Bonding With Risk: Corporate Investment and Savings in Risky Financial Assets*

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Abstract

We study the rationale behind firms' investment in risky financial assets by formulating a dynamic model in which firms allocate their precautionary savings to both safe and risky securities. In equilibrium, risky financial asset holdings are positively related to the sensitivity of a firm's financing deficit to the risky asset returns—the "financing deficit beta." Using a comprehensive sample of US corporate financial asset holdings, we find evidence of a positive correlation between risky financial asset holdings and financing deficit betas that capture firms' incentives to hedge medium-to-long term interest-rate risk. Precautionary motives are stronger in small and R&D-intensive firms.

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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, henceforth DGHH) shows that risky financial assets represent more than 40% of S&P 500 firms' financial asset holdings, or 6% of their total book assets. DGHH find that, after properly adjusting for the cost of capital, the value of a dollar invested in risky financial assets is lower than in safe assets, suggesting that poor corporate governance and CEO overconfidence play a role in S&P 500 firms' decisions to invest in risky financial assets. Moreover, firms take into account tax considerations when making financial asset portfolio decisions. For example, Darmouni and Mota (2023, henceforth DM) show that cross-border taxation influences large multinational firms' choice of holding marketable securities abroad, as a way to reduce taxes on repatriated earnings.[1]

While these studies point to non-precautionary motives, such as corporate governance and tax considerations, to hold risky financial assets, their findings are based on samples of very large firms (S&P 500 companies in DGHH and the largest 200 firms by asset size in DM). Therefore, it remains an open question whether precautionary reasons are important to explain risky financial asset holdings across a wider sample of firms.

In this paper, we explore firms' precautionary motives to hold risky financial assets both theoretically and empirically. First, we characterize the optimal allocation of corporate savings within a dynamic model of corporate investment with costly external financing. We show that when a firm's financing deficit—the difference between investment needs and internal funds—is positively correlated with the returns on risky financial assets, investing in these assets increases firm value by improving the alignment over time between internal cash flows and investment opportunities. We then collect data on the composition of savings for a large sample of US firms and find empirical evidence in line with the model's predictions: in the cross-section of firms, the value of corporate risky financial asset holdings is positively correlated with the financing deficit beta, which measures the sensitivity of a firm's financing deficit to the returns on the risky financial asset.

Our model features firms that choose investment in physical capital, subject to adjustment costs, and face aggregate and idiosyncratic profitability shocks. External financing is costly, and firms can transfer liquidity over time for precautionary reasons. Compared to previous dynamic models of corporate savings, such as Riddick and Whited (2009), in which firms can only hold riskless financial assets, we allow firms to invest both in a safe and a

[1] See also Foley, Hartzell, Titman, and Twite (2007), who document that high repatriation taxes create incentives for firms to retain earnings overseas and result in high cash holdings, and De Simone, Piotroski, and Tomy (2018), who find that expected reductions in repatriation taxes stimulate overseas cash holdings.

risky security—namely a bond, as risky financial asset holdings in the data mostly consist of bond securities—to study the role of risky financial assets as a saving option.

The model shows that the difference between investment funding demand and internally generated profits—the firm's financing deficit—represents the key determinant of saving behavior. To the extent that the risky bond returns are correlated with the firm' financing deficit, the firm can hedge the risk of incurring costly external financing by investing in the bond. To quantify these precautionary motives, we measure the sensitivity of the financing deficit to the bond return, which we name the financing deficit beta. As in our model firms are heterogeneous in terms of size and profitability, the financing deficit beta differs across firms: in regression analysis on simulated data, we show that firms' optimal risky bond holdings are positively associated with their financing deficit betas.

To test this key empirical prediction from the model, we use a machine learning algorithm to extract information disclosed in the footnotes of the SEC 10-K filings, generating firm-year observations on the fair value of corporate risky financial asset holdings.[2] Our final sample contains 19,163 observations from 2009—when the Financial Accounting Standard Board's Statement of Financial Accounting Standards (SFAS) No. 157 became implemented—to 2018 for 2,882 US firms. To the best of our knowledge, this is the most comprehensive sample of corporate risky financial asset holdings available to date.

Our empirical strategy consists of two steps. First, we obtain firm-level estimates of the financing deficit beta by performing time-series regressions of the financing deficit on the return of the reference risky financial asset, which in our main specifications is either the Bloomberg US Aggregate Bond Market Index return or the reverse change in the 10-year Treasury bond yields. In the second step, we conduct cross-sectional regressions of the fair value of risky financial asset holdings, scaled either by the firm's total assets or the total value of financial assets, on the financing deficit beta estimates obtained in the first step.

Consistent with the model's predictions, we find that the financing deficit beta is positively and significantly associated both with the value of risky financial assets scaled by total assets, and with the fraction of risky financial assets in the total savings portfolio. In terms of economic magnitude, the effects are large. For example, a one standard deviation increase in the financing deficit beta computed using the Bloomberg index is associated with 0.79% higher corporate risky financial asset holdings as a fraction of total assets, an increase that represents nearly 20% of the average risky financial asset holdings in our sample (4.1% of total assets).

[2]The information regarding the fair value of financial instruments is usually disclosed in the 10-K filing footnote named "Fair Value Measurements." However, the name of the footnote can be different across firms or time. Appendix B provides a detailed description of the data extraction algorithm.

To examine the economic mechanism at play in more detail, we conduct several tests. First, we estimate the cross-sectional regressions for sub-samples of small and large firms. Consistent with the model's prediction that precautionary motives are more relevant for small firms, we find that the coefficients associated with the financing deficit beta are positive and significant for small firms, while statistical significance is weaker for large firms. These results are in line with DGHH and DM, who show that other factors, such as the quality of corporate governance and tax considerations, play a more relevant role than precautionary reasons in the savings portfolio decisions of very large firms.

Second, we investigate which types of risk firms aim to hedge when choosing the composition of their financial asset portfolio. To do so, we reestimate the financing deficit betas using bonds with different maturities (the Fed Funds rate, and the 1-, 2-, 3-, 5-, and 10-year Treasury bonds) as the reference risky security in the first-stage regressions. We then estimate the second-stage regressions of the determinants of risky financial asset holdings using these alternative financing deficit betas. Our results show that both the magnitude and significance of the estimated coefficients associated with the financing deficit beta are monotonically increasing in the maturity of the reference bond. These findings suggest that firms use risky financial assets to hedge against uncertainties in their financing deficit related to medium-to-long term interest-rate risk. We then perform the same analysis estimating financing deficit betas based on the equity market return, the liquidity factor from Pástor and Stambaugh (2003), and the reverse change in investment-grade and high-yield corporate bond spreads. We find significant coefficients only for the financing deficit betas based on corporate bonds, pointing to credit risk as an additional potential precautionary motive other than interest-rate risk.

Finally, we study whether risky financial asset decisions depend on the type of capital in which firms invest. Splitting our sample according to the intensity of firms' R&D investment, we find that the financing deficit beta is significantly associated with the amount of risky financial assets held by high-R&D firms, while there is a weaker association for low-R&D firms. In addition, we recompute the financing deficit beta using measures of investment in tangible and intangible capital: the second-stage regression coefficients are significant for both measures, pointing to the fact that the economic mechanism is active for investments in both types of capital.

This paper contributes both to the theoretical and empirical literature on corporate savings. Our model is most closely related to dynamic discrete-time models of firm investment and cash holdings such as Gamba and Triantis (2008), Riddick and Whited (2009), Eisfeldt and Muir (2016), Begenau and Palazzo (2021), Gao, Whited, and Zhang (2021), and Falato, Kadyrzhanova, Sim, and Steri (2022).[3] Compared to these models, which assume that firms can only save by investing in a riskless bond, we introduce a risky security as an additional saving option. This extension allows us to study firms' optimal savings portfolio decisions in the presence of risky financial assets.

More broadly, our paper relates to the risk-management literature. The key economic mechanism at work in our model can be traced back to Smith and Stulz (1985) and Froot, Scharfstein, and Stein (1993), who develop models in which firms choose their risk-management policies to smooth cash flows and reduce, respectively, the expected costs of bankruptcy and the costs of external financing. Moreover, the role of state-contingent liquidity provision that risky financial assets play in our model is similar to the one that credit lines play in Acharya, Almeida, Ippolito, and Perez (2014) and Nikolov, Schmid, and Steri (2019).

Our model also shares similarities with DGHH, who study risky financial assets as a saving option. However, in contrast to their three-period model, we develop a fully dynamic model that we can calibrate in the data to analyze the rich dynamic interactions between corporate investment and saving behavior. In this sense, our theoretical framework is also related to recent macroeconomic models that study the aggregate impact of corporate savings (see Li, 2023; Ferreira, 2023).

The empirical literature on cash holdings has documented the link between corporate savings and several firm-specific characteristics, such as cash flow volatility, growth opportunities, asset tangibility, and CEO compensation (see, e.g., Opler, Pinkowitz, Stulz, and Williamson, 1999; Bates, Kahle, and Stulz, 2009; Liu and Mauer, 2011; Graham and Leary, 2018; Pinkowitz, Stulz, and Williamson, 2016), as well as economy-wide factors like corporate taxation and interest rates (see Foley, Hartzell, Titman, and Twite, 2007; Azar, Kagy, and Schmalz, 2016; De Simone, Piotroski, and Tomy, 2018; Faulkender, Hankins, and Petersen, 2019).

Within this literature, our paper is most closely related to the small but growing number of empirical studies on the composition of corporate savings. Brown (2014) and Cardella, Fairhurst, and Klasa (2021) analyze which firm characteristics relate to the decision to hold cash versus marketable securities; DGHH find evidence supporting tax considerations, corporate governance issues, and CEO overconfidence in the determination of risky financial asset holdings for S&P 500 firms; DM focus on the holdings of marketable securities of corporate giants, and argue that tax optimization and reaching for yield are the main reasons behind the rise in these firms' corporate bond holdings up to the 2017 tax reform, and their subse-

[3] For related models in continuous time, see Bolton, Chen, and Wang (2011), Décamps, Mariotti, Rochet, and Villeneuve (2011), and Hugonnier, Malamud, and Morellec (2015).

quent fall; and Chen and Duchin (2022) hand-collect data on the financial asset portfolios of oil and gas companies to study the risk-taking behavior of distressed firms. Our contribution to this literature is to highlight the relevance of precautionary reasons in explaining savings portfolio decisions across a wide sample of firms.

The paper is organized as follows. Section 2 analyzes the dynamic model of investment and cash holdings; Section 3 describes the data and compares our sample with the ones collected by DGHH and DM; Section 4 presents the results of the empirical analysis; and Section 5 concludes.

2. Model

In this section, we develop an infinite-horizon discrete-time model of corporate investment in which firms can accumulate cash for precautionary reasons. Our main contribution to the existing literature is to allow firms to invest in two financial securities: besides a risk-free security (as, for example, in Riddick and Whited, 2009; Nikolov and Whited, 2014; Eisfeldt and Muir, 2016; Begenau and Palazzo, 2021; Gao, Whited, and Zhang, 2021), firms can also invest in a risky bond.

We start by describing the firm's technology and investment frictions, and introducing the two saving options for the firm. We then define the firm's cash flows and optimization problem, calibrate the model, and discuss the equilibrium optimal policies for investment and savings in the risk-free and risky financial assets. Finally, we derive the predictions that we investigate in the empirical part of the paper.

2.1. Technology and Investment

For firm j in period t, the operating profits generated by physical capital k_{jt} are

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

where α is a parameter that captures the curvature of the profit function, and x_t and z_{jt} denote the aggregate and idiosyncratic profitability shocks, respectively. Both x_t and z_{jt} are assumed to be $AR(1)$ processes:

$$x_t = \rho_x x_{t-1} + \sigma_x \varepsilon_t^x \tag{2}$$

and

$$z_{jt} = \rho_z z_{jt-1} + \sigma_z \varepsilon_{jt}^z, \tag{3}$$

where $\varepsilon_t^x \sim \mathcal{N}(0,1)$ and $\varepsilon_{jt}^z \sim \mathcal{N}(0,1)$, ε_t^x is independent of ε_{jt}^z, and ε_{jt}^z and ε_{lt}^z are independent for $j \neq l$. The parameters ρ_x and ρ_z capture the persistence, and σ_x and σ_z the conditional volatility, of the aggregate and idiosyncratic profitability shocks, respectively.

The firm accumulates capital according to

$$k_{jt+1} = (1-\delta)k_{jt} + i_{jt+1}, \tag{4}$$

where i_{jt+1} denotes the investment in physical capital and δ is the depreciation rate. As in Riddick and Whited (2009), we assume that the firm incurs both fixed and quadratic capital adjustment costs

$$Adj_{jt}^k = \mathbf{1}\left[i_{jt+1} \neq 0\right] \psi_{i1} k_{jt} + \frac{\psi_{i2}}{2}\left(\frac{k_{jt+1} - (1-\delta)k_{jt}}{k_{jt}}\right)^2 k_{jt}, \tag{5}$$

where $\mathbf{1}[\cdot]$ denotes the indicator function, and the parameters ψ_{i1} and ψ_{i2} capture the fixed and quadratic components, respectively, of the capital adjustment costs.

2.2. *Stochastic Discount Factor and Financial Securities*

Following Gomes and Schmid (2010), we assume the stochastic discount factor to be

$$\log M(x_t, x_{t+1}) = \log(\eta) - \gamma(x_{t+1} - x_t), \tag{6}$$

where $\eta \in (0,1)$ is the time-preference parameter, and γ is the risk-aversion parameter.[4] Given this specification of the stochastic discount factor, the risk-free rate is

$$r_f(x_t) = \frac{1}{\mathbf{E}\left[M(x_t, x_{t+1})|x_t\right]} - 1 = \frac{1}{\eta}\exp\left(-\gamma(1-\rho)x_t - \frac{\gamma^2\sigma_x^2}{2}\right) - 1.$$

We assume that the firm can invest in two financial securities. As standard in dynamic models of corporate cash holdings, the first is a risk-free security with a maturity of one period. We set the coupon rate of this risk-free security to $\overline{r}_f = r_f(0) = 2.22\%$, where $r_f(0)$ is the risk-free rate in the aggregate neutral state ($x = 0$). Given the stochastic discount

[4]Stochastic discount factors of this form are widely used in dynamic asset pricing and corporate finance models. See, for example, Zhang (2005); Livdan, Sapriza, and Zhang (2009); Warusawitharana and Whited (2015).

factor, the price $q^c(x_t)$ of this risk-free security is

$$q^c(x_t) = \mathbf{E}\left[M(x_t, x_{t+1})(1+\overline{r}_f)\right] = \frac{1+\overline{r}_f}{1+r_f(x_t)}. \tag{7}$$

In addition to the risk-free security, we assume that firms can invest in a risky bond.[5] Similar to Gomes, Jermann, and Schmid (2016) and Lorenzoni and Werning (2019), we assume that the risky bond has a maturity of $1/\mu$ periods, and the same coupon rate as the risk-free security, $\overline{r}_f$. The parameter μ determines the fraction of the bond's notional value that matures in every period and, thus, its degree of interest risk. Indeed, the price $q^s(x_t)$ of the risky bond is given by

$$\begin{aligned} q^s(x_t) =& \mathbf{E}\left[M(x_t, x_{t+1})\left(\mu + \overline{r}_f + (1-\mu)q^s(x_{t+1})\right)|x_t\right] \\ =& \frac{\mu + \overline{r}_f}{1+r_f(x_t)} + (1-\mu)\mathbf{E}\left[M(x_t, x_{t+1})q^s(x_{t+1})|x_t\right]. \end{aligned} \tag{8}$$

The first addend in Eq. (8) represents the value of the fixed component of the bond's payoff, which is the sum of the matured notional value μ and the coupon payment $\overline{r}_f$, discounted at the risk-free rate. The second addend captures the value of the risky payoff, i.e. the discounted value of the resale price $q^s(x_{t+1})$, which is uncertain at time t, of the fraction $1-\mu$ of the bond that does not mature in period $t+1$.

