0.0111)
lagged Tobin's q	0.0027***	0.0165***	-0.0077***	0.0187***
	(0.0003)	(0.0028)	(0.0028)	(0.0025)
lagged size	-0.0155***	0.0012	0.2885***	-0.0209
	(0.0058)	(0.0143)	(0.0496)	(0.0175)
Constant	0.1710***	0.1784	-1.8720***	0.3970***
	(0.0400)	(0.1104)	(0.2850)	(0.1271)
Observations	16,077	16,089	14,838	16,077
R-squared	0.163	0.299	0.0497	0.326
Controls	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y

This table reports results for testing the relationship between investment, R&D expenditure, dividend, total expenditure, and the fair value of risky financial assets by estimating the following regression equation

$$y_{jt} = \theta_1 risky\ assets_{jt-1} + \theta_2 safe\ assets_{jt-1} + \theta_3 q_{jt-1} + controls + \mu_j + \mu_t + \varepsilon_{jt},$$

where the dependent variable y_{jt} can be either one of the investment rate i_{jt}, R&D expenditure rate rd_{jt}, dividend rate div_{jt}, or total expenditure rate tex_{jt}; *risky assets* refers to the fair value of risky financial assets over physical capital; *safe assets* refers to cash over physical capital. Detailed definitions of all variables are presented in table A.1. Standard errors in parenthesis are clustered at SIC level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 9
Saving Behavior — Control Variables

Panel A. Non-Dividend Payer as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0473	0.0471	0.0402	0.0336	0.0381	0.0326
SE($\hat{\gamma}^{\beta}$)	0.0054	0.0054	0.0045	0.0054	0.0068	0.0062
$\hat{\gamma}^{FCH}$	0.0815	0.0775	0.0814	0.0762	0.0771	0.0761
SE($\hat{\gamma}^{FCH}$)	0.0169	0.0168	0.0167	0.0180	0.0181	0.0184
Panel B. Credit Rating as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0482	0.0480	0.0409	0.0344	0.0390	0.0333
SE($\hat{\gamma}^{\beta}$)	0.0053	0.0052	0.0043	0.0052	0.0066	0.0060
$\hat{\gamma}^{FCH}$	0.1668	0.1636	0.1653	0.1614	0.1630	0.1626
SE($\hat{\gamma}^{FCH}$)	0.0148	0.0140	0.0153	0.0155	0.0144	0.0158
Panel C. KZ Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0438	0.0444	0.0370	0.0306	0.0348	0.0293
SE($\hat{\gamma}^{\beta}$)	0.0073	0.0071	0.0061	0.0065	0.0081	0.0072
$\hat{\gamma}^{FCH}$	-0.4812	-0.4702	-0.4832	-0.4863	-0.4723	-0.4856
SE($\hat{\gamma}^{FCH}$)	0.0679	0.0681	0.0671	0.0682	0.0703	0.0699
Panel D. WW Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0461	0.0455	0.0382	0.0339	0.0373	0.0328
SE($\hat{\gamma}^{\beta}$)	0.0086	0.0088	0.0074	0.0075	0.0100	0.0084
$\hat{\gamma}^{FCH}$	-0.1927	-0.1946	-0.1889	-0.1912	-0.1953	-0.1897
SE($\hat{\gamma}^{FCH}$)	0.0989	0.0985	0.0993	0.0981	0.0965	0.0974
Panel E. HP Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0490	0.0487	0.0415	0.0350	0.0386	0.0330
SE($\hat{\gamma}^{\beta}$)	0.0055	0.0055	0.0047	0.0056	0.0070	0.0064
$\hat{\gamma}^{FCH}$	0.4081	0.4030	0.4053	0.4037	0.3914	0.3962
SE($\hat{\gamma}^{FCH}$)	0.0685	0.0686	0.0692	0.0718	0.0713	0.0726
Investment Measure	i	rd	tex	i	rd	tex
q-Theory Investment Measure	Y	Y	Y	N	N	N
Controls	Y	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y	Y

This table reports results from Fama-Macbeth cross-sectional regressions of following model

$$risky\ assets_{jt} = \gamma_t^{\beta}\hat{\beta}_j^F + \gamma_t^{FCH} FCH_{jt-1} + \gamma_t^{FCL}(FCL_{jt-1} + FCH_{jt-1}) + controls + \mu_{sic} + \varepsilon_{jt}$$

where $risky\ assets$ is the fair value of risky financial assets over physical capital; $\hat{\beta}_j^F$ is funding gap beta estimated from time-series regressions; FCH_{jt} is financing constraint dummy and FCL_{jt} is financing unconstraint dummy based on respective financing constraint index.

Table 10
Investment, Dividend and Savings — Peters and Taylor (2017)'s Total q

VARIABLES	(1) investment	(2) rd	(3) dividend	(4) tex
lagged risky assets	0.0121**	0.0334***	0.0494**	0.0562***
	(0.0055)	(0.0095)	(0.0228)	(0.0143)
lagged safe assets	0.0429***	0.0309***	0.0706***	0.1258***
	(0.0081)	(0.0046)	(0.0186)	(0.0112)
lagged Tobin's q	0.0089***	0.0051***	-0.0075	0.0219***
	(0.0018)	(0.0009)	(0.0064)	(0.0020)
lagged size	-0.0108***	0.0030	0.0660***	-0.0210***
	(0.0027)	(0.0023)	(0.0070)	(0.0035)
Constant	0.1003***	0.0074	-0.4227***	0.2440***
	(0.0183)	(0.0147)	(0.0461)	(0.0236)
Observations	14,925	14,937	13,775	14,925
R-squared	0.145	0.171	0.0681	0.255
Controls	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y

This table reports results for testing the relationship between investment, R&D expenditure, dividend, total expenditure, and the fair value of risky financial assets by estimating the following regression equation

$$y_{jt} = \theta_1 risky\ assets_{jt-1} + \theta_2 safe\ assets_{jt-1} + \theta_3 q_{jt-1} + controls + \mu_j + \mu_t + \varepsilon_{jt},$$

where the dependent variable y_{jt} can be each of the investment rate i_{jt}, R&D expenditure rate rd_{jt}, dividend rate div_{jt}, or total expenditure rate tex_{jt}; $risky\ assets$ refers to the fair value of risky financial assets over sum of physical and intangible capital; $safe\ assets$ refers to cash over sum of physical and intangible capital. Detailed definitions of all variables are presented in table A.1. Standard errors in parenthesis are clustered at SIC level. $^{*}p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 11
Saving Behavior — Peters and Taylor (2017)'s Total q

Panel A. Non-Dividend Payer as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0230	0.0231	0.0240	0.0149	0.0199	0.0171
SE($\hat{\gamma}^{\beta}$)	0.0052	0.0050	0.0050	0.0033	0.0043	0.0026
$\hat{\gamma}^{FCH}$	0.0032	0.0032	0.0036	0.0027	0.0033	0.0025
SE($\hat{\gamma}^{FCH}$)	0.0013	0.0013	0.0013	0.0014	0.0012	0.0014
Panel B. Credit Rating as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0238	0.0242	0.0245	0.0152	0.0205	0.0172
SE($\hat{\gamma}^{\beta}$)	0.0051	0.0049	0.0050	0.0032	0.0042	0.0026
$\hat{\gamma}^{FCH}$	0.0243	0.0241	0.0242	0.0238	0.0236	0.0236
SE($\hat{\gamma}^{FCH}$)	0.0032	0.0032	0.0033	0.0033	0.0032	0.0033
Panel C. KZ Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0242	0.0260	0.0237	0.0157	0.0219	0.0168
SE($\hat{\gamma}^{\beta}$)	0.0055	0.0057	0.0055	0.0033	0.0047	0.0026
$\hat{\gamma}^{FCH}$	-0.0472	-0.0466	-0.0469	-0.0467	-0.0465	-0.0464
SE($\hat{\gamma}^{FCH}$)	0.0084	0.0082	0.0084	0.0083	0.0082	0.0083
Panel D. WW Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0226	0.0223	0.0237	0.0143	0.0190	0.0167
SE($\hat{\gamma}^{\beta}$)	0.0055	0.0053	0.0054	0.0035	0.0045	0.0028
$\hat{\gamma}^{FCH}$	-0.0207	-0.0206	-0.0206	-0.0204	-0.0199	-0.0207
SE($\hat{\gamma}^{FCH}$)	0.0081	0.0080	0.0082	0.0082	0.0080	0.0082
Panel E. HP Index as Financing Constraint Index						
$\hat{\gamma}^{\beta}$	0.0276	0.0282	0.0273	0.0180	0.0240	0.0189
SE($\hat{\gamma}^{\beta}$)	0.0056	0.0054	0.0055	0.0036	0.0046	0.0029
$\hat{\gamma}^{FCH}$	0.0428	0.0450	0.0422	0.0410	0.0442	0.0409
SE($\hat{\gamma}^{FCH}$)	0.0108	0.0113	0.0106	0.0111	0.0114	0.0107
Investment Measure	i	rd	tex	i	rd	tex
q-Theory Investment Measure	Y	Y	Y	N	N	N
Controls	Y	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y	Y