We choose to model the risky financial asset as a bond security for two reasons. First, the majority of risky financial assets held by firms are bond securities, as documented by DGHH and DM.[6] Therefore, modeling the risky financial asset as a bond security captures the actual liquidity management practices of firms found in the data. The second reason is tractability: as shown in subsections 2.3 and 2.4 below, with this specification we avoid the issue of having to track (for tax purposes) the risky bond's return, which is jointly determined by both the previous-period and current-period values of the aggregate state variables.[7] Thus, our assumption reduces the dimensionality of the dynamic problem and

[5]As the model features only one type of risky financial assets, the bond security, for the rest of the paper we will use the terms "bond," "risky bond," "risky security," and "risky financial asset" interchangeably.

[6]As explained in Section 3 below, the machine learning algorithm that we use to construct our dataset does not collect information on the specific types of financial assets held by firms. However, we verify manually for a randomly selected subset of our sample that the majority of risky financial asset holdings consists of bond securities.

[7]A stochastic return R_{t+1} needs to satisfy the pricing equation $1 = \mathbf{E}\left[M(x_t, x_{t+1})R_{t+1}|x_t\right]$. Therefore, R_{t+1} depends in general both on x_t and x_{t+1}, which means that two state variables are needed to track its value. We also studied an alternative version of the model featuring an equity market security with payoffs linear in $M(x_t, x_{t+1})$. Under this assumption, the number of state variables increases from five to six. The main intuition and numerical predictions are qualitatively the same.

allows a more efficient and accurate numerical solution of the model.

2.3. Cash Flows

To derive the firm's cash flows, we start by defining the value of the firm's financial portfolio. In period $t-1$, the firm makes its financial portfolio decisions by choosing the notional value of the investment in the risky-free security c_{jt}, and in the risky bond s_{jt} for next period t. Therefore, the value of the firm's financial portfolio in period t is

$$(1+\overline{r}_f)c_{jt} + (\mu + \overline{r}_f)s_{jt} + q^s(x_t)(1-\mu)s_{jt}, \tag{9}$$

and the taxable income for the firm is

$$TI_{jt} = \exp(x_t + z_{jt})k_{jt}^{\alpha} - \delta k_{jt} + \overline{r}_f c_{jt} + \overline{r}_f s_{jt}. \tag{10}$$

Notice that, following Gomes, Jermann, and Schmid (2016) and Lorenzoni and Werning (2019), we assume that only coupon payments for financial securities, but not capital gains, are taxed. This assumption has two advantages. First, as we mentioned above, with this assumption it is not necessary to track the stochastic capital gains of the bond security, thus reducing the problem's dimensionality. Second, this assumption ensures that firms' savings in financial assets are bounded. Indeed, taxation on capital gains could lead firms to hold an infinite amount of bond securities, if the tax benefits generated by negative capital gains exceeded the amount of coupon taxes.

Managing risky financial assets implies for the firm a quadratic adjustment cost

$$Adj_{jt}^s = \frac{\psi_{s2}}{2}\left(\frac{s_{jt+1} - (1-\mu)s_{jt}}{k_{jt}}\right)^2 k_{jt}, \tag{11}$$

where $\psi_{s2} \geq 0$ is the bond adjustment cost parameter. We introduce this adjustment cost because bonds are often traded in illiquid markets, and their trading implies financial frictions such as transaction costs. Moreover, we allow the adjustment cost to be scaled by physical capital, so that large firms benefit from a lower marginal adjustment cost of risky financial assets, capturing their better access to over-the-counter markets and trading relationships with market makers.

Overall, the firm's cash flow e_{jt} is equal to the after-tax operating profits of the firm, plus depreciation and the value of the firm's financial asset portfolio, minus the sum of the investment and adjustment costs in both physical capital and financial assets:

$$\begin{aligned} e_{jt} =&(1-\tau)TI_{jt} + \delta k_{jt} + c_{jt} + \mu s_{jt} + q^s(x_t)(1-\mu)s_{jt} \\ &- i_{jt+1} - Adj^k_{jt} - q^c(x_t)c_{jt+1} - q^s(x_t)s_{jt+1} - Adj^s_{jt}. \end{aligned} \tag{12}$$

Positive values of e_{jt} represent distributions to the firm's investors, and negative values imply an infusion of external financing. When $e_{jt} < 0$, we assume that the firm incurs external financing costs Λ_{jt}, so that net distributions are:

$$d_{jt} = e_{jt} - \Lambda_{jt}. \tag{13}$$

Following Belo, Lin, and Yang (2018), we specify the external financing cost function as

$$\Lambda_{jt} = \mathbf{1}\left[e_{jt} < 0\right] \exp(\overline{\xi} - \xi_x x_t) \left(\xi_0 + \xi_1 |e_{jt}| + \frac{\xi_2}{2} e^2_{jt}\right), \tag{14}$$

where ξ_0, ξ_1, and ξ_2 denote, respectively, the fixed, linear, and quadratic external financing cost parameters, $\overline{\xi}$ is a scaling parameter, and $\exp(-\xi_x x_t)$ is a factor that, for $\xi_x > 0$, captures counter cyclical external financing costs. We introduce a time-varying factor in the cost of external financing to account for fluctuations in macroeconomic conditions, so that it is more costly for firms to tap the capital markets during economic downturns. This assumption also alleviates the concern that our results are driven by pro-cyclical supply of external financing.[8] To summarize, the firm can finance its operations using internally-generated operating cash flows, savings in the risk-free and risky financial assets, or external funds. Notice that, as other models that focus on optimal corporate savings (for example, Riddick and Whited, 2009; Nikolov and Whited, 2014), we do not differentiate between debt and equity in the composition of external financing.

2.4. *The Firm's Problem*

The value of the firm, v_{jt}, is equal to the present value of future net distributions, d_{jt}, discounted by the stochastic discount factor, as defined by the following Bellman equation:

$$v(x,z,s,c,k) = \max_{s',c',k'} \; d(x,z,s,c,k,s',c',k') + \mathbf{E}\left[M(x,x')v(x',z',s',c',k')|x,z\right], \tag{15}$$

[8] We also studied a model without counter-cyclical external financing costs ($\xi_x = 0$), and found that our results do not hinge on this assumption.

where, for simplicity of notation, we omit the indices j and t and use primes to denote state variables for period $t+1$. Overall, the dynamic problem in Eq. (15) is characterized by five state variables (x, z, s, c, k) and three control variables (s', c', k'). As the model has no closed-form analytical solution, we solve for the equilibrium numerically by value-function iteration (see Appendix C for details).

2.5. *Calibration*

We calibrate the model using the parameters reported in Table 1. Most values are either directly taken or calculated based on the existing literature. In terms of parameters that describe the aggregate economy, we set the persistence ρ_x and the conditional standard deviation σ_x of the aggregate shock at the annualized values from Gomes and Schmid (2010).[9] We calibrate the stochastic discount factor parameters η and γ to generate an average annual risk-free rate of 2.13% and an average stock return of 6.26%, similar to the values in Gomes and Schmid (2010). We set the inverse maturity of the bond μ to match a bond beta of 0.2 (similar to the value in Fama and French, 1993) in the neutral aggregate state ($x = 0$). Our calibrated parameter value $\mu = 0.4$ implies an average bond maturity of 2.5 years, and an average bond return of 3.27%. Finally, the corporate tax rate τ is 20%, as in Gomes and Schmid (2010), and we take the parameter that governs the degree of counter-cyclicality of external financing costs, $\xi_x = 12$, from Belo, Lin, and Yang (2018).[10]

The parameters that describe firm operations are from Riddick and Whited (2009), including the persistence $\rho_z = 0.66$ and conditional standard deviation $\sigma_z = 0.121$ of the idiosyncratic shock, the curvature parameter $\alpha = 0.75$ of the profit function, the depreciation rate $\delta = 0.15$, the fixed and quadratic capital adjustment cost parameters ($\psi_{i1} = 0.039$ and $\psi_{i2} = 0.049$, respectively), and the fixed, linear, and quadratic external financing cost parameters ($\xi_0 = 0.389$, $\xi_1 = 0.053$, and $\xi_2 = 0.0002$, respectively).

[Insert Table 1 around here]

We calibrate the remaining two parameters, the scaling parameter of external financing costs $\overline{\xi}$ and the bond adjustment cost parameter ψ_{s2}, to jointly match the following two moments: (1) the average ratio of the fair value of risky financial assets over physical capital, and (2) the average ratio of the value of safe financial assets over capital.

[9] Gomes and Schmid (2010) assume an aggregate shock $x_t^M = \rho_x^M x_{t-1} + \sigma_x^M \varepsilon_t^M$ at monthly frequency M with persistence and volatility parameters $\rho_x^M = 0.983$ and $\sigma_x^M = 0.0023$, respectively, from which we derive $\rho_x = \rho_x^{M12} = 0.983^{12} = 0.8140$, and $\sigma_x = \sqrt{\frac{1-0.983^{24}}{1-0.983^2}}0.0023 = 0.0073$.

[10] Our assumed value for the corporate tax rate is widely used in the literature (see, for example, Nikolov and Whited, 2014; Falato, Kadyrzhanova, Sim, and Steri, 2022; Nikolov, Schmid, and Steri, 2019).

To understand the reason for the choice of these two target moments, notice first that the scaling parameter $\overline{\xi}$ affects directly firms' incentives to save for precautionary reasons—higher external financing costs lead firms to hold more financial assets (both risky and safe). Second, the bond adjustment cost parameter ψ_{s2} influences the cost of holding risky financial assets relative to the cost of holding safe financial assets—for higher values of ψ_{s2}, firms substitute risky with safe financial assets.

To illustrate these effects, Figure 1 shows the results of a comparative statics experiment using the calibrated model. Panels A and C on the left column plot the average simulated ratios of risky and safe financial assets to capital, respectively, as functions of the external financing cost parameter $\overline{\xi}$. Panels B and D on the right column plot the same moments as functions of the bond adjustment cost parameter ψ_{s2}.

[Insert Figure 1 around here]

The comparative statics analysis shows that financial asset holdings are increasing functions of the external financing cost parameter $\overline{\xi}$. Indeed, financing frictions increase precautionary demand for both risky (Panel A) and safe (Panel C) financial assets. Moreover, we find that firms hold less risky financial assets for higher values of the bond adjustment cost parameter ψ_{s2} (Panel B). On the other hand, in response to higher ψ_{s2}, firms substitute risky with safe financial asset holdings (Panel D). Overall, these differential effects on the target moments allow us to achieve identification of the two parameters.[11]

Table 2 shows the simulated moments from the calibration and the corresponding values in the real data. Panel A of Table 3 contains the definitions of the variables used for calibration in the model, and Panel B reports how we construct the real-data variables.[12] Our calibration matches well the target moments for $\overline{\xi}$ and ψ_{s2}. In particular, the average value of risky financial assets over physical capital k ($PPEGT$ in the data) is 19.1% in the model and 20.3% in the data, while the average value of safe financial assets over k is 61.0% in the model and 61.5% in the data. Regarding the untargeted moments, the calibrated model also generates similar investment and profitability rates as in the data, while it overestimates the weight of risky financial assets in firms' financial portfolios.

[11]The calibrated values are $\overline{\xi} = 0.17$ and $\psi_{s2} = 0.0063$, with standard errors of 0.0149 and 0.0002, respectively. See Appendix C for details on the computation of standard errors.

[12]See Section 3 for details of the sample construction. Notice that, both in the model and the real data, the variables are scaled by capital (k in the model and Compustat item $PPEGT$ in the data). Therefore, some of the variable definitions for the real data sample in Panel B of Table 3 differ from those used in the main empirical analysis, reported in Table 5, which are scaled by total assets (Compustat item AT) to be consistent with previous empirical studies.

Finally, Columns 3 and 4 of Table 2 report the calibration moments for small firms, defined both in the model and data as the firms below the median level of total assets in a given year, and in Columns 5 and 6 the moments for large firms. Overall, the differences in moments between small and large firms are less accentuated in the model than in the data.

[Insert Table 2 and Table 3 around here]

2.6. Precautionary Motive and Corporate Financial Assets

To understand the role that risky financial assets play in our model as a hedge against external financial costs, consider how the aggregate profitability shock x affects the firm's investment decisions. Assuming for illustration purposes that $\overline{\xi} = \xi_x = \xi_2 = 0$, and that Eq. (15) is differentiable with respect to k', the first-order condition for optimal investment yields

$$\underbrace{\left[1 + \mathbf{1}\left[e(\cdot) < 0\right] \xi_1\right]}_{MC\ of\ Financing} \underbrace{\left(1 + \psi_{i2} \frac{k'^{*} - (1-\delta)k}{k}\right)}_{MC\ of\ Inv.\ with\ Internal\ Funds} + \kappa^{*} = \underbrace{\mathbf{E}\left[M(x, x') \frac{\partial v(x', z', s', c', k'^{*})}{\partial k'^{*}} \middle| x \right]}_{MV\ of\ Investment}, \tag{16}$$

where k'^{*} denotes the optimal capital level for next period, and κ^{*} is the Lagrange multiplier associated with external financing constraint in Eq. (14). The right-hand side of Eq. (16) represents the marginal value of investment, while the left-hand side the marginal cost, including the potential costs of external financing when $e(\cdot) < 0$.

Panel A of Figure 2 plots the marginal value and marginal cost functions of investment at two different states ("high" and "low") of the aggregate profitability shock x, for the simple case of constant returns to scale ($\alpha = 1$). Under this assumption, the marginal value is constant as a function of investment. As the aggregate profitability shock is persistent over time, a high value of x in the current period implies a high conditional expectation of next period's profitability shock x', which increases the expected profitability of next period's capital stock. Therefore, the marginal value of investment is increasing in x, as shown by the shift from the solid blue line (low x) to the dash-dotted green line (high x) in Panel A of Figure 2.

The slope of the marginal cost function, instead, is determined by the marginal capital adjustment cost ψ_{i2} and the cost of external financing ξ_1. In particular, for low levels of investment, internal funds are sufficient to finance investment needs, so that the slope of the marginal cost function is equal to ψ_{i2}. However, when $e(\cdot) < 0$ the firm starts to tap external financing, so that the slope increases to $(1 + \xi_1)\psi_{i2}$. The aggregate profitability shock affects the amount of internal funds generated by the firm and, hence, the threshold $e(\cdot) = 0$ below which the firm needs to raise external funds and the slope of the marginal cost function changes. As shown in Panel A of Figure 2, this threshold occurs at a lower level of investment when x is low (dashed red line) compared to when x is high (dash-double-dotted purple line), because in the latter case the higher operating profits extend the internal funding capacity of the firm.

[Insert Figure 2 around here]

As shown in Eq. (16), the optimal level of investment is determined by the intersection between the marginal value and marginal cost functions. In Panel A of Figure 2, the optimal level of investment for low x is represented by the blue asterisk. In this case, the equilibrium investment is low enough to be financed through internal funds. On the contrary, when x is high, investment is constrained by financing frictions. Indeed, at the point where the marginal value and cost functions intersect (red asterisk), internal funds are exhausted, but the firm does not find it valuable to issue external financing. The reason is that, at this point, the marginal value of investment is higher than the marginal cost if the firm had additional internal funding, but lower than the marginal cost with external financing.

In this scenario, the firm can use financial assets to manage the level of internal funds available to finance investment and, hence, reduce external financing costs. To see this point, notice that the firm incurs these costs when the financing deficit, defined as the difference between investment needs and net operating profits after tax, exceeds the cash flows from financial assets, that is when

$$\begin{aligned} &\underbrace{k'^{*} - (1-\delta)k + Adj^{k} - (1-\tau)\exp(x+z)k^{\alpha} - \tau\delta k}_{Financing\ Deficit} > \\ &\underbrace{(1+(1-\tau)\overline{r}_f)c - q^{c}(x)c'}_{Cash\ Flow\ from\ Safe\ Fin\ Assets} + \underbrace{(\mu+(1-\tau)\overline{r}_f)s + (1-\mu)q^{s}(x)s - q^{s}(x)s' - Adj^{s}}_{Cash\ Flow\ from\ Risky\ Fin\ Assets}. \end{aligned} \tag{17}$$

Consider the firm's choice to invest in safe or risky financial assets in period $t-1$, which affects the budget condition in period t. Assume that, in $t-1$, the firm decides to reallocate one dollar from safe financial assets, investing $c-1$ instead of c dollars, to risky financial assets, which in this case amount to $s+1$ instead of s dollars. In period t, ceteris paribus, the cash flows available for investment (the right-hand side of Eq. (17)) will change by

$$\underbrace{(1+(1-\tau)\overline{r}_f)(-1)}_{\$1\ Less\ Safe\ Fin\ Assets} + \underbrace{(\mu+(1-\tau)\overline{r}_f) + (1-\mu)q^{s}(x)}_{\$1\ More\ Risky\ Fin\ Assets} = (1-\mu)\left(q^{s}(x)-1\right). \tag{18}$$

Therefore, if the current-period bond price $q^s(x)$ is greater (smaller) than one, risky financial assets will increase (decrease) the cash flows available to meet the firm's investment needs in period t. As in our calibration the risky bond bears positive market risk (the bond's beta is 0.2), the bond price $q^s(x)$ is positively correlated with the aggregate profitability shock x, so that $q^s(x)$ will be greater (smaller) than one when x is positive (negative). In summary, increasing risky financial asset holdings will increase (decrease), ceteris paribus, the funding available to the firm for investment in times of high (low) aggregate profitability, i.e. when $x > 0$ ($x < 0$).

Figure 2 illustrates how, in our model, risky financial assets allow firms to transfer liquidity across aggregate profitability states. In particular, Panel B shows the effects of reallocating one dollar from safe to risky financial assets in period $t - 1$. Compared to Panel A, the higher amount of risky financial assets increases (reduces) the amount of internal funding available in period t when aggregate profitability x is high (low) because of the high (low) market price of the bond $q^s(x)$. This effect is indicated by the shift to the right (left) in the threshold at which $e(\cdot) = 0$, and the slope of the marginal cost function increases from ψ_{i2} to $(1 + \xi_1)\psi_{i2}$, in Panel B compared to Panel A. In the scenario illustrated in Panel B, the option to invest in the risky security allows the firm to avoid hitting the financing constraints in both the low and high x states when setting the optimal investment (blue and red asterisks, respectively). Overall, the comparison between Panels A and B of Figure 2 shows how investing in the risky financial asset can alleviate external financing costs for the firm.

2.7. *Policy Functions*

We now use the full model at the calibrated parameters to explore the role of bond securities s and aggregate profitability x in shaping the following investment and saving policies in equilibrium: (1) the investment rate i'/k; (2) the firm's distributions/infusions of external financing e/k; the notional value of corporate savings in (3) risky s'/k and (4) safe c'/k financial assets, scaled by capital; (5) the firm's total savings in financial assets $(s'+c')/k$; and (6) the composition of the firm's financial asset portfolio, $s'/(s' + c')$. Figure 3 plots these variables as a function of s for three values of the aggregate profitability shock x. We set all remaining state variables at their average simulated values in the calibration.

[Insert Figure 3 around here]

As the aggregate profitability shock is persistent over time, when x is high (dash-dotted green line), investing in physical capital is valuable. In this case, firms liquidate all bond securities (Panel C) and safe financial assets (Panel D) to fund investment (Panel A) and reduce costly external financing (Panel B). On the contrary, for low values of aggregate profitability (dashed blue line), firms reduce their size by divesting physical capital, and they distribute the proceeds to investors (Panels A and B). Moreover, as a function of s, firms keep a constant amount of total savings in financial assets (Panel E), but the composition of savings changes substantially (Panel F). Indeed, for higher values of s, firms prefer to liquidate safe rather than risky financial assets, to avoid incurring bond adjustment costs.

Finally, when the aggregate profitability shock is at its median level (solid red line), firms set the investment rate to zero to avoid incurring the fixed capital adjustment cost (Panel A). In this region of inactive investment, firms distribute funds to investors (Panel B), but they also accumulate precautionary savings to meet future financing needs (Panel E). While the amount of these precautionary savings is relatively constant as a function of s, its composition changes, as firms substitute safe financial assets with the risky bond, to save on the bond adjustment costs.

In our model, the key reason why firms invest in the risky security is to generate a better matching between investment needs and internal funds and, thus, reduce external financing costs. To illustrate this point, Panel A of Figure 4 plots the financing deficit scaled by physical capital,

$$FD = \frac{k' - (1-\delta)k + Adj^k - (1-\tau)\pi - \tau\delta k}{k}, \tag{19}$$

as a function of the aggregate profitability shock x, for a large (solid blue line) and a small firm (dashed red line). In this plot, the financing deficit increases in x for both firms, because at higher values of x the increase in investment demand is larger than the increase in operating profits. However, the financing deficit is larger for the small firm, which generates lower profits and needs to invest at a higher rate to achieve its optimal scale.

[Insert Figure 4 around here]

To avoid costly external financing, a firm can fund its financing deficit by investing either in the safe asset or in the risky bond. In particular, as shown in Panel B of Figure 4, the risky bond's excess return, $q^s(x_t)/q^s(x_{t-1}) - 1 - r_f(x_{t-1})$, is positive in good times, i.e. when aggregate profitability x is high. As bond returns are positively correlated with the financing deficit of the firm, by investing in the risky bond, the firm can transfer liquidity to states in which it is most needed. Moreover, firms have higher incentives to invest in the risky bond the higher is the sensitivity of their financing deficit to the bond return. For example, the small firm in Panel A (dashed red line) has a stronger desire for liquidity, and thus higher incentives to invest in the risky bond, compared with the large firm (solid line).

2.8. *Empirical Predictions*

As discussed in the previous subsection, our model predicts that the more sensitive a firm's financing deficit is to the risky bond returns, the stronger the incentives for the firm to invest in the bond to alleviate external financing costs. To gauge the magnitude of these precautionary incentives, we estimate a firm-level time-series regression of the financing deficit on the risky bond return

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt}, \tag{20}$$

where j and t index the firm and year, respectively, and $R_t^B = q^s(x_t)/q^s(x_{t-1}) - 1$ is the bond return, using the data simulated from the model. The coefficient of interest β_j^D, which we define as the financing deficit beta, measures the sensitivity of the firm's financing deficit to the bond return and, thus, the firm's incentives to hold risky financial assets.[13]

To quantify the effect of the financing deficit beta on firms' saving behavior, in a second-stage we perform the regression

$$FinAssets_{jt} = \zeta_t + \phi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt}, \tag{21}$$

where $FinAssets_{jt}$ is the fair value of the risky bond scaled either by physical capital or total financial assets (the variables defined as *Risky* and *FinComp*, respectively, in Panel A of Table 3), ζ_t captures year fixed effects, $\hat{\beta}_j^D$ denotes the estimated value of the financing deficit beta from Eq. (20), and $Controls_{jt}$ include the firm's Tobin's Q, profitability, and size.[14]

Columns 1 and 2 of Table 4 present the estimation results of Eq. (21) for the full sample of simulated firms. Consistent with the economic intuition discussed above, in our model the financing deficit beta is positively associated with corporate investment in risky financial assets, both as a fraction of capital and as a fraction of total financial assets. In terms of magnitude, a one standard deviation increase in the financing deficit beta is associated with an increase in risky financial asset holdings equal to 0.484% of capital (Column 1) and to a 0.512% increase in the weight of risky financial assets in the financial portfolio (Column

[13]Notice that we measure this sensitivity at the firm level. In our model, heterogeneity across firms arises because of different realizations of the firm-specific profitability shock z_{jt}, which affect the size and amount of savings of each firm over time. Therefore, the differences across firms in the estimated $\hat{\beta}_j^D$ reflect heterogeneity in profitability, size, and corporate savings across firms over the simulated time period, which is comparable in length to the real data sample.

[14]Notice that the main coefficient of interest, ϕ, was not a targeted moment in our calibration in subsection 2.5.

2).[15]

Columns 3 to 8 of Table 4 show the estimation results of Eq. (21) for different subsamples of firms based on size.[16] Overall, the relationship between the financing deficit beta and investment in risky financial assets is stronger for small firms, as indicated by the larger regression coefficients for small (Columns 3 and 4) compared to large (Columns 5 and 6) and giant firms (Columns 7 and 8). Testing whether these predictions from the model hold in the real data is the main objective of the next sections.

[Insert Table 4 around here]

3. Data

In this section, we describe the data sources and the construction of the sample used for the model calibration and for the empirical analysis. Moreover, we provide a comparison between our data sample and the ones in the previous studies on the composition of corporate savings by DGHH and DM.

3.1. Sample Construction

We start from the sample of firms in the Compustat annual database from 2009, when SFAS No. 157 was implemented, to 2018. We apply standard data filters, dropping regulated utilities (SIC 4900-4999), firms in the financial industry (SIC 6000-6999), and observations with missing or negative total assets (Compustat item AT) or property, plant and equipment ($PPEGT$). We then merge the resulting sample with data on the fair value of risky financial assets that we collect from the companies' 10-K filings on the SEC's Electronic Data Gathering, Analysis, and Retrieval (EDGAR) system based on the company's Central Index Key (CIK) and by fiscal year. To collect information from EDGAR, we use a machine learning algorithm, which we outline below and describe in greater detail in Appendix B.[17] We discuss our definition of risky financial assets in subsection 3.2. We drop observations for which the value of risky financial assets exceeds total assets, which are likely caused by algorithm errors, and observations with $PPEGT$ lower than 5 million dollars, to eliminate the effect of micro firms on our results. Finally, as discussed in more detail in subsection 3.3,

[15]The mean and standard deviation of the simulated financing deficit betas are 3.02 and 1.07, respectively.

[16]To create the subsamples, each year we rank all simulated firms by size, as defined in Table 3. Small (large) firms are those below (above) median size, while giant firms are those in the top quintile of the size distribution.

[17]Appendix B also presents the results of an out-of-sample accuracy test for the algorithm.

we complement our dataset with additional firm-year observations from the sample collected by DM.[18] For each year, we winsorize all variables in ratios at the 1st and 99th percentiles.

Table 5 reports the definitions of the variables used in the empirical analysis, and Table 6 presents summary statistics for the final sample, which consists of 19,163 observations for 2,882 firms. In terms of the composition of corporate savings, the average ratio of the fair value of risky financial assets to total assets (variable *Risky*) is 4.1%, while the average ratio of safe financial assets to total assets (*Safe*) is 14.4%.

[Insert Table 5 and Table 6 around here]

3.2. Classification of Financial Assets and Comparison with DGHH

We now discuss how we classify the many types of securities reported in the 10-K filings into the two categories of "risky" or "safe" financial assets, and highlight the differences with the definitions used by DGHH.

In their paper, DGHH define safe assets to include 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 US Treasury securities. This definition of safe assets differs from the standard measure of cash holdings used in the corporate finance literature, which equals the sum of "cash and cash equivalents" and "short-term investments" from the company's balance sheet. As noticed by DGHH, the standard definition used in the literature may include non-money-like financial assets, which they classify instead as risky.

Based on the Federal Reserve's classification, DGHH collect information on the fair value of financial assets from the notes in 10-K filings. They do so manually, which allows them to deal with complicated reporting structures and detect relevant and omitted items on a case-by-case basis.[19] While this data collection approach has many benefits in terms of accuracy, its main drawback is that it is difficult to scale to a large number of firms. In particular, DGHH focus only on the subsample of industrial firms that are included in the S&P 500 index for the period 2009 to 2012, and their final sample consists of 1,727 yearly observations for 446 firms.

[18] We thank Olivier Darmouni and Lira Mota for making their dataset available.

[19] Some firms do not report all of their financial asset holdings in the disclosing table. In their Appendices, DGHH describe the example of Intel (ticker INTC). This company, in its 10-K filing for fiscal-year 2012, did not report the amount of cash holdings in the table disclosing the value of financial assets. DGHH can detect this omitted item by comparing the total value of cash equivalents reported in the table with the amount of cash and cash equivalents in the balance sheet. Moreover, some firms report the fair value of their financial assets within text narratives, rather than using tabular presentations.

In our paper, we follow a different approach to extract information on financial assets from a firm's 10-K statement, and to determine whether a specific security is risky or safe. More specifically, we start from two observed patterns in the disclosure practice of firms: (1) when the reporting table is incomplete, the omitted items are more likely to be safe assets;[20] and (2) the names of the items reported as safe financial assets are more standard across firms and, thus, easier to detect, compared to risky financial assets. Based on these considerations, we estimate the value of risky financial assets by first identifying in the disclosing tables the safe securities, and then summing up the fair value of all remaining securities.[21]

More precisely, our classification procedure requires to define a list of safe securities, which we construct based on the definitions of Compustat items *CH* and *IVST*. We first classify as safe all securities in Compustat item *CH*, which includes cash, bank receivables, bank drafts, bank acceptances, deposits, checks, letters of credit, and money orders. For securities in *IVST*, we categorize commercial papers, treasuries, and money market funds as safe financial assets. We then classify as risky financial assets all securities not belonging to the list of safe securities.

The main benefit of our data collection approach is that it can efficiently gather information on financial assets for a large number of firms, extending well outside the S&P 500 sample, and allowing us to investigate the heterogeneity in saving behavior across different types of firms. To compare our financial asset holdings data with DGHH, we split our sample into S&P 500 and non-S&P 500 firms and present summary statistics in Table 7.

[Insert Table 7 around here]

Panel A of Table 7 reports the firm coverage in our sample: between 2009 and 2018, the S&P 500 index included 575 firms, and our scraped sample covers 304 of them (53%). Among the 575 firms, 144 are in the finance or utility industry. For the remaining 431 firms, 127 are not included in our sample for the following three reasons: (1) they are filtered out by the sample selection procedure; (2) they do not have a table in their 10-Ks to report the fair value of financial asset holdings; or (3) they have a table but not in the specific format

[20] As noted by DGHH, "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, US government and agency debt securities, US municipal debt securities, foreign government debt securities, corporate debt securities, mortgage-backed securities, and other debt securities." This disclosure requirement means that firms can choose whether to report or not safe assets like cash in the 10-K footnote on the fair value of financial assets.

[21] Following DM and DGHH, all securities related to restricted assets, pension plan assets, assets held for compensation, hedging activities, and any liabilities reported in the relevant 10-K footnotes are not considered as financial assets and, hence, are excluded.

we target.[22]

For comparison purposes, panel B of Table 7 presents summary statistics on risky financial asset holdings of S&P 500 and non-S&P 500 firms in the same format as Panel B of Table II in DGHH. For both S&P 500 and non-S&P 500 firms, we sort our sample into quintiles by the size of the financial portfolio, measured by either total financial assets (sub-panels A and C) or total financial assets scaled by total assets (sub-panels B and D), and report the average fair value of safe and risky financial assets for each quintile. Consistent with DGHH, we find that, for S&P 500 firms, the size of the financial asset portfolio is positively associated with the weight of risky financial assets in the portfolio (sub-panels A and B). However, we also find similar patterns for non-S&P 500 firms (sub-panels C and D), although non-S&P 500 firms with the largest financial portfolios invest less heavily in risky financial assets than S&P 500 firms. For example, measured by total financial assets over total assets, S&P 500 firms in the top quintile of the financial portfolios hold 18.6% of total assets, or 41.0% of financial assets, in risky financial assets, while these ratios are 13.9% and 26.5% for non-S&P 500 firms.[23]

Figure 5 documents how the aggregate composition of corporate savings evolved over the sample period for S&P 500 and non-S&P 500 firms. In particular, Panel A plots the ratios of aggregate risky and safe financial asset holdings to aggregate total assets, while Panel B reports the ratio of aggregate risky to total financial assets. Several patterns emerge: (1) as documented by DGHH, S&P 500 firms hold a significant amount of risky financial assets, growing over the sample period to reach in 2017 a level representing over 10% (50%) of total assets (total financial assets); (2) after 2017, S&P 500 firms reduce their financial asset holdings, consistent with the repatriation tax channel documented by DM; and (3) non-S&P 500 firms' aggregate holdings in safe financial assets are similar to those of S&P 500 firms, but non-S&P 500 firms' risky financial asset holdings are substantially lower than S&P 500 firms, though not negligible.

[22] As described in Appendix B, we only target the most common type of reporting table, which is used in the vast majority of cases, conditional on information on financial assets being reported in a tabular format. Notice that some firms do not report financial asset holdings in a table, due to multiple reasons: (1) the firm does not hold financial assets; (2) the firm holds financial assets for which disclosure is not compulsory; (3) the firm discloses information within a text narrative.