This table reports results from Fama-Macbeth cross-sectional regressions of following model

$$risky\ assets_{jt} = \gamma_t^{\beta}\hat{\beta}_j^F + \gamma_t^{FCH}FCH_{jt-1} + \gamma_t^{FCL}(FCL_{jt-1} + FCH_{jt-1}) + controls + \mu_{sic} + \varepsilon_{jt}$$

where $risky\ assets$ is the fair value of risky financial assets over sum of physical and intangible capital; $\hat{\beta}_j^F$ is funding gap beta estimated from time-series regressions; FCH_{jt} is financing constraint dummy and FCL_{jt} is financing unconstraint dummy based on respective financing constraint index.

Table 12
Investment, Dividend and Savings — Measurement Errors

VARIABLES	(1) investment	(2) rd	(3) dividend	(4) tex
lagged risky financial assets	0.0044	0.0759	0.1365	0.0679
	(0.0096)	(0.0699)	(0.4842)	(0.0758)
lagged Tobin's q	0.0058***	0.0468***	-0.1398***	0.0542***
	(0.0010)	(0.0172)	(0.0402)	(0.0174)
lagged safe assets	0.0200***	0.0087	0.3907***	0.0303
	(0.0065)	(0.0313)	(0.0830)	(0.0368)
lagged size	-0.0662***	-0.0473*	1.1439***	-0.1237***
	(0.0094)	(0.0258)	(0.2299)	(0.0247)
Constant	0.0129**	-0.0607***	0.1295***	-0.0512**
	(0.0059)	(0.0210)	(0.0392)	(0.0223)
Observations	13,263	13,281	12,016	13,263
Kleibergen-Paap F	60.1643	60.0585	65.8374	60.1643
Year FEs	Y	Y	Y	Y
Firm FEs	Y	Y	Y	Y

This table reports results for testing the relationship between investment, R&D expenditure, dividend, total expenditure, and the fair value of risky financial assets by estimating the following regression equation

$$y_{jt} = \theta_1 risky\ assets^*_{jt-1} + \theta_2 safe\ assets_{jt-1} + \theta_3 q^*_{jt-1} + \mu_j + \mu_t + \varepsilon_{jt},$$

with

$$\begin{aligned} risky\ assets_{jt-1} =& risky\ assets^*_{jt-1} + \varepsilon^{rf}_{jt-1} \\ q_{jt-1} =& q^*_{jt-1} + \varepsilon^{q}_{jt-1}, \end{aligned}$$

where the dependent variable y_{jt} can be either one of the investment rate i_{jt}, R&D expenditure rate rd_{jt}, dividend rate div_{jt}, or total expenditure rate tex_{jt}; $risky\ assets$ refers to the fair value of risky financial assets over physical capital; $safe\ assets$ refers to cash over physical capital; $risky\ assets^*_{jt-1}$ and q^*_{jt-1} are true values of risky financial asset holdings and q. Detailed definitions of all variables are presented in table A.1. Standard errors in parenthesis are clustered at SIC level. Erickson and Whited (2012) report bootstrapped standard errors are accurate for instrumental variable regressions in their simulation analysis. Bootstrapped standard errors are similar to clustered standard errors reported here. $^*p < 0.1$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Table 13
Saving Behavior — Corporate Governance, Risk-Seeking and Overconfidence

	Panel A. Non-Dividend Payer as Financing Constraint Index					
$\hat{\gamma}^{\beta}$	0.1016	0.1126	0.1182	0.1145	0.0893	0.0912
SE($\hat{\gamma}^{\beta}$)	0.0239	0.0260	0.0257	0.0236	0.0254	0.0224
$\hat{\gamma}^{FCH}$	-0.0678	-0.0673	-0.0661	-0.0728	-0.0655	-0.0710
SE($\hat{\gamma}^{FCH}$)	0.0610	0.0612	0.0620	0.0626	0.0519	0.0549
	Panel B. Credit Rating as Financing Constraint Index					
$\hat{\gamma}^{\beta}$	0.1023	0.1135	0.1190	0.1148	0.0895	0.0909
SE($\hat{\gamma}^{\beta}$)	0.0251	0.0275	0.0271	0.0248	0.0267	0.0237
$\hat{\gamma}^{FCH}$	0.0845	0.0954	0.0943	0.0793	0.0938	0.0863
SE($\hat{\gamma}^{FCH}$)	0.0293	0.0310	0.0303	0.0297	0.0285	0.0290
	Panel C. KZ Index as Financing Constraint Index					
$\hat{\gamma}^{\beta}$	0.1071	0.1169	0.1221	0.1167	0.0939	0.0929
SE($\hat{\gamma}^{\beta}$)	0.0270	0.0289	0.0287	0.0249	0.0289	0.0241
$\hat{\gamma}^{FCH}$	-0.2567	-0.2511	-0.2462	-0.2485	-0.2371	-0.2380
SE($\hat{\gamma}^{FCH}$)	0.0409	0.0382	0.0368	0.0459	0.0363	0.0362
	Panel D. WW Index as Financing Constraint Index					
$\hat{\gamma}^{\beta}$	0.1010	0.1121	0.1174	0.1124	0.0879	0.0888
SE($\hat{\gamma}^{\beta}$)	0.0253	0.0273	0.0269	0.0245	0.0258	0.0225
$\hat{\gamma}^{FCH}$	-0.0339	-0.0384	-0.0517	-0.0507	-0.0242	-0.0484
SE($\hat{\gamma}^{FCH}$)	0.1634	0.1606	0.1596	0.1618	0.1446	0.1381
	Panel E. HP Index as Financing Constraint Index					
$\hat{\gamma}^{\beta}$	0.1037	0.1135	0.1192	0.1189	0.0884	0.0910
SE($\hat{\gamma}^{\beta}$)	0.0253	0.0275	0.0269	0.0252	0.0270	0.0240
$\hat{\gamma}^{FCH}$	0.1546	0.1456	0.1446	0.1886	0.0958	0.1047
SE($\hat{\gamma}^{FCH}$)	0.1152	0.1145	0.1124	0.1231	0.1127	0.1137
Investment Measure	*i*	*rd*	*tex*	*i*	*rd*	*tex*
q-Theory Investment Measure	Y	Y	Y	N	N	N
Controls	Y	Y	Y	Y	Y	Y
Industry FEs	Y	Y	Y	Y	Y	Y

This table reports results from Fama-Macbeth cross-sectional regressions of following model

$$\begin{aligned} risky\ assets_{jt} =& \gamma_t^{\beta}\hat{\beta}_j^F + \gamma_t^{FCH} FCH_{jt-1} + \gamma_t^{FCL}(FCL_{jt-1} + FCH_{jt-1}) \\ &+ CG + RS + OC + controls + \mu_{sic} + \varepsilon_{jt} \end{aligned}$$

where $risky\ assets$ is the fair value of risky financial assets over physical capital; $\hat{\beta}_j^F$ is funding gap beta estimated from time-series regressions; FCH_{jt} is financing constraint dummy and FCL_{jt} is financing unconstraint dummy based on respective financing constraint index. *CG, RS* and *OC* refer to control variables for corporate governance, risk-seeking incentives and CEO overconfidence respectively.