[23] As an additional exercise to compare our sample to the one in DGHH, we estimate in our data the same regression of the determinants of risky financial assets as in their paper, using the specification in Column 1 of their Table III. Our results are both qualitatively and quantitatively similar to theirs. In addition, we also find that the regression results for non-S&P 500 firms are similar to those for S&P 500 firms. One noteworthy difference is that the coefficient on leverage is positively and significantly associated with the amount of risky financial assets for non-S&P 500 firms, but it is not statistically significant for S&P 500 firms, similar to Table III in DGHH. The detailed results are presented in Table A.1.

[Insert Figure 5 around here]

3.3. *Sample Comparison with DM*

We now compare our sample with the one manually collected by DM. As the focus of their paper is different than ours, they use an alternative classification of financial assets, categorizing them as either cash-like instruments or marketable securities. To summarize the differences between our two approaches, we classify as risky financial assets all securities except cash, bank receivables, bank drafts, bank acceptances, deposits, checks, letters of credit, money orders, commercial papers, treasuries, and money market funds, while DM exclude from the marketable securities cash, money market funds, deposits, and commercial papers. Hence, the most noteworthy difference between our "risky financial assets" and their "marketable securities" is the treatment of US treasuries, which represent one of the most common non-cash financial securities held by firms. While our measure of risky financial assets excludes US treasuries, their definition of marketable securities includes them.

To perform a direct comparison between these two measures, we merge their data sample, which contains information for 200 large firms betwen 2000 and 2021, with ours. We then construct, for the observations in the merged sample, two variables: marketable securities over total assets, and marketable securities over total financial assets. The correlation between our variable, risky financial assets, and their one for marketable securities is 79% scaling by total assets, and 66% scaling by total financial assets. Given the high correlation between the two measures, we decide to incorporate into our final sample the firm-year observations from DM that are not in our original sample. Doing so, we create the most comprehensive dataset, to the best of our knowledge, on corporate financial assets in the literature to date.[24]

4. Empirical Results

In this section, we test the empirical predictions of the model. We start by providing an empirical measure of the financing deficit beta, to quantify the incentives to hold risky financial assets at the firm level. We then analyze how this measure is related to risky financial asset holdings and to the composition of corporate savings in the cross-section of

[24]The number of additional observations from DM that we include in our sample is 309, or 1.6% of the final sample. Our results hold with or without including these additional data points. Moreover, Table A.3 of the appendix shows that our main results are robust to measuring risky financial assets with the Compustat item *IVST*, which includes treasuries, similar to the measure of marketable securities in DM, and which is available for a longer time period than our sample.

firms, and investigate the differences between small and large firms. Third, we ask which risk factors can explain corporate savings in risky financial assets. Finally, we test the robustness of our results with respect to alternative measures of investment and capital.

4.1. Measuring the Financing Deficit Beta

As discussed in subsection 2.8, in our model a key determinant of firms' incentives to hold risky financial assets is the financing deficit beta β_j^D, which measures the sensitivity of the financing deficit to the bond return. To estimate the financing deficit beta in the real data, we first define the financing deficit FD_{jt} for firm j in quarter t as the difference between the investment rate and equity cash flows scaled by capital (Table 5 reports the variables' definitions).[25]

[Insert Table 5 around here]

We then estimate the financing deficit beta by performing firm-level regressions, using quarterly data, of Eq. (20),

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt},$$

where we measure R_{t-1}^B either as the return on the Bloomberg US Aggregate Bond Market Index (henceforth, "the Agg"), or the reverse change in the 10-year US Treasury bond yield in quarter $t-1$.[26] The financing deficit betas estimated using the Agg and the 10-year Treasury bond have mean values of 0.331 and 0.725, respectively.[27] These values imply that, for an average firm, the financing deficit tends to be larger when bond market returns are higher. For example, the average estimate $\hat{\beta}_j^D = 0.331$ means that a one standard deviation increase in the Agg return is associated with an average increase in the financing deficit equal to 1.04% of capital. Therefore, on average, firms have an incentive to invest in bonds, as the bond market provides high returns when their financing deficit is large. This empirical finding aligns with the role that risky financial assets play in our model, serving as a hedge against firms' funding shortfalls related to their investment needs.

[25]In subsection 4.6, we test the robustness of our results using alternative measures of investment and capital.

[26]The Agg is a value-weighted market-wide index that tracks US investment-grade bonds, including corporate bonds, Treasury and government agency bonds, as well as mortgage- and asset-backed securities. As of July 1st 2022, the weighted average maturity of the Agg is 8.76 years. As an alternative, we choose the reverse change in the yield on Treasury bonds with the closest maturity (10 years) to the average maturity of the Agg index. We study the effects of choosing different maturities for Treasury bonds in subsection 4.4.

[27]These two alternative measures of the financing deficit beta have a correlation coefficient of 0.704. See Table 6 for additional summary statistics.

4.2. Cross-Sectional Analysis of Risky Financial Assets

We start our study of the relationship between the financing deficit beta and the amount and composition of risky financial assets by performing a sorting analysis. We proceed in two steps. First, in each year we sort firms into deciles according to the absolute value of the estimated financing deficit beta, $|\hat{\beta}_j^D|$, and we obtain the residuals in risky financial asset holdings by subtracting the year-decile mean holdings. We perform this step to tease out the effect of cash flow volatility: as the absolute value of beta is positively correlated with cash flow volatility, large values of both positive and negative beta imply strong precautionary motives to save, leading firms to hold larger amounts of both safe and risky financial assets. In the second step, we sort firms into deciles according to the value of beta, and we compute the decile means of the residuals obtained from the first step. We perform this analysis both measuring risky financial assets scaled by total assets, and by total financial assets.

Figure 6 presents the results. Panels A and C use betas based on the Agg index, while Panels B and D employ the 10-year US Treasury bond as the reference security. Panels A and B show that a positive association exists between the financing deficit beta and the amount of risky financial asset holdings as a fraction of total assets. Panels C and D show how the composition of corporate savings is also related to the financing deficit beta: consistent with the model, firms with higher financing deficit beta hold a larger fraction of risky financial assets in their savings portfolios.

[Insert Figure 6 around here]

We extend these empirical results by performing a multivariate analysis of financial asset holdings based on the following regression,

$$FinAssets_{jt} = \zeta_{sic,t} + \phi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt}, \tag{22}$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ can be the fair value of risky financial assets over total assets, the value of safe financial assets over total assets, or the value of risky over total financial assets (variables *Risky*, *Safe*, or *FinComp*, respectively, defined in Table 5); $\zeta_{sic,t}$ represents industry-year fixed effects; and $\hat{\beta}_j^D$ is the estimated firm-level financing deficit beta.[28]

Table 8 presents the regression results of Eq. (22). Consistent with our model predictions in Table 4, we find that risky financial asset holdings (*Risky*) are positively and significantly

[28] We cluster standard errors at the industry level. In appendix A.2, we perform a robustness check estimating Eq. (22) using the Fama and MacBeth (1973) procedure.

associated with financing deficit betas, both using the beta measure based on the Agg index (Column 1) and the Treasury bond (Column 2). In terms of magnitude, a one standard deviation increase in the financing deficit beta based on the Agg index (Treasury bond) is associated with 0.79% (0.80%) higher risky financial asset holdings as a fraction of total assets, an increase that represents 19.4% of the average risky financial asset holdings (4.1% of total assets) in our sample. Overall, these results show that the financing deficit beta captures firms' incentives to invest in risky financial assets.

[Insert Table 8 around here]

To test whether our measure also proxies for firms' incentives to invest in safe financial assets, we estimate the regression in Eq. (22) using as dependent variable the amount of safe financial assets, *Safe*, measured as the ratio of Compustat items CH and AT.[29] The results in Column 3 of Table 8 show that the financing deficit beta based on the Agg index return is not significantly related to the amount of safe financial assets. Column 4 shows that the betas computed using the reverse change in the 10-year Treasury bond yield are positively correlated with the amount of safe financial assets, with a coefficient that is significant at the 5% level. The difference in significance between Columns 3 and 4 may be due to the fact that CH includes many safe interest-bearing securities, such as Treasuries. Therefore, compared with the beta measure based on the Agg, the beta computed using the Treasury bond can capture better the firms' incentives to invest in safe interest-bearing securities.

Columns 5 and 6 of Table 8 show the estimation results for the composition of financial assets. The dependent variable is the fraction of risky over total financial assets ($FinComp$). As predicted by our model, we find that both of our financing deficit beta measures are positively and significantly (at the 1% level) associated with the weight of risky financial assets in firms' savings portfolios. In particular, a one standard deviation increase in the financing deficit beta based on the Agg index (10-year Treasury bond) is associated with a 1.64% (1.71%) increase in the weight of risky financial assets in corporate savings portfolios. This effect accounts for 11.2% of the average ratio of risky to total financial assets (14.6%) in our sample.

[29] As the main focus of our analysis is on risky financial assets, our algorithm does not collect information on the value of safe financial assets, which we measure using Compustat item CH. This choice is supported by the findings in DM, who show that CH closely matches their hand-collected data on "Cash-Like" financial assets, defined as the sum of cash, deposits, money-market funds, and commercial paper (see Figure 3 in DM).

4.3. Small vs. Large Firms

We now analyze the differences in saving behavior between small and large firms. While the results in Table 8 for the full sample of firms show that, in line with the findings of DGHH and DM, risky financial asset holdings are positively associated with firm size, our aim is to examine the relevance of precautionary motives for the portfolio decisions of these two groups of firms. To do so, we create two subsamples of small and large firms, defined each year as the firms below or above the median value of total assets at the end of the previous year, respectively.

Table 9 presents the regression results of Eq. (22) using as dependent variables the amount and composition, respectively, of risky financial assets for small (Panel A) and large firms (Panel B).[30] Consistent with the model's prediction that small firms have stronger incentives than large firms to invest in risky financial assets for precautionary reasons (cf. results in Table 4), the financing deficit beta is significantly positively associated with the amount of risky financial asset holdings for small firms (Columns 1 and 2 in Panel A), while the regression coefficients for large firms are smaller and have a lower degree of statistical significance (Columns 1 and 2 in Panel B). In terms of economic magnitude, the effects for small firms are sizable: a one standard deviation increase in the financing deficit beta based on the Agg index (Treasury bond) is associated with an average increase in risky financial asset holdings equal to 0.92% (0.76%) as a fraction of total assets.

[Insert Table 9 around here]

Columns 3 and 4 of Table 9 show the results using as the dependent variable the ratio of risky over total financial assets. A one standard deviation increase in the financing deficit beta based on the Agg index (Treasury bond) is related to a 1.55% (1.40%) higher weight of risky financial assets in the savings portfolios of small firms (Panel A). We find that similar results hold for large firms (Panel B), although with somewhat weaker statistical significance.

Overall, these results highlight the importance of precautionary motives in small firms' decisions to invest in risky financial assets, whereas their relevance diminishes for large firms. This observation aligns with the findings of DGHH and DM, who demonstrate that other factors, including managerial overconfidence, corporate governance issues, and tax considerations, are more closely associated with the savings portfolio choices of very large firms.

[30]In unreported analysis, we also performed the regressions using the sub-sample of S&P 500 firms, as in DGHH. The results are very similar to those in Panel B of Table 9 for large firms.

4.4. Interest-Rate Risk and Financial Asset Holdings

To further understand the source of risk captured by the financing deficit beta, we compute alternative beta measures by estimating Eq. (20) using several different maturities for the reference bond returns R^B_{t-1}: the Fed Funds rate (over night), and Treasury bonds with maturity of 1, 2, 3, 5, and 10 years.

The regression results in Panel A of Table 10 show that all beta measures show a positive and strongly significant association with the amount of firms' risky financial asset holdings (variable *Risky*). Moreover, the magnitude of the regression coefficients increases monotonically the longer is the maturity of the reference bond used to estimate beta (from 0.015 using the Fed Funds rate to 0.064 using the 10-year Treasury bond). This result indicates that the type of risk that firms intend to hedge by investing in risky financial assets is related to medium-to-long term interest-rate risk.

[Insert Table 10 around here]

This finding is confirmed by Panel B, in which the dependent variable is the fraction of risky over total financial assets (*FinComp*). Indeed, the regression coefficients are larger the longer is the maturity of the reference bond used to estimate the financing deficit beta. Moreover, for short maturities, up to 2 years, the coefficients associated with betas are not statistically significant. These results align with the notion that firms can hedge against short-term interest-rate risk using a wide variety of safe or risky financial assets, while there are fewer securities among those we classify as safe that can be used to hedge long-term interest-rate risk. Therefore, the betas derived from short-term bonds tend to have a positive association with both safe and risky holdings, thereby diminishing the overall correlation between the betas and the proportion of risky financial assets in the portfolio. On the contrary, as firms have fewer options among the securities classified as safe financial assets to hedge against long-term interest-rate risk, the betas based on long-term bonds are positively and significantly correlated with the portion of risky financial assets.

4.5. Can Other Risk Factors Explain Saving Behavior?

In this section, we explore whether risk factors other than interest-rate risk can help explain firms' investment in risky financial assets. To do so, we estimate the financing deficit beta in Eq. (20) using the returns of several alternative reference assets: (1) the quarterly value-weighted equity market return; (2) the quarterly liquidity factor return from Pástor and Stambaugh (2003); and the reverse change in the (3) investment-grade and (4) high-yield corporate bond spreads over the Fed Funds rate.[31]

Table 11 shows the estimation results for the cross-sectional regressions of the determinants of risky financial assets in Eq. (22). The regressions reported in odd-numbered columns include only the alternative beta measures (*BetaAlt*), while in even-numbered columns we add as a control variable the beta estimated using the reverse change in the yield of the 10-year Treasury bond (*BetaTre*), which captures interest risk and is one of the standard beta measures used for the main analysis in the previous sections (cf. Table 8).

[Insert Table 11 around here]

The results reported in the odd-numbered columns show that the only coefficients that are statistically significant at the 5% level are the ones associated with the beta based on equity market returns, with negative values both on risky financial assets over total assets (variable *Risky*, Panel A) and over total financial assets (*FinComp*, Panel B). However, the even-numbered columns show that the results change substantially once we also control for the beta based on the reverse change in the 10-year Treasury bond yield. In particular, the coefficients associated with the beta based on the equity return become statistically insignificant (Column 2 in both panels), while the coefficients associated with the beta based on the reverse change in the investment-grade bond spread (Column 6) are positive and statistically significant in both panels, and the coefficient on the beta based on the reverse change in the high-yield bond spread (Column 8) is significant at the 5% level in Panel A. The differing results between odd- and even-numbered columns can be attributed to the fact that the beta estimates based on the Treasury bond are negatively correlated with the betas based on the alternative reference assets.[32] Finally, it is important to notice that the coefficients associated with the beta based on the Treasury bond remain positive and statistically significant across all specifications, and the magnitudes are similar to those in Table 8.

Overall, these results suggest that, in addition to interest-rate risk, precautionary reasons related to credit risk also affect firms' financial asset portfolio decisions, while factors associated with equity market returns or liquidity do not seem to play a significant role for the composition of corporate savings.

[31]The source for the equity market returns is Kenneth French's data library. We obtain data on the investment-grade and high-yield corporate bonds from the FRED website: we use the ICE BofA BBB US Corporate Index Option-Adjusted Spread and the ICE BofA US High Yield Index Option-Adjusted Spread, respectively.

[32]The correlation coefficients between the beta based on the 10-year Treasury bond and the betas based on the equity market return, liquidity factor, investment-grade bond spread, and high-yield bond spread are -0.42, -0.09, -0.32, and -0.40, respectively.

4.6. Alternative Measures of Investment and Capital

In this section, we perform two separate tests to investigate whether the type of investment and capital used to compute the financing deficit beta matters in the determination of risky financial asset holdings. Indeed, previous studies have found that intangible capital is an important factor in firms' cash-holding decisions (e.g., Begenau and Palazzo, 2021; Falato, Kadyrzhanova, Sim, and Steri, 2022; Li, 2023).

In the first test, we estimate Eq. (22) for the sub-samples of firms with R&D expenditures above and below the sample-wide yearly median, respectively. Table 12 shows that the regression coefficients associated with beta are positive both for high and low R&D firms (Panels A and B, respectively), but their statistical significance is strong only for high R&D firms. This finding aligns with the idea that firms investing heavily in innovation are highly incentivized to hedge factors related to interest-rate risk, given the higher cost of external financing for intangible investments (see, for example, Hall and Lerner, 2010).