A Existence of Solution

The Bellman equation for the firm's problem is

$$(Tv)(x) = \sup_{y \in \Gamma(x)} D(x,y) + \mathbf{E}\big[Mv(y)\big],$$

It can be verified that if $v(x) \leq g(x)$, then

$$\begin{aligned} &\sup_{y \in \Gamma(x)} D(x,y) + \mathbf{E}\big[Mv(y)\big] \leq \sup_{y \in \Gamma(x)} D(x,y) + \mathbf{E}\big[Mg(y)\big] \\ \implies \qquad &(Tv)(x) \leq (Tg)(x). \end{aligned}$$

And

$$\begin{aligned} (T(v+c))(x) &= \sup_{y \in \Gamma(x)} D(x,y) + \mathbf{E}\big[M\big(v(y)+c\big)\big] \\ &= \sup_{y \in \Gamma(x)} D(x,y) + \mathbf{E}\big[Mv(y)\big] + \mathbf{E}\big[Mc\big] \\ &= (Tv)(x) + \frac{1}{1+r_f}c. \end{aligned}$$

So the Blackwell's sufficient conditions are satisfied, (e.g., Stokey, Lucas, & Edward, 1989), and the solution to this model exists.

B Numerical Solution

The model is solved by value function iteration. The aggregate productivity and idiosyncratic productivity are both approximated by discrete Markov chains with 7 grid points ($N_x = 7,\ N_z = 7$) using Rouwenhorst (1992) method. The grid points for the fraction of savings in the market-security s are distributed between [0,1] using following formula

$$s = \big(\frac{n_s - 1}{N_s - 1}\big)^2 \in \mathcal{S},\ n_s = 1, 2, \cdots, N_s,\ \text{with } N_s = 25,$$

so the grid points for s are denser closer to zero. I put more grid points for s close to zero due to the fact that the marginal cost of holding the market-security is increasing and the points close to zero are more frequently used. But the results are both qualitatively and quantitatively similar when the grid points are evenly distributed between [0,1]. The grid points for "cash" holding c are evenly distributed between [0,1] using following formula

$$c = \frac{n_c - 1}{N_c - 1} \in \mathcal{C}, \; n_c = 1, 2, \cdots, N_c, \text{ with } N_c = 51.$$

The value function $v(x^-, x, z, s, c)$, and policy functions $s'^*(x^-, x, z, s, c)$ and $c'^*(x^-, x, z, s, c)$ are all initialized as $N_x \times N_x \times N_z \times N_s \times N_c$ five-dimensional matrices with all entries filled with zeros. The Bellman equation is updated by value function iteration

$$\begin{aligned}
v^n(x^-, x, z, s, c) &= \max_{\{s', c'\} \in \mathcal{S}' \times \mathcal{C}'} \; d + (1 - \delta + i')\mathbf{E}\big[M(x, x')v^{n-1}(x, x', z', s', c')|x, z\big] \\
d(x^-, x, z, s, c, s', c', i') &= \big[1 + \lambda_1 \mathbf{1}[e < 0]\big]e \\
e(x^-, x, z, s, c, s', c', i') &= (1 - \tau)\big[\exp(\beta_\pi x + z) - f\big] + \tau\delta - i' - \frac{\psi_i}{2} i'^2 \\
&\quad + (1 - \tau)c\big[(1 - s)r_f(x^-) + s r_M(x^-, x)\big] + c \\
&\quad - \exp(\psi_a s')c'(1 - \delta + i'),
\end{aligned}$$

where v^{n-1} is the current guess of the value function, v^n is the updated value function, and i' solves the optimality condition for investment conditional on $(x^-, x, z, s, c, s', c')$

$$\big[1 + \lambda_1 \mathbf{1}[e < 0]\big](1 + \exp(\psi_a s')c' + \psi_i i') + \mu^* = \mathbf{E}\big[M(x, x')v^{n-1}(x, x', z', s', c')|x, z\big].$$

The convergence criteria is set as $\max |v^n(x^-, x, z, s, c) - v^{n-1}(x^-, x, z, s, c)| < 10^{-4}$. Once the convergence criteria is satisfied v is set to v^n, and the optimal policy functions are updated using

$$\{s'^*, c'^*\} = \operatorname*{arg\,max}_{\{s', c'\} \in \mathcal{S}' \times \mathcal{C}'} \; d + (1 - \delta + i'(s', c'))\mathbf{E}\big[M(x, x')v(x, x', z', s', c')|x, z\big].$$

C Variable Definitions

Table A.1
Variable Definitions

Definition	Notation	Construction
Firm Level Key Variables		Variables in italics are Compustat items
Physical Capital	k	*PPEGT*
Investment	I	*CAPX*
R&D Expenditure	RD	*XRD*, 0 if missing
Dividend	DIV	*DV+PRSTKC-SSTK*
Total Expenditure	TEX	*CAPX+XRD*, *XRD* is set to 0 if missing
Book Equity	BE	*AT-LT-RE*
Sales of Book Equity	SEF	*SSTK*
Debt Financing	DF	*DLTIS*
Net Debt Financing	NDF	*DLTIS-DLTR*
Market Value	MV	*CSHO×PRCC_F+DLTT+DLC-ACT*
Fair Value of Risky Financial Assets	$FVRFA$	Scraped from 10-K Filings
Investment Rate	i_{jt}	I_{jt}/k_{jt-1}
R&D Expenditure Rate	rd_{jt}	RD_{jt}/k_{jt-1}
Dividend Rate	div_{jt}	DIV_{jt}/k_{jt-1}
Total Expenditure Rate	tex_{jt}	$(I_{jt} + RD_{jt})/k_{jt-1}$
Risky Financial Assets	$risky\ assets_{jt}$	$FVRFA_{jt}/k_{jt-1}$
Safe Financial Assets	$safe\ assets_{jt}$	CH_{jt}/k_{jt-1}
Lagged Risky Financial Assets	$risky\ assets_{jt-1}$	$FVRFA_{jt-1}/k_{jt-1}$
Lagged Safe Financial Assets	$safe\ assets_{jt-1}$	CH_{jt-1}/k_{jt-1}
Tobin's q	q_{jt}	MV_{jt}/k_{jt}
Firm Level Control Variables		Variables in italics are Compustat items
Size	$size$	$\log(AT_{jt})$
MB	MB	$(AT_{jt} - CEQ_{jt} + PRCC\_F_{jt} \times CSHO_{jt})/(AT_{jt})$
Cash Flow	$cash\ flow$	$(OIBDP_{jt} - XINT_{jt} - TXT_{jt} - DVC_{jt})/(AT_{jt-1})$
Dividend Dummy	div_dummy	1 if *DVC*>0, 0 otherwise
Leverage	lev	$(DLTT_{jt} + DLC_{jt})/AT_{jt}$
Net Working Capital	NWC	$(WCAP_{jt} - CHE_{jt})/AT_{jt}$
CAPX over Assets	$capex$	$CAPX_{jt}/AT_{jt-1}$
R&D Expenditure over Assets	rdx	$XRD_{jt}/AT_{jt-1}, XRD = 0$ if missing
Acquisition Expenditure over Assets	$aqcx$	AQC_{jt}/AT_{jt-1}
Aggregate Variables		
Price Level	P_t	Producer Price Index from BLS
Real GDP	GDP_t	Real GDP of Chained 2009 Dollars from BEA
Aggregate Investment		$(\sum_j I_{jt}/P_t)/(\sum_j k_{jt-1})$
Aggregate R&D Expenditure		$(\sum_j RD_{jt}/P_t)/(\sum_j k_{jt-1})$
Aggregate Dividend		$(\sum_j DIV_{jt}/P_t)/(\sum_j k_{jt-1})$
Aggregate Total Expenditure		$(\sum_j (I_{jt} + RD_{jt})/P_t)/(\sum_j k_{jt-1})$
Aggregate Change in Book Equity		$(\sum_j (BE_{jt} - BE_{jt-1})/P_t)/(\sum_j k_{jt-1})$
Aggregate Sales of Equity		$(\sum_j SEF_{jt}/P_t)/(\sum_j k_{jt-1})$
Aggregate Debt Financing		$(\sum_j DF_{jt}/P_t)/(\sum_j k_{jt-1})$
Aggregate Net Debt Financing		$(\sum_j NDF_{jt}/P_t)/(\sum_j k_{jt-1})$

D Description of The Algorithm

To scrape the fair value of risky financial assets from the SEC 10-K filings, I first target all the tables with reporting structure similar to Table A.2. For a table to become a target, two basic conditions are necessary: (1) the table contains at least one dollar symbol ($), this dollar symbol is used to break table header information from table content information (numerical information), and all rows above first appearance of dollar symbol are classified as table header information; (2) fair value hierarchy information is presented in the table header information. Fair value hierarchy information is information required to be disclosed by SFAS No. 157. More specifically, assets are required to be classified into 3 categories: Level 1 assets includes assets with quoted prices in active markets for identical assets; Level 2 assets includes assets without quoted prices in active markets, where other observable inputs are required; Level 3 assets includes assets with unobservable inputs. When the firm reports multiple years' information in the same table, the table is also classified as a target. The target table structure is used by about 80% of firm-year filings disclosing fair value information, but unfortunately it is not the structure chosen by some very large firms (e.g., Apple Inc. and Alphabet Inc.).