[Insert Table 12 around here]

In the second empirical test, we estimate the financing deficit betas using three alternative measures of the investment rate: (1) investment in tangible capital, *InvTan*, computed as the ratio of Compustat items $CAPEX$ and $PPEGT$; (2) investment in intangible capital, *InvInt*, obtained as $(XRD+0.3XSGA)/K^{Int}$, where the numerator represents investment in knowledge and organizational capital, measured following Hulten and Hao (2008), Eisfeldt and Papanikolaou (2014), Sun and Xiaolan (2019), and Peters and Taylor (2017), and K^{Int} denotes the replacement cost of intangible capital by Peters and Taylor (2017); and (3) the total investment rate, *InvTot*, which reflects investment in both tangible and intangible capital, and is computed as $(CAPEX + XRD + 0.3XSGA)/(PPEGT + K^{Int})$.[33]

The results for the cross-sectional regressions of Eq. (22) in Table 13 show that risky financial assets scaled by total assets (Panel A) and by total financial assets (Panel B) are both positively and significantly associated with all different measures of the financing deficit beta. Hence, we conclude that hedging incentives exist for both tangible and intangible investment.

[Insert Table 13 around here]

[33]The average annual investment rates *InvTan*, *InvInt*, and *InvTot* are 6.3%, 4.0%, and 10.5%, respectively. See Table A.4 for full summary statistics.

5. Conclusion

As first documented by DGHH, the composition of corporate savings is more complex than traditionally assumed. Given the substantial investments in risky financial assets made by industrial firms, it is important to understand the motivations behind such investments. In this paper, we address this question by developing a dynamic model of firms' financial portfolio decisions, and showing that corporate investment in risky financial assets can emerge as an equilibrium outcome driven by financing frictions and macroeconomic fluctuations. The key insight from our model is that firms have higher incentives to invest in risky financial assets the higher is the sensitivity of their financing deficit—defined as the difference between investment needs and internal funds—to the risky financial asset returns.

To empirically test the model's predictions, we construct the most comprehensive sample to date of US firms' corporate risky financial asset holdings. Our main finding is that the financing deficit beta—our empirical measure of the financing deficit's sensitivity to risky financial asset returns—estimated using bond market returns is positively correlated with corporate risky financial asset holdings, as predicted by the model. When we investigate alternative risk factors, we find that measures of the financing deficit beta related to medium-to-long term interest-rate risk are the ones to explain best the cross-sectional behavior of corporate savings in risky financial assets. Moreover, these precautionary motives are more relevant for small and R&D-intensive firms.

The findings from this study open up several avenues for further analysis. Firstly, while we consider two broad classes ("safe" or "risky") of financial assets, a more granular examination of the different types of securities held by firms could shed light on the specific drivers of corporate portfolio decisions. This detailed analysis may reveal how various financial asset classes contribute differently to firms' hedging objectives. Secondly, delving deeper into the determinants of risky financial asset holdings could enrich our understanding of the broader spectrum of factors influencing corporate saving behaviors. For example, investigating how firms adjust their financial asset portfolios in response to the actions of product market competitors or industry peers may uncover complex interplays between market dynamics and corporate financial portfolio strategies. Incorporating these aspects in future research could enrich our understanding of corporate savings and financial asset investments.

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Figures and Tables

Fig. 1: Comparative Statics. This figure plots the model-simulated average ratios of risky (top row) and safe (bottom row) financial asset holdings over capital k, as functions of two calibrated parameters: the external financing cost scaling parameter $\overline{\xi}$ (left column), and the quadratic bond management cost parameter ψ_{s2} (right column). The values of the remaining parameters are presented in Table 1, and the definitions of the variables are in Table 3.

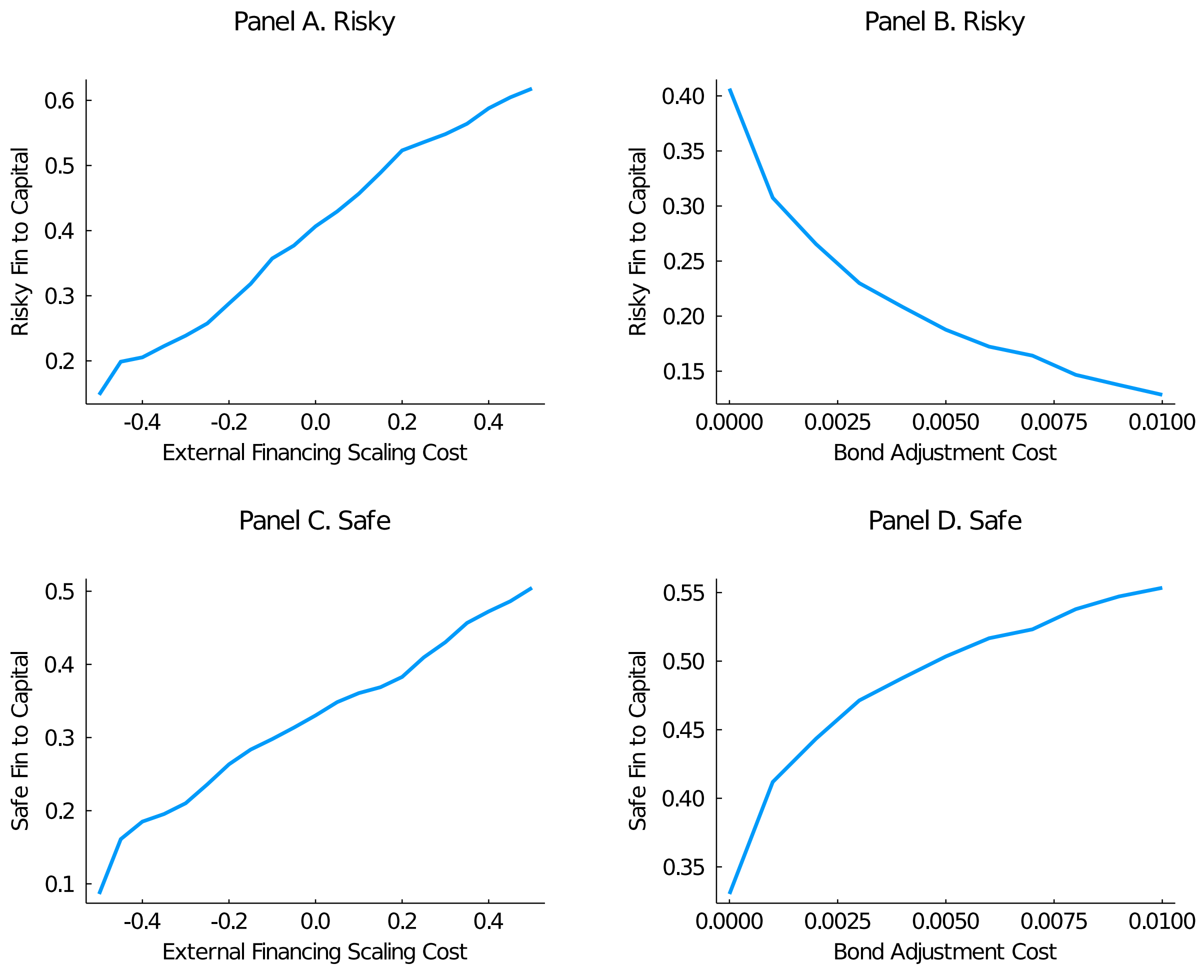
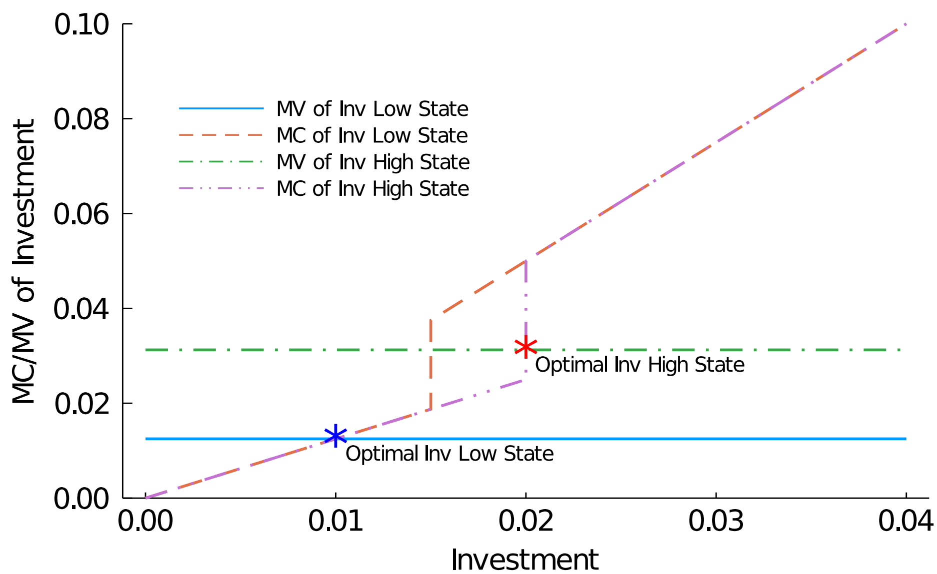


Fig. 2: Precautionary Motives and Risky Financial Assets. This figure illustrates the first-order conditions for optimal investment to highlight the precautionary role of risky financial assets in the model. Each panel plots the marginal value and marginal cost of investment, defined in Eq. (16), in the simple case with $\alpha = 1$ and $\overline{\xi} = \xi_x = \xi_2 = 0$, for high and low states of the aggregate profitability shock, x. In Panel A, the firm saves in the risk-free security, while in Panel B the firm invests in the risky financial asset. Panel A illustrates a scenario in which optimal investment is capped by external financing frictions when x is high, but the firm has extra liquidity when x is low. In Panel B, by diverting its savings from the safe to the risky financial asset, the firm can alleviate the financing constraints in the high state, without increasing the total amount of savings.

Panel A. Optimal Investment with Safe Financial Assets



Panel B. Optimal Investment with Risky Financial Assets

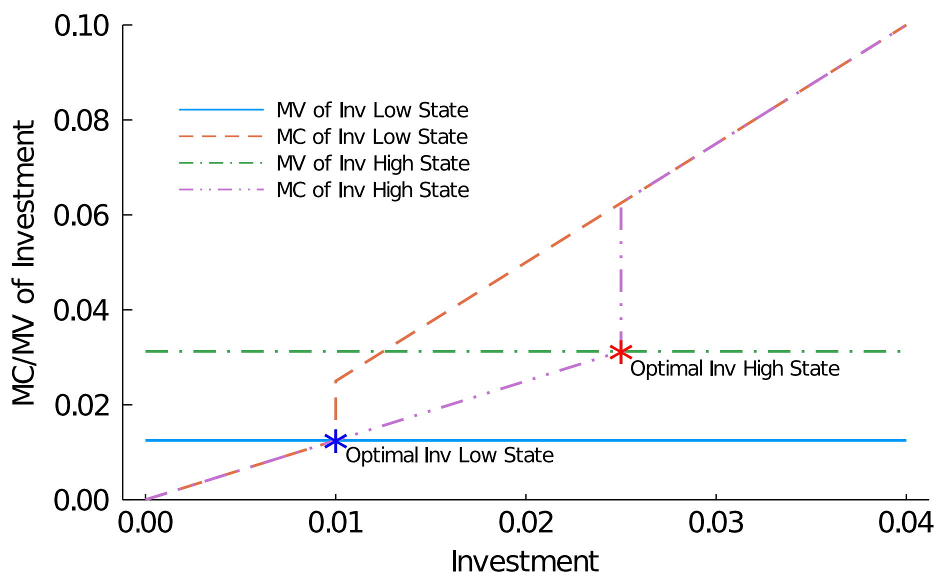


Fig. 3: Policy Functions. This figure plots the following optimal policy functions for different levels of the aggregate profitability shock x: the investment rate (Panel A), distributions/external financing (Panel B), risky financial asset holdings (Panel C), safe financial asset holdings (Panel D), and total financial asset holdings (Panel E) as fractions of capital k, and the savings portfolio composition, defined as risky financial assets over total financial assets (Panel F), against current period risky financial asset holdings s. The other state variables (z, c, and k) are set to their average simulated values in the calibration. The optimal policies are based on the calibrated parameters reported in Table 1. The dotted reference lines in Panels B, C, and D represent the loci of points corresponding to zero distributions, zero trading in risky financial assets, and zero adjustment in safe financial assets, respectively.

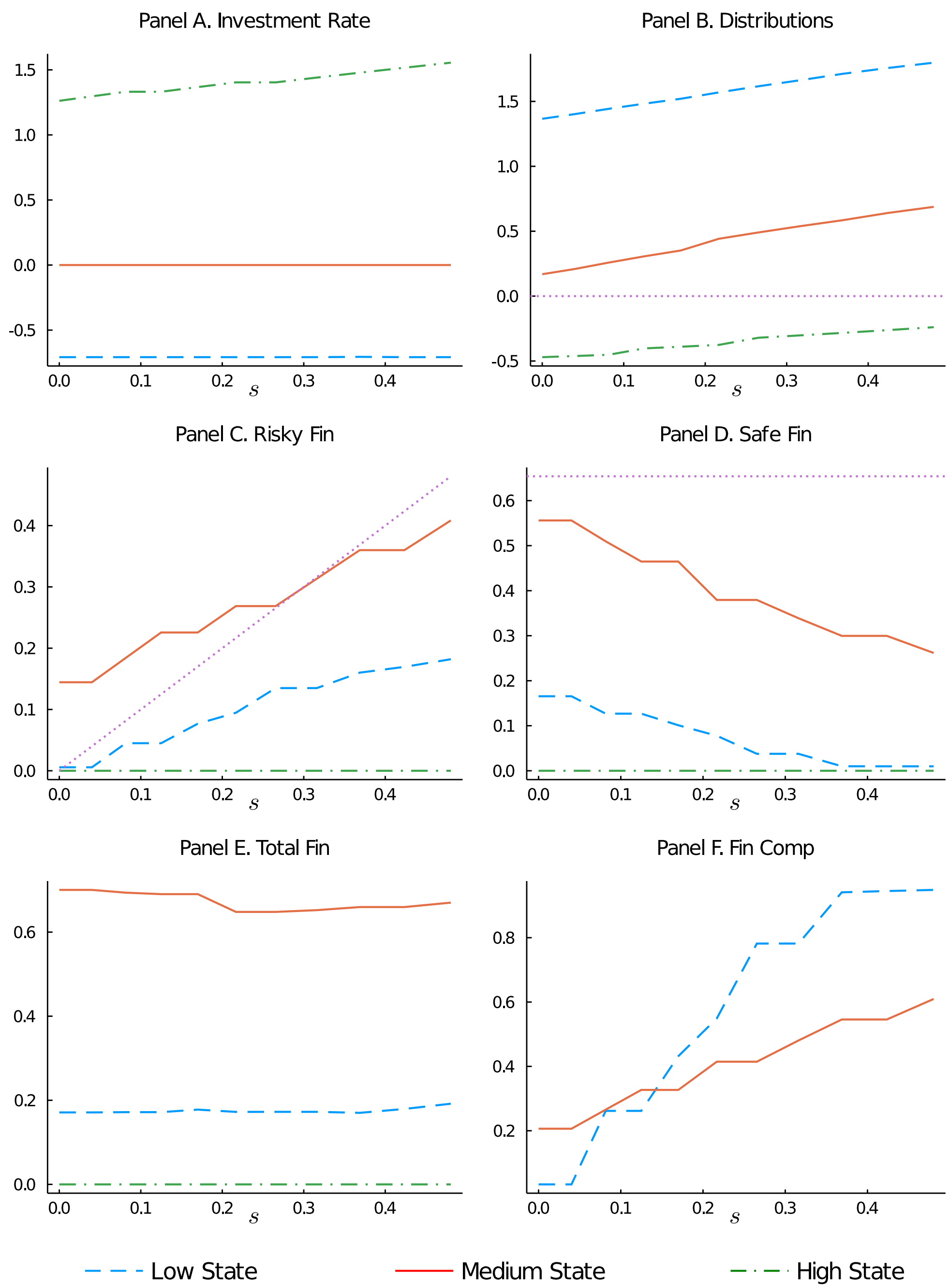


Fig. 4: Financing Deficit and the Incentives to Invest in the Risky Security. Panel A plots the financing deficits, defined in Eq. (19), of a small and a large firm, as functions of the aggregate profitability shock x. The small (large) firm has capital k set to the median gridpoint below (above) the point that is closest to the simulated average k, according to the calibration parameters in Table 1. All remaining state variables are set to their mean values in the simulation. The large firm has a financing deficit that is weakly positively correlated with x (solid line), while the correlation is stronger for the small firm (dashed line). Panel B plots the excess return of the risky bond against the aggregate profitability shock. The small firm (dashed line in Panel A) has stronger incentives to invest in the risky financial asset, as it provides higher returns in those states in which the firm faces large financing deficits.

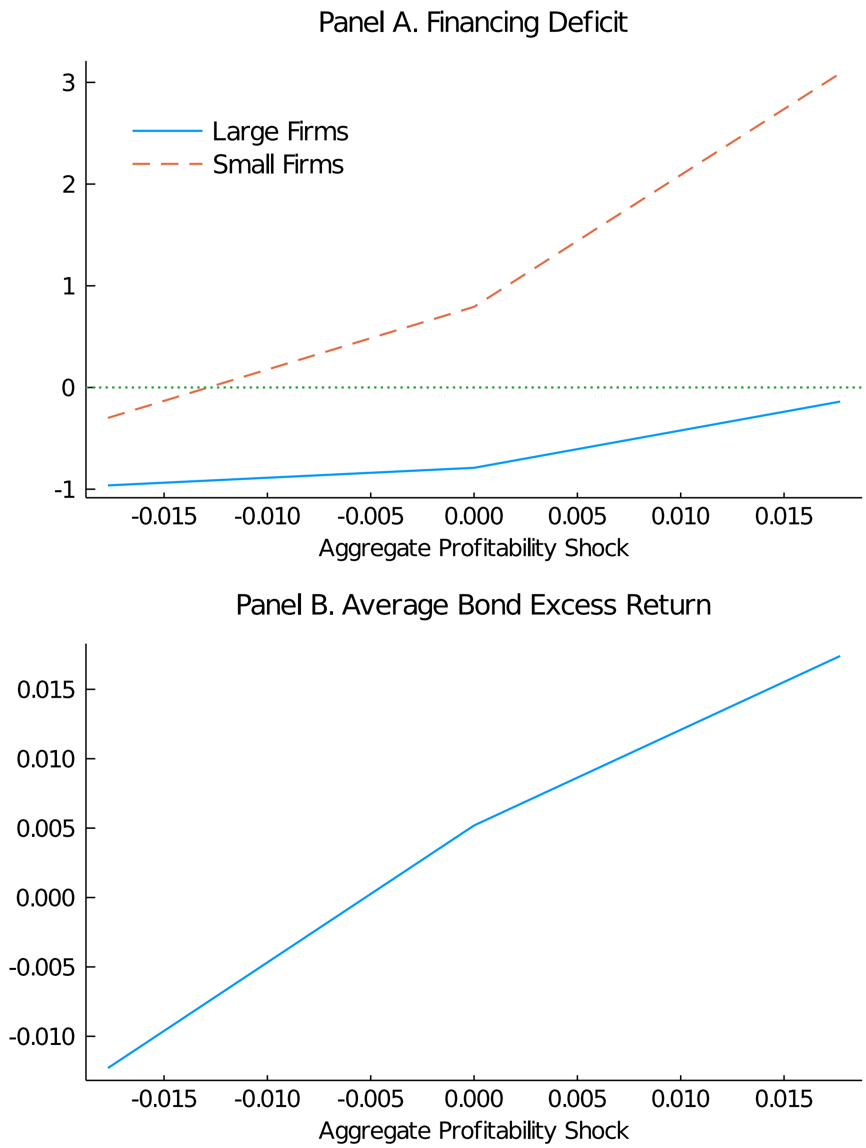
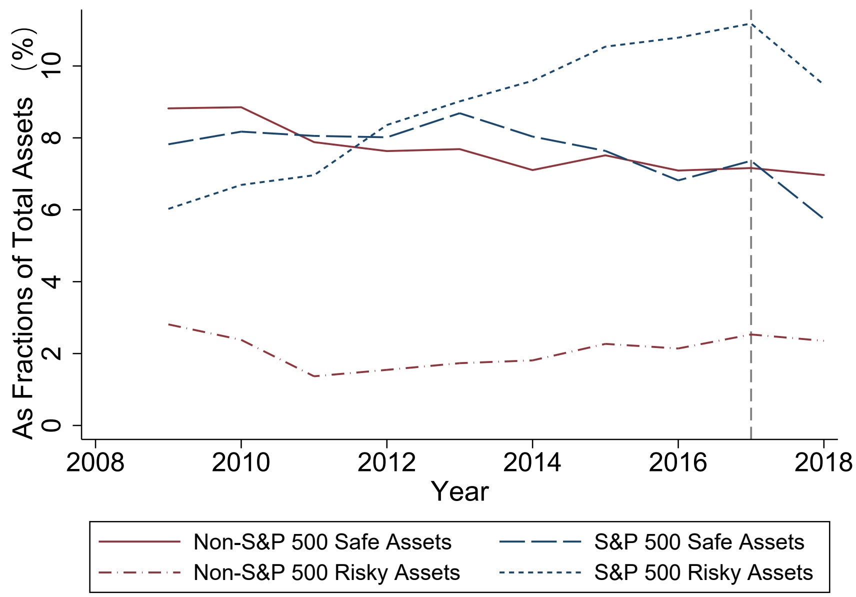


Fig. 5: Savings Portfolio Composition of S&P 500 and Non-S&P 500 Firms. This figure plots the aggregate value of safe and risky financial assets scaled by aggregate total assets (Panel A), and the fraction of aggregate risky over total financial assets (Panel B) for both S&P and non-S&P 500 firms. The sample covers the years 2009 to 2018. Subsection 3.1 describes the sample construction.

Panel A. Risky and Safe Financial Assets of S&P 500 and Non-S&P 500 Firms



Panel B. Fractions of Risky Financial Assets of S&P 500 and Non-S&P 500 Firms

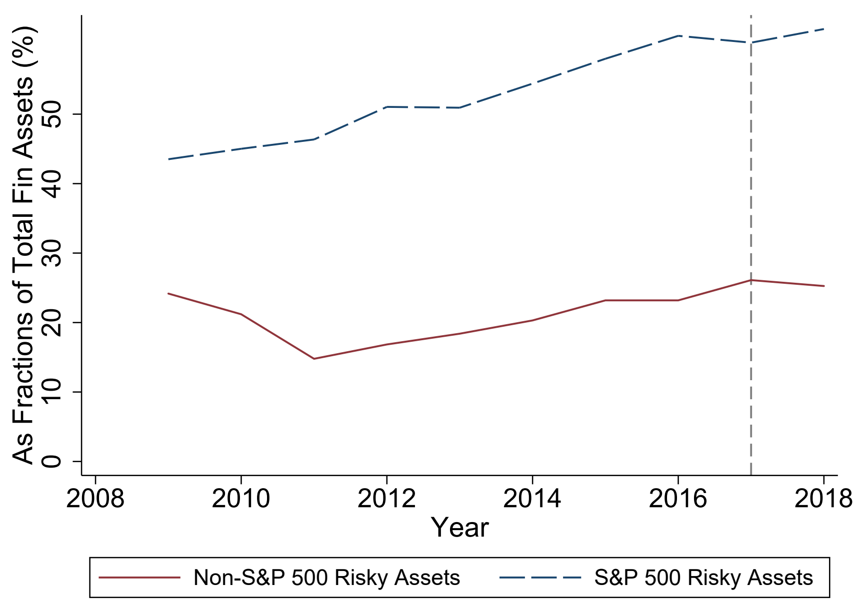


Fig. 6: Financing Deficit Beta and Corporate Financial Assets. This figure plots the relationship between the financing deficit beta and risky financial asset holdings. The figure is constructed using a two-step sorting analysis. In the first step, each year we sort firms into deciles based on the absolute value of the financing deficit beta estimate, and we compute, by subtracting the year-decile mean, the residuals in firms' risky financial asset holdings. As the absolute value of beta is correlated with cash flow volatility, this step teases out the effects of volatility on saving behavior. The second step is to sort firms each year into deciles based on the financing deficit beta, and compute the decile means of the residuals from the first step. The graphs plot the decile means from the second step. The financing deficit beta is estimated for each firm using the time-series regression in Eq. (20), $FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt}$, where FD_{jt} is the financing deficit of firm j in quarter t, and R_{t-1}^B is the Bloomberg US Aggregate Bond Market Index return (Panels A and C) and the reverse change in the 10-year Treasury bond yield (Panels B and D). Panels A and B plot decile means of the residuals in risky financial assets to total assets against the financing deficit beta, while Panels C and D use risky financial assets scaled by total financial assets. The sample period is 2009 to 2018. Subsection 3.1 provides the details of the sample construction.

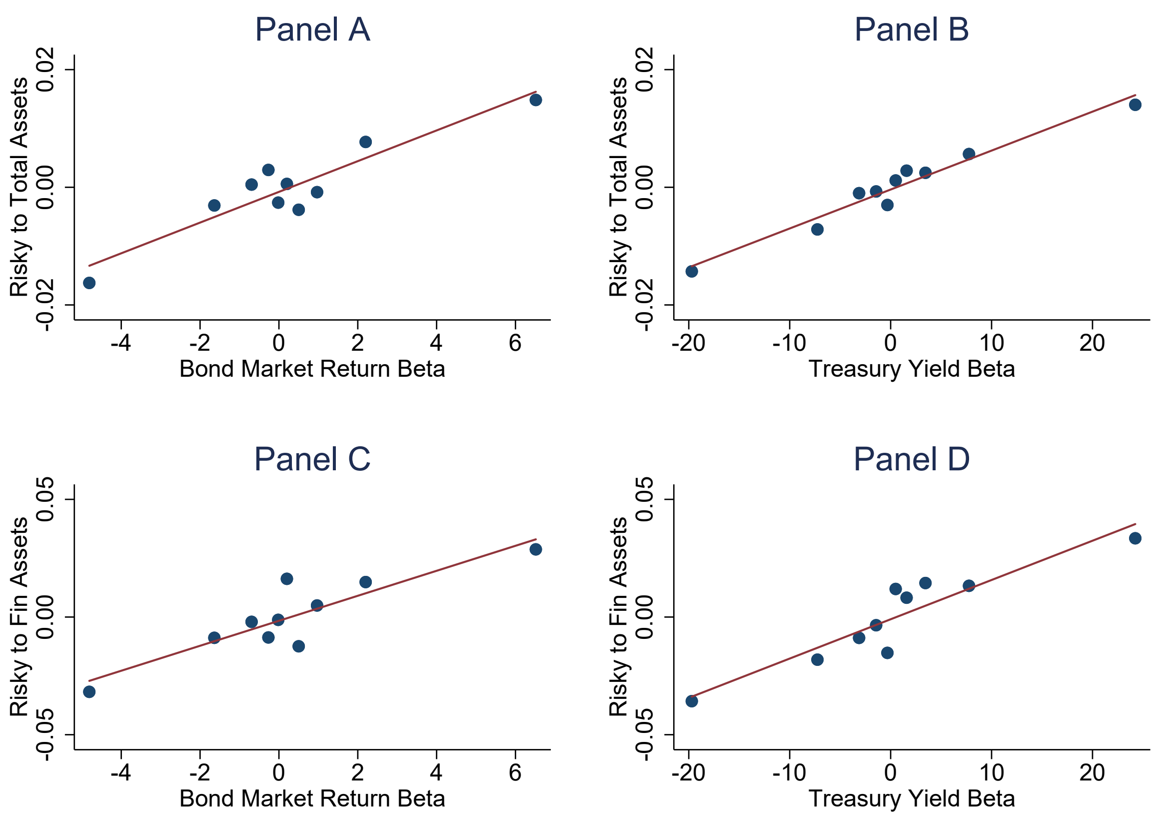


Table 1: Calibration Parameters. This table reports the parameters used in the model calibration. The parameters describing the aggregate environment (Panel A) are taken from the literature whenever possible. GS (2010) stands for Gomes and Schmid (2010) and BLY (2018) for Belo, Lin, and Yang (2018). The time-preference parameter η is set to generate an average annual risk-free rate of 2.13%. The risk-aversion parameter γ is chosen to match an average annual equity return of 6.26%. The inverse-bond maturity μ is chosen to generate an average bond market beta of 0.2. The variables x and z denote the aggregate and idiosyncratic profitability shocks, respectively. The parameters related to firm operations (Panel B) are directly taken from Riddick and Whited (2009), denoted by RW (2009). In Panel C, the bond adjustment cost parameter ψ_{s2} and the scaling parameter of external financing costs $\overline{\xi}$ are jointly calibrated based on sample moments.

Panel A. Parameters of the Aggregate Environment

Parameter	Value	Description	Source
τ	0.20	Corporate tax rate	GS (2010)
ρ_x	0.8140	Persistence parameter of x	GS (2010)
σ_x	0.0073	Conditional standard deviation of x	GS (2010)
ξ_x	12	Countercyclicality of external financing costs	BLY (2018)
η	0.955	Time-preference parameter	Calibrated
γ	30	Risk-aversion parameter	Calibrated
μ	0.40	Inverse bond maturity	Calibrated

Panel B. Parameters Describing Firm Operations

Parameter	Value	Description	Source
ρ_z	0.66	Persistence parameter of z	RW (2009)
σ_z	0.121	Conditional standard deviation of z	RW (2009)
α	0.75	Curvature parameter of the profit function	RW (2009)
δ	0.15	Depreciation rate	RW (2009)
ψ_{i1}	0.039	Fixed capital adjustment cost parameter	RW (2009)
ψ_{i2}	0.049	Quadratic capital adjustment cost parameter	RW (2009)
ξ_0	0.389	Fixed external financing cost parameter	RW (2009)
ξ_1	0.053	Linear external financing cost parameter	RW (2009)
ξ_2	0.0002	Quadratic external financing cost parameter	RW (2009)

Panel C. Calibrated Model-Specific Parameters

Parameter	Value	Description	Source
ψ_{s2}	0.0063	Quadratic bond adjustment cost parameter	Calibrated
$\overline{\xi}$	0.17	External financing cost scaling parameter	Calibrated

Table 2: Real and Simulated Moments. This table reports the average values of the variables of interest in the calibration using the data simulated from the model (Columns 1, 3, and 5) and the real data (Columns 2, 4, and 6). We obtain the simulated moments by solving the model at the parameter values reported in Table 1 according to the numerical procedure described in Appendix C, and simulating 50 samples of 3,000 firms over 50 years. The real-data moments are based on our final sample, described in section 3. Columns 1 and 2 report the moments for the full samples. Columns 3 and 4 report the moments for small firms, and 5 and 6 for large firms. For both the simulated and the real data, we split the sample into small and large firms by the median value of total assets in any given year. Table 3 presents detailed definitions for the variables constructed from the model and the real data. The real data variables are winsorized each year at the 1% and 99% levels.

	Full Sample		Small Firms		Large Firms	
	(1)	(2)	(3)	(4)	(5)	(6)
	Model	Data	Model	Data	Model	Data
Risky	0.191	0.203	0.201	0.261	0.182	0.144
Safe	0.610	0.615	0.683	0.843	0.537	0.385
FinComp	0.388	0.146	0.383	0.145	0.392	0.148
InvTot	0.306	0.338	0.341	0.464	0.271	0.211
LQ	3.246	4.590	3.548	5.280	2.944	3.891
LProf	0.263	0.218	0.258	0.056	0.268	0.380

Table 3: Definitions of the Variables Used in the Calibration. This table presents the definitions of the variables from the model (Panel A), and their empirical counterparts in the real data (Panel B), used to compute the moments reported in Table 2. The subscripts j and t denote the firm and year, respectively. In Panel B, FV represents the fair value of risky financial assets that our algorithm collects from corporate 10-K filings, as described in section 3. All other abbreviations refer to the item names of the variables in Compustat. All variables are at the annual frequency.

Panel A. Model-Based Simulated Variables

Variable	Definition
Risky	$\left[\left(\mu+(1-\tau)\overline{r}_f\right)s_{jt}+q_t^s(1-\mu)s_{jt}\right]/k_{jt-1}$
Safe	$\left(1+(1-\tau)\overline{r}_f\right)c_{jt}/k_{jt-1}$
FinComp	$\dfrac{\left(\mu+(1-\tau)\overline{r}_f\right)s_{jt}+q_t^s(1-\mu)s_{jt}}{\left(\mu+(1-\tau)\overline{r}_f\right)s_{jt}+q_t^s(1-\mu)s_{jt}+\left(1+(1-\tau)\overline{r}_f\right)c_{jt}}$
InvTot	i_{jt}/k_{jt-1}
LQ	$\left[v_{jt-1}-\left(\mu+(1-\tau)\overline{r}_f\right)s_{jt-1}-q_{t-1}^s(1-\mu)s_{jt-1}-\left(1+(1-\tau)\overline{r}_f\right)c_{jt-1}\right]/k_{jt-1}$
LProf	π_{jt-1}/k_{jt-1}
LSize	$\log\left(k_{jt-1}+\left(\mu+(1-\tau)\overline{r}_f\right)s_{jt-1}+q_{t-1}^s(1-\mu)s_{jt-1}+\left(1+(1-\tau)\overline{r}_f\right)c_{jt-1}\right)$
FD	InvTot-LProf

Panel B. Data Variables Used in Calibration

Variable	Definition
Risky	$FV_{jt}/PPEGT_{jt-1}$
Safe	$CH_{jt}/PPEGT_{jt-1}$
FinComp	$FV_{jt}/(FV_{jt}+CH_{jt})$
InvTot	$(CAPEX_{jt}+XRD_{jt})/PPEGT_{jt-1}$
LQ	$(CSHO_{jt-1}\times PRCC\_F_{jt-1}+DLTT_{jt-1}+DLC_{jt-1}-ACT_{jt-1})/PPEGT_{jt-1}$
LProf	$OIBDP_{jt-1}/PPEGT_{jt-1}$

Table 4: Regressions of Risky Financial Asset Holdings Using the Simulated Data. This table reports the regression results of Eq. (21) using data simulated from the model. We obtain the simulated data by solving the model at the parameter values reported in Table 1 according to the numerical procedure described in Appendix C, and simulating 50 samples of 3,000 firms over 50 years. The dependent variable is the value of risky financial assets scaled by capital (variable *Risky* in odd-numbered columns), or by total financial assets (variable *FinComp* in even-numbered columns). The variable *Beta* is the financing deficit beta estimated at the firm level using the regression in Eq. (20). Table 3 reports the definitions of the variables. The regressions include year fixed effects. Columns 1 and 2 report the results for the full simulated sample, 3 and 4 for small firms (below median size), 5 and 6 for large firms (above median), and 7 and 8 for giant firms (top quintile). Standard errors in parentheses are clustered at the firm level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

	Full Sample		Small Firms		Large Firms		Giant Firms	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VARIABLES	Risky	FinComp	Risky	FinComp	Risky	FinComp	Risky	FinComp
Beta	0.452***	0.485***	0.347***	0.342***	0.231***	0.320***	0.106***	0.214**
	(0.047)	(0.082)	(0.047)	(0.095)	(0.037)	(0.085)	(0.037)	(0.096)
LQ	3.758***	-0.942***	4.253***	-0.288	4.074***	-2.126***	4.166***	-1.872***
	(0.175)	(0.221)	(0.181)	(0.219)	(0.179)	(0.374)	(0.182)	(0.404)
LProf	-44.519***	-111.359***	-58.697***	-130.629***	-39.682***	-93.406***	-37.117***	-94.562***
	(1.992)	(3.761)	(2.149)	(4.120)	(1.918)	(3.914)	(1.973)	(3.976)
LSize	1.371***	5.002***	-3.280***	8.295***	5.102***	1.667	3.720***	-3.881***
	(0.503)	(0.954)	(0.729)	(1.175)	(0.450)	(1.056)	(0.491)	(1.192)
Observations	7,500,000	7,500,000	3,750,000	3,750,000	3,750,000	3,750,000	1,500,000	1,500,000
R-squared	0.519	0.391	0.553	0.422	0.542	0.414	0.572	0.463
Cluster Level	Firm	Firm	Firm	Firm	Firm	Firm	Firm	Firm
Year FEs	Y	Y	Y	Y	Y	Y	Y	Y

Table 5: Definitions of the Variables Used in the Empirical Analysis. This table presents the definitions of the variables used in the empirical analysis of sections 3, 4, and Appendix A. FV is the fair value of risky financial assets that we collect from the corporate 10-K filings using the algorithm described in Appendix B. The variable K^{Int} is the intangible capital measure from Peters and Taylor (2017). All other variables are from Compustat, and we report them in the table using their Compustat item names. All original items are in millions of US dollars and have annual frequency, unless otherwise noted. The sample period is from 2009 to 2018.

Variable	Definition
FV	Fair Value of Risky Financial Assets
Risky	FV_{jt}/AT_{jt-1}
Safe	CH_{jt}/AT_{jt-1}
FinComp	$FV_{jt}/(FV_{jt}+CH_{jt})$
LQ	$(AT_{jt-1}-CEQ_{jt-1}+CSHO_{jt-1}\times PRCC\_F_{jt-1})/AT_{jt-1}$
LProf	$OIBDP_{jt-1}/AT_{jt-1}$
LSize	$\log(AT_{jt-1})$
InvTotPPE (Quarterly)	$(CAPEX_{jt}+XRD_{jt})/PPEGT_{jt-1}$
CF (Quarterly)	$\frac{OIBDP_{jt-1}-(XINT_{jt-1}+TXT_{jt-1}+CDVC_{jt-1}-\Delta DLTT_{jt-1}-\Delta DLC_{jt-1})}{PPEGT_{jt-1}}$
FD (Quarterly)	InvTotPPE - CF
K^{Int}	Intangible Capital from Peters and Taylor (2017)
InvTan (Quarterly)	$CAPEX_{jt}/PPEGT_{jt-1}$
InvInt (Quarterly)	$(XRD_{jt}+0.3XSGA_{jt})/K^{Int}_{jt-1}$
InvTot (Quarterly)	$(CAPEX_{jt}+XRD_{jt}+0.3XSGA_{jt})/(PPEGT_{jt-1}+K^{Int}_{jt-1})$

Table 6: Summary Statistics. This table reports the summary statistics of the variables used in the main empirical analysis of section 4. The measures of financial asset holdings used as dependent variables in our main regressions are the fair value of risky and safe financial assets over total assets (*Risky* and *Safe*, respectively), and the fair value of risky financial assets over total financial assets (*FinComp*). The main independent variable of interest is the financing deficit beta (*Beta*), obtained estimating the regression $FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt}$, where j and t index firm and quarter, respectively, FD_{jt} is the financing deficit of firm j in quarter t, and R_{t-1}^B is either the Bloomberg US Aggregate Bond Market Index return (for *BetaAgg*) or the reverse change in the 10-year Treasury bond yield (for $BetaTre$) during quarter $t-1$. Control variables include lagged Tobin's Q (LQ), lagged profitability ($LProf$), and lagged firm size ($LSize$). Detailed variable definitions are presented in Table 5. The sample covers 2,882 firms from 2009 to 2018. All variables in ratios are winsorized at the 1% and 99% percentiles by year, and *BetaAgg* and $BetaTre$ are winsorized at 5% and 95%.

	N	Mean	St. Dev.	Min	Max
Risky	19,163	0.041	0.107	0.000	0.758
Safe	18,978	0.144	0.169	0.000	1.156
FinComp	18,921	0.146	0.256	0.000	0.983
BetaAgg	2,882	0.331	3.153	-6.944	10.535
BetaTre	2,882	0.725	12.423	-28.486	46.259
LQ	19,163	1.885	1.311	0.430	9.558
LProf	19,163	0.074	0.186	-1.205	0.428
LSize	19,163	6.677	2.115	1.618	13.590

Table 7: Sample Comparison with DGHH. This table presents summary statistics of risky financial asset holdings. Panel A reports the number of S&P 500 and non-S&P 500 firms in our sample. To compare our sample with DGHH, Panel B presents average risky financial asset holdings of S&P 500 and non-S&P 500 firms in the same format as Panel B of Table II in DGHH. Sub-panels A and B show the financial asset holdings of S&P 500 firms, sorted by the size of total financial assets, and by total financial assets scaled by total assets, respectively. Sub-panels C and D report these statistics for non-S&P 500 firms.

Panel A. Firm Coverage

Description	Number of Firms
S&P 500 firms between 2009 and 2018	575
S&P 500 firms in our sample	304
Non-S&P 500 firms in our sample	2,578
Total number of firms in our sample	2,882

Panel B. Risky Financial Asset Holdings

Quintile	Low	2	3	4	High
A. Total Fin Assets S&P 500 Firms					
Safe Fin Assets/Book Assets	0.040	0.096	0.124	0.146	0.123
Risky Fin Assets/Book Assets	0.003	0.014	0.031	0.050	0.135
Safe Fin Assets/Total Fin Assets	0.893	0.906	0.864	0.841	0.621
Risky Fin Assets/Total Fin Assets	0.107	0.094	0.136	0.159	0.379
B. Total Fin Assets/Book Assets S&P 500 Firms					
Safe Fin Assets/Book Assets	0.018	0.051	0.094	0.152	0.214
Risky Fin Assets/Book Assets	0.003	0.005	0.009	0.032	0.186
Safe Fin Assets/Total Fin Assets	0.878	0.915	0.911	0.831	0.590
Risky Fin Assets/Total Fin Assets	0.122	0.085	0.089	0.169	0.410
C. Total Fin Assets non-S&P 500 Firms					
Safe Fin Assets/Book Assets	0.067	0.132	0.155	0.169	0.163
Risky Fin Assets/Book Assets	0.008	0.026	0.035	0.053	0.066
Safe Fin Assets/Total Fin Assets	0.916	0.867	0.872	0.836	0.802
Risky Fin Assets/Total Fin Assets	0.084	0.133	0.128	0.164	0.198
D. Total Fin Assets/Book Assets non-S&P 500 Firms					
Safe Fin Assets/Book Assets	0.012	0.047	0.100	0.181	0.347
Risky Fin Assets/Book Assets	0.001	0.006	0.012	0.031	0.139
Safe Fin Assets/Total Fin Assets	0.909	0.895	0.894	0.859	0.735
Risky Fin Assets/Total Fin Assets	0.091	0.105	0.106	0.141	0.265

Table 8: Regressions of Corporate Financial Asset Holdings—Main Results. This table reports the results of the following regression for the full sample:

$$FinAssets_{jt} = \zeta_{sic,t} + \phi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt},$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ is either the fair value of risky financial assets over total assets ($Risky$ in Columns 1 and 2), safe financial assets over total assets ($Safe$ in Columns 3 and 4), or the fair value of risky financial assets over total financial assets ($FinComp$ in Columns 5 and 6); $\zeta_{sic,t}$ are industry×year fixed effects; the control variables are LQ, $LProf$, and $LSize$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated from the following time-series regression for each firm j:

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt},$$

where j and t index firm and quarter, respectively; FD_{jt} is the financing deficit of firm j in quarter t; and R_{t-1}^B is either the Bloomberg US Aggregate Bond Market Index return ("Agg Bond") or the reverse change in the 10-year Treasury bond yield ("Treasury") during quarter $t-1$. Table 5 presents the definitions of the variables, and subsection 3.1 describes the sample construction. Standard errors in parentheses are clustered at the industry level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

VARIABLES	(1) Risky	(2) Risky	(3) Safe	(4) Safe	(5) FinComp	(6) FinComp
Beta	0.252***	0.064***	0.092	0.049**	0.520***	0.138***
	(0.046)	(0.011)	(0.086)	(0.020)	(0.111)	(0.026)
LQ	1.404***	1.425***	3.746***	3.743***	1.211**	1.251**
	(0.253)	(0.253)	(0.269)	(0.267)	(0.498)	(0.493)
LProf	-2.119*	-2.228*	-8.733**	-8.682**	-0.718	-0.926
	(1.172)	(1.151)	(3.833)	(3.798)	(2.360)	(2.314)
LSize	0.273**	0.265**	-1.205***	-1.208***	1.223***	1.206***
	(0.136)	(0.134)	(0.114)	(0.114)	(0.259)	(0.259)
Observations	19,163	19,163	18,972	18,972	18,910	18,910
R-squared	0.163	0.163	0.329	0.330	0.137	0.138
Beta Type	Agg Bond	Treasury	Agg Bond	Treasury	Agg Bond	Treasury
Cluster Level	Industry	Industry	Industry	Industry	Industry	Industry
Ind×Year FEs	Y	Y	Y	Y	Y	Y

Table 9: Regressions of Risky Financial Asset Holdings—Small vs. Large Firms. This table reports the results of the following regression for the subsamples of small (Panel A) and large firms (Panel B):

$$FinAssets_{jt} = \zeta_{sic,t} + \phi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt},$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ is the fair value of risky financial assets over total assets (*Risky*, Columns 1 and 2 in both Panels) or the fair value of risky financial assets over total financial assets (*FinComp*, Columns 3 and 4 in both Panels); $\zeta_{sic,t}$ are industry×year fixed effects; the control variables are LQ, $LProf$, and $LSize$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated from the following time-series regression for each firm j:

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt},$$

where j and t index firm and quarter, respectively; FD_{jt} is the financing deficit of firm j in quarter t; and R_{t-1}^B is either the Bloomberg US Aggregate Bond Market Index return ("Agg Bond") or the reverse change in the 10-year Treasury bond yield ("Treasury") during quarter $t-1$. The two subsamples of small and large firms are defined by the firms below or above, respectively, the median value of total assets at the end of the previous year. Table 5 presents the definitions of the variables, and subsection 3.1 describes the sample construction. Standard errors in parentheses are clustered at the industry level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Panel A. Small Firms

VARIABLES	(1) Risky	(2) Risky	(3) FinComp	(4) FinComp
Beta	0.291***	0.061***	0.493***	0.113***
	(0.067)	(0.015)	(0.141)	(0.028)
Observations	9,269	9,269	9,179	9,179
R-squared	0.165	0.163	0.143	0.142
Beta Type	Agg Bond	Treasury	Agg Bond	Treasury
Cluster Level	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y

Panel B. Large Firms

VARIABLES	(1) Risky	(2) Risky	(3) FinComp	(4) FinComp
Beta	0.129	0.051**	0.535**	0.173***
	(0.101)	(0.022)	(0.256)	(0.062)
Observations	9,330	9,330	9,163	9,163
R-squared	0.237	0.238	0.225	0.226
Beta Type	Agg Bond	Treasury	Agg Bond	Treasury
Cluster Level	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y

Table 10: Interest-Rate Risk and Corporate Financial Asset Holdings. This table presents the results of the following regression:

$$FinAssets_{jt} = \zeta_{sic,t} + \phi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt},$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ is the fair value of risky financial assets over total assets (*Risky*, Panel A) or the fair value of risky financial assets over total financial assets (*FinComp*, Panel B); $\zeta_{sic,t}$ are industry×year fixed effects; the control variables are LQ, $LProf$, and $LSize$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated from the following time-series regression for each firm j:

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt},$$

where j and t index firm and quarter, respectively; FD_{jt} is the financing deficit of firm j in quarter t; and R_{t-1}^B is the reverse change in the Fed Funds rate (Column 1), 1-year (Column 2), 2-year (Column 3), 3-year (Column 4), 5-year (Column 5) and 10-year (Column 6) Treasury bond yield in quarter $t-1$, respectively. Table 5 presents the definitions of the variables, and subsection 3.1 describes the sample construction. Standard errors in parentheses are clustered at the industry level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Panel A. Risky Financial Assets over Total Assets

VARIABLES	(1) Risky	(2) Risky	(3) Risky	(4) Risky	(5) Risky	(6) Risky
Beta	0.015***	0.027***	0.030***	0.041***	0.063***	0.064***
	(0.003)	(0.005)	(0.008)	(0.010)	(0.012)	(0.011)
Observations	19,163	19,163	19,163	19,163	19,163	19,163
R-squared	0.161	0.163	0.162	0.162	0.164	0.163
Beta Type	Fed Funds	1-Y Tre	2-Y Tre	3-Y Tre	5-Y Tre	10-Y Tre
Cluster Level	Industry	Industry	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y	Y	Y

Panel B. Risky Financial Assets over Total Financial Assets

VARIABLES	(1) FinComp	(2) FinComp	(3) FinComp	(4) FinComp	(5) FinComp	(6) FinComp
Beta	0.004	0.026*	0.031*	0.055***	0.115***	0.138***
	(0.010)	(0.014)	(0.017)	(0.021)	(0.026)	(0.026)
Observations	18,910	18,910	18,910	18,910	18,910	18,910
R-squared	0.134	0.135	0.135	0.135	0.137	0.138
Beta Type	Fed Funds	1-Y Tre	2-Y Tre	3-Y Tre	5-Y Tre	10-Y Tre
Cluster Level	Industry	Industry	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y	Y	Y

Table 11: Regressions of Risky Financial Asset Holdings—Alternative Risk Factors. This table presents the results of the following regression:

$$FinAssets_{jt} = \zeta_{sic,t} + \phi\hat{\beta}_j^{Alt} + Controls_{jt-1} + \varepsilon_{jt},$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ is the fair value of risky financial assets over total assets (*Risky*, Panel A) or the fair value of risky financial assets over total financial assets (*FinComp*, Panel B); $\zeta_{sic,t}$ are industry×year fixed effects; the control variables are LQ, $LProf$, and $LSize$; and $\hat{\beta}_j^{Alt}$, the alternative financing deficit beta measure, is estimated from the following time-series regression for each firm j:

$$FD_{jt} = \alpha_j + \beta_j^{Alt} R_{t-1}^B + \varepsilon_{jt},$$

where j and t index firm and quarter, respectively; FD_{jt} is the financing deficit of firm j in quarter t; and R_{t-1}^B is either the equity market return (Columns 1 and 2), the liquidity factor return from Pástor and Stambaugh (2003) (Columns 3 and 4), the reverse change in the investment-grade corporate bond spread over the Fed Funds rate (Columns 5 and 6), or in the high-yield corporate bond spread (Columns 7 and 8). Even-numbered columns include as a control the financing deficit beta computed using the reverse change in the 10-year Treasury bond yield, $BetaTre$. Table 5 presents the definitions of the variables, and subsection 3.1 describes the sample construction. Standard errors in parentheses are clustered at the industry level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Panel A. Risky Financial Asset over Total Assets

VARIABLES	(1) Risky	(2) Risky	(3) Risky	(4) Risky	(5) Risky	(6) Risky	(7) Risky	(8) Risky
BetaAlt	-0.850**	-0.403	-0.174	-0.102	0.027*	0.058***	-0.007	0.085**
	(0.350)	(0.380)	(0.344)	(0.349)	(0.014)	(0.015)	(0.041)	(0.040)
BetaTre		0.055***		0.063***		0.079***		0.075***
		(0.012)		(0.011)		(0.013)		(0.012)
Observations	19,163	19,163	19,163	19,163	19,163	19,163	19,163	19,163
R-squared	0.161	0.163	0.159	0.163	0.160	0.165	0.159	0.164
BetaAlt Type	Equity	Equity	Liquidity	Liquidity	Inv Spread	Inv Spread	HY Spread	HY Spread
Cluster Level	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y	Y	Y	Y	Y

Panel B. Risky Financial Assets over Total Financial Assets

VARIABLES	(1) FinComp	(2) FinComp	(3) FinComp	(4) FinComp	(5) FinComp	(6) FinComp	(7) FinComp	(8) FinComp
BetaAlt	-1.777**	-0.787	0.203	0.361	0.021	0.084**	-0.082	0.107
	(0.684)	(0.693)	(0.602)	(0.610)	(0.032)	(0.034)	(0.093)	(0.083)
BetaTre		0.121***		0.140***		0.162***		0.152***
		(0.025)		(0.027)		(0.027)		(0.024)
Observations	18,910	18,910	18,910	18,910	18,910	18,910	18,910	18,910
R-squared	0.136	0.138	0.134	0.138	0.134	0.138	0.134	0.138
BetaAlt Type	Equity	Equity	Liquidity	Liquidity	Inv Spread	Inv Spread	HY Spread	HY Spread
Cluster Level	Industry	Industry	Industry	Industry	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y	Y	Y	Y	Y

Table 12: Regressions of Risky Financial Asset Holdings—High vs. Low R&D Firms. This table reports the results of the following regression for the subsamples of high R&D (Panel A) and low R&D firms (Panel B):

$$FinAssets_{jt} = \zeta_{sic,t} + \phi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt},$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ is the fair value of risky financial assets over total assets (*Risky*, Columns 1 and 2 in both Panels) or the fair value of risky financial assets over total financial assets (*FinComp*, Columns 3 and 4 in both Panels); $\zeta_{sic,t}$ are industry×year fixed effects; the control variables are LQ, $LProf$, and $LSize$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated from the following time-series regression for each firm j:

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt},$$

where j and t index firm and quarter, respectively; FD_{jt} is the financing deficit of firm j in quarter t; and R_{t-1}^B is either the Bloomberg US Aggregate Bond Market Index return ("Agg Bond") or the reverse change in the 10-year Treasury bond yield ("Treasury") during quarter $t-1$. The two subsamples of high and low R&D firms are defined by the firms above or below, respectively, the median value of R&D expenditure in the year. Table 5 presents the definitions of the variables, and subsection 3.1 describes the sample construction. Standard errors in parentheses are clustered at the industry level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Panel A. High R&D Firms

VARIABLES	(1) Risky	(2) Risky	(3) FinComp	(4) FinComp
Beta	0.301***	0.066***	0.544***	0.139***
	(0.047)	(0.012)	(0.109)	(0.023)
Observations	9,281	9,281	9,180	9,180
R-squared	0.168	0.167	0.141	0.141
Beta Type	Agg Bond	Treasury	Agg Bond	Treasury
Cluster Level	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y

Panel B. Low R&D Firms

VARIABLES	(1) Risky	(2) Risky	(3) FinComp	(4) FinComp
Beta	0.135	0.054**	0.428**	0.118*
	(0.085)	(0.024)	(0.216)	(0.061)
Observations	9,285	9,285	9,153	9,153
R-squared	0.172	0.174	0.183	0.183
Beta Type	Agg Bond	Treasury	Agg Bond	Treasury
Cluster Level	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y

Table 13: Investment Type and Risky Financial Asset Holdings. This table reports the results of the following regression:

$$FinAssets_{jt} = \zeta_{sic,t} + \phi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt},$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ is either the fair value of risky financial assets over total assets ($Risky$, Panel A) or the fair value of risky financial assets over total financial assets ($FinComp$, Panel B); $\zeta_{sic,t}$ are industry×year fixed effects; the control variables are LQ, $LProf$, and $LSize$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated from the following time-series regression for each firm j:

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt},$$

where j and t index firm and quarter, respectively; FD_{jt} is the financing deficit of firm j in quarter t, measured using both tangible and intangible investment ($InvTot$, Columns 1 and 4 in both Panels), tangible investment ($InvTan$, Columns 2 and 5 in both Panels), or intangible investment ($InvInt$, Columns 3 and 6 in both Panels), as indicated by "Tot", "Tan", and "Int," respectively, in the "FD Type" row; and R_{t-1}^B is either the Bloomberg US Aggregate Bond Market Index return ("Agg Bond") or the reverse change in the 10-year Treasury bond yield ("Treasury") during quarter $t-1$. Table 5 presents the definitions of the variables, and subsection 3.1 describes the sample construction. Standard errors in parentheses are clustered at the industry level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

Panel A. Risky Financial Assets over Total Assets

VARIABLES	(1) Risky	(2) Risky	(3) Risky	(4) Risky	(5) Risky	(6) Risky
Beta	0.346***	0.270***	0.034**	0.044**	0.068***	0.011***
	(0.103)	(0.062)	(0.015)	(0.017)	(0.011)	(0.004)
Observations	19,221	19,153	18,009	19,221	19,153	18,009
R-squared	0.161	0.163	0.160	0.160	0.163	0.161
FD Type	Tot	Tan	Int	Tot	Tan	Int
Beta Type	Agg Bond	Agg Bond	Agg Bond	Treasury	Treasury	Treasury
Cluster Level	Industry	Industry	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y	Y	Y

Panel B. Risky Financial Assets over Total Financial Assets

VARIABLES	(1) FinComp	(2) FinComp	(3) FinComp	(4) FinComp	(5) FinComp	(6) FinComp
Beta	0.976***	0.579***	0.131**	0.178***	0.152***	0.032**
	(0.259)	(0.146)	(0.052)	(0.063)	(0.028)	(0.014)
Observations	18,968	18,900	17,773	18,968	18,900	17,773
R-squared	0.137	0.137	0.142	0.137	0.138	0.142
FD Type	Tot	Tan	Int	Tot	Tan	Int
Beta Type	Agg Bond	Agg Bond	Agg Bond	Treasury	Treasury	Treasury
Cluster Level	Industry	Industry	Industry	Industry	Industry	Industry
Controls	Y	Y	Y	Y	Y	Y
Ind×Year FEs	Y	Y	Y	Y	Y	Y

Appendix A. Additional Results

This appendix presents additional empirical results and robustness checks. The order of the tables follows the organization of the topics in the paper. First, for comparison purposes, we estimate the baseline regression in DGHH using our data sample. Second, we perform the estimation of the determinants of risky financial asset holdings, Eq. (22), using the Fama and MacBeth (1973) method. We then check the robustness of our results measuring the value of risky financial asset holdings with Compustat item IVST, instead of the value collected from 10-K filings using our algorithm. Finally, we provide summary statistics for the alternative measures of the investment rate and financing deficit betas used in the analysis of subsection 4.6.

A.1. Baseline Regression in DGHH

Table A.1 presents the results of the following regression, which employs the specification in Column 1 of Table III in DGHH, estimated using our data sample:

$$FinComp_{jt} = \alpha_0 + \alpha_1 FinDGHH_{jt} + \beta' X_{jt} + FE + \varepsilon_{jt}, \qquad \text{A.1}$$

where j and t index firm and year, respectively. The dependent variable ($FinComp$) is risky financial assets scaled by total financial assets, and the key independent variable ($FinDGHH$) is total financial assets scaled by total assets. The control variables in X_{jt} are constructed using the definitions in DGHH, and FE represents fixed effects for the industry and year. We estimate this regression for different sub-samples, including S&P 500 firms (similar to DGHH), non-S&P 500 firms, large (small) firms with total assets above (below) the median value in a given year, and for the full sample.

For S&P 500 firms, all independent variables exhibit relations with risky financial asset holdings that are similar to DGHH, both qualitatively and quantitatively, except cash flow (CF) and leverage (Lev). More specifically, DGHH find a weakly positive association between cash flow and risky financial asset holdings, and a positive but statistically insignificant coefficient between leverage and risky financial asset holdings. Instead, for our sample of S&P 500 firms, we find insignificantly negative associations for both variables. Moreover, we find that the size of the financial portfolio ($FinDGHH$), firm size, capital expenditure, and cash flow volatility exhibit significant coefficients across the different sub-samples.

[Insert Table A.1 around here]

A.2. Main Results Using Fama and MacBeth (1973) Regression

Table A.2 presents the regression results of Eq. (22) using the Fama and MacBeth (1973) procedure. The results in this table correspond to Columns 1, 2, 5, and 6 in Table 8, and they are qualitatively and quantitatively similar to the main results.

[Insert Table A.2 around here]

A.3. Main Results Based on Compustat Item IVST

As documented by DGHH and DM, firms hold financial assets in accounts other than cash and cash equivalents. As a consequence, the Compustat item *CHE* (cash and cash equivalents), which is the sum of items *CH* (cash) and *IVST* (short-term investments), tends to underestimate firms' financial asset holdings. Therefore, our measure gives a more comprehensive coverage of firms' risky financial assets.

Compared with *IVST*, we exclude from the list of risky securities commercial papers, treasuries, and money market funds, which makes our measure more conservative than *IVST* in classifying risky financial assets. Overall, the correlation between our variable *Risky* and *IVST/AT* is 71%, while the correlation between *FinComp* and *IVST/CHE* is 67%.

To test the robustness of our results under the alternative measures of risky financial assets based on Compustat data, we estimate the regression in Eq. (22) using *IVST* to compute the dependent variables (*IVST/AT* and *IVST/CHE* instead of *Risky* and *FinComp*, respectively). Table A.3 presents the results. Due to the availability of $IVST$ from Compustat, the results are based on an extended sample spanning from 1999 to 2018. The results based on Compustat item *IVST* are consistent with those in Table 8.[34]

[Insert Table A.3 around here]

A.4. Summary Statistics for Alternative Measures of Investment and Beta

Table A.4 presents the summary statistics of alternative measures of investment and the corresponding financing deficit betas (Panel A), and the correlation matrix between the different financing deficit betas (Panel B). The alternative measures of investment are tangible investment (*InvTan*), intangible investment (*InvInt*), and total investment (*InvTot*), as defined in Table 5. The alternative measures of the financing deficit beta are computed as the sensitivity of each of these measures of investment to the Agg index return, or the

[34]The same conclusion holds when estimating the regressions for the sample period 2009 to 2018.

reverse change in the 10-year Treasury bond yield. The betas in this table correspond to the betas used in Table 13.

[Insert Table A.4 around here]

Appendix B. Details of the Data Collection Algorithm

To collect the fair value of risky financial assets from the SEC 10-K filings, we first target all the tables with reporting structure similar to Table B.1. 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 (i.e., numerical information). 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 three 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, for which other observable inputs are required; "Level 3" assets includes assets with unobservable inputs.

Overall, this target table structure is used by about 80% of firm-year filings disclosing fair value information, conditional on the disclosure being in tabular format. Our algorithm excludes data reported in tables with a different format than the one described above, and data reported within a text narrative. Moreover, when the firm reports information for multiple years in the same table, the table is also classified as a target.

[Insert Table B.1 around here]

For all tables with the target structure, we scrape up to six long sentences—defined as those with more than five words—before the table as text information used to identify whether the target table contains information on financial asset holdings.[35] We then determine information on the year and unit of measurement (thousands, millions, etc.) for the target table in following way:

[35] If the target table is preceded by another table, and the number of long sentences between them is less than six, we collect all sentences between the two tables.

1. First, we search for this information within the target table.

2. If we cannot identify year information or unit information in the target table, we reversely search the scraped text before the table until we find the first information on year and unit of measurement.

3. If we still cannot identify information on year or unit for the target table, we scrape all the text in the filing and use the year information or unit information with the highest frequency.

4. After identifying information on year and unit, for all the target tables scraped from the same filing, we only keep tables with the most recent year information.

The target table may be used not only to disclose information on the fair value of corporate financial assets, but also for other purposes, including disclosing the value of pension plan assets, intangible assets (e.g., goodwill), assets held for compensation, liabilities, etc. To identify tables with relevant information regarding financial assets, we randomly select 1,500 10-K filings as the training sample for a machine learning algorithm that classifies target tables. In particular, the sample of 10-K filings contains 527 target tables, of which 333 report fair value information on corporate financial assets. We manually tag the tables from this training sample by reading the six sentences before each table, together with the table header. We then exploit a simple n-gram method and L1-regularized logit regression to classify all tables. The regularization parameter is tuned to 0.6, based on this training sample.

Even if a target table is classified as containing relevant information, it may also contain additional information that we aim to discard. Therefore, for all tables classified as containing information on corporate financial assets, we drop securities related to restricted cash, pension plan assets, any liabilities, assets held for compensation, and hedging activities. We do so based on the subhead "Additional Information," as shown in Table B.1, and on the security name. We then classify a security as risky if it 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. Next, we sum up the fair value of all risky securities to obtain firm-year observations on risky financial asset holdings. Finally, for all firms with at least one firm-year observation regarding the fair value of risky financial assets found between 2009 and 2018, we set the value of risky financial asset holdings to zero for the other years with missing information.

To check the accuracy of the algorithm, we perform an out-of-sample test by selecting a random sample of 500 10-K filings, which contain 112 target tables. Table B.2 shows that the overall accuracy rate of the algorithm in the testing sample is 83.93%: the algorithm accurately scrapes 94 firm-year observations, while it makes 10 mistakes determining whether a table is the one containing relevant information, 6 mistakes determining whether a specific type of security is risky or not, and 2 mistakes are due to unforeseen table structures.

[Insert Table B.2 around here]

Appendix C. Numerical Details

For a given value of the vector of structural parameters

$$\theta = (\tau,\ \rho_x,\ \sigma_x,\ \xi_x,\ \eta,\ \gamma,\ \mu,\ \rho