For all tables with the target structure, I scrape up to six long sentences before the table (unless there is not enough sentences between the target table and the table before the target table, in which case the sentences before the table before the target table is unlikely to be relevant for the target table), as text information used to classify the target table. Long sentence is defined as a sentence with more than five words. Then I determine the year and unit information for the target table in following orders: first, I search year information and unit information within the target table; if I cannot identify year information or unit information in the target table, I reversely search the scraped text before the table until I find the first year information or the first unit information; if I still cannot identify year or unit information for the target table, I scrape all the text in the filing and use the year information or unit information with highest frequency as year information or unit information for the target table. After identifying year and unit information, for all the target tables scraped from the same filing, I only keep tables with most recent year information.

The target table is not only used to disclose fair value information regarding corporate financial assets, it is also used to disclose fair value information for other purposes, including fair value of pension plan assets, intangible assets (e.g., goodwill), fair value of assets held for compensation, liabilities and so on. To identify tables with relevant information regarding corporate savings in risky financial assets, I randomly select 1,500 10-K filings as training sample to train a machine learning algorithm to classify all target tables. There are 527 target tables from these 1,500 10-K filings, and 333 of them are tables containing fair value information of corporate financial assets. I manually tag tables from the training sample, use the six sentences before the target table together with table header information as text information, and exploit a simple n-gram method and L1-regularized Logit regression to classify all the tables.

Even if a target table is classified as the table containing relevant information, it does not mean the target table only contains relevant information. So for all tables classified as tables containing corporate financial assets information, based on "Additional Information" defined in Table A.2 and security name, I drop securities related to restricted cash, pension plan assets, any liabilities, assets held for compensation, and hedging activities. Then I classify a security as risky if the security is not cash, bank receivables, bank drafts, bank acceptances, deposits, checks, letters of credit, money order, commercial paper, treasury, money market funds, or cash equivalents, and sum up the fair value of all risky financial assets as firm-year observations. Finally, for all firms with at least one firm-year observation of fair value of risky financial assets between 2009 and 2018, the fair value of risky financial assets between 2009 and 2018 is set to 0 if missing.

Figure A.1 shows the true fair value of risky financial assets against the fair value of risky financial assets scraped by the algorithm for an out of training sample accuracy test. Both true values and scraped values are log transformed for visualization. Table A.3 summarizes the test results. The overall accuracy rate of the algorithm is 83.93% in this testing sample. The algorithm accurately scrapes 94 firm-year observations of fair value of risky financial assets out of 112 testing observations. The algorithm makes 10 mistakes determining whether a table is the table containing relevant information, and 6 mistakes determining whether a specific type of security is risky or not (these two types of error can be further reduced). Two mistakes are due to unforeseen table structures (probably the only way to avoid this type of error is manually collecting the data).

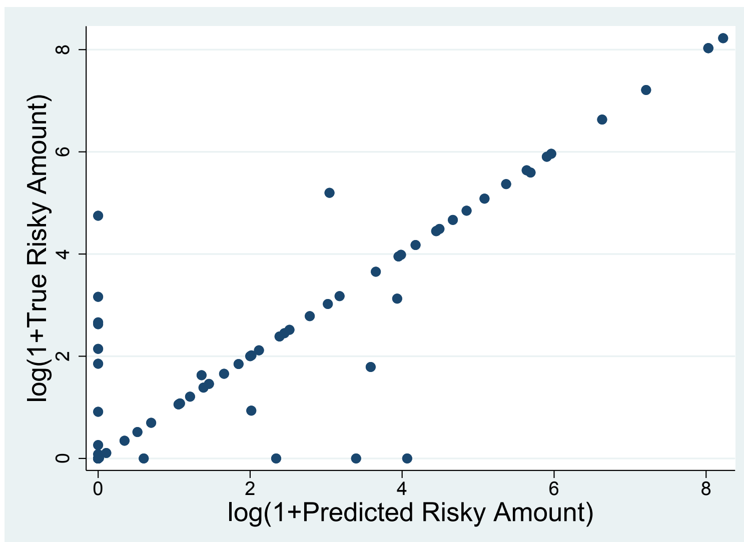

Figure A.1
Out of Sample Accuracy Test
This figure shows the true fair value of risky financial assets against the fair value of risky financial assets scraped by the algorithm for 112 randomly selected out of training sample firm-year observations. Both true values and scraped values are log transformed for visualization.

Table A.2
Typical Target Table Structure

			(**Potential Other Information**, e.g., Year, Unit)		
		(Total)	Level 1 Synonyms	Level 2 Synonyms	Level 3 Synonyms
(**Potential Other Information**)			(**Potential Other Information**, e.g., Year, Unit)		
(**Additional Information**, e.g., Assets)					
Security	$	(3,000)	1,000	1,000	1,000
...		(...)	...	...	...
(Total Synonyms)		(...)	...	...	...

This table presents the standard structure of tables I target. Information in brackets are not necessary to become target table but sometimes helpful for later information extraction and data construction. For a table to become a target, two basic conditions are necessary: (1) the table contains at least one dollar symbol ($), this dollar symbol is used to break table header information from table content information (numerical information), and all rows above first appearance of dollar symbol are classified as table header information; (2) fair value hierarchy information is presented in table header information. Fair value hierarchy information is information required to be disclosed by SFAS No. 157. More specifically, assets are required to be classified into 3 categories: Level 1 assets includes assets with quoted prices in active markets for identical assets; Level 2 assets includes assets without quoted prices in active markets, where other observable inputs are required; Level 3 assets includes assets with unobservable inputs. When the firm reports multiple years' information in the same table, the table is also classified as target.

Table A.3
Out of Sample Accuracy Test

Source of Errors	Classification	Security Type	Table Structure	Total
# of Errors	10	6	2	18
% of Errors	8.93%	5.36%	1.79%	16.07%
Testing Sample Size		112		

This table reports an out of sample accuracy test of the algorithm used to scrape the fair value of risky financial assets. The algorithm accurately scrapes 94 firm-year observations of fair value of risky financial assets out of 112 testing observations. The algorithm makes 10 mistakes determining whether a table is the table containing relevant information and 6 mistakes determining whether a specific type of security is risky or not (these two types of error can be further reduced). 2 mistakes are due to unforeseen table structures (probably the only way to avoid this type of error is manually collecting the data).

E Financing Constraint Indices

KZ index, WW index, and HP index are constructed as

$$
\begin{aligned}
KZ\ index = & -1.001909\Big[\frac{IB + DP}{\text{lagged } PPENT}\Big] + 0.2826389\Big[\frac{AT + PRCC\_F \times CSHO - CEQ - TXDB}{AT}\Big] \\
& + 3.139193\Big[\frac{DLTT + DLC}{DLTT + DLC + SEQ}\Big] - 39.3678\Big[\frac{DVC + DVP}{\text{lagged } PPENT}\Big] \\
& - 1.314759\Big[\frac{CHE}{\text{lagged } PPENT}\Big] \\
WW\ index = & -0.091\Big[\frac{IB + DP}{AT}\Big] \\
& - 0.062\Big[\text{indicator set to one if } DVC + DVP \text{ is positive, and zero otherwise}\Big] \\
& + 0.021\Big[\frac{DLTT}{AT}\Big] - 0.044\Big[\log AT\Big] \\
& + 0.102\Big[\text{average three-digit SIC industry sales growth}\Big] \\
& - 0.035\Big[\text{sales growth}\Big] \\
HP\ index = & -0.737 Size + 0.043 Size^2 - 0.040 Age
\end{aligned}
$$

where variables in italics are Compustat items. In computing HP index, *Size* equals the log of inflation-adjusted Compustat item *AT* (in 2004 dollars), and *Age* is the number of years the firm is listed with a nonmissing stock price on Compustat. I follow Hadlock and Pierce (2010) and Farre-Mensa and Ljungqvist (2016) and cap *Size* at (the log of) $4.5 billion and *Age* at 37 years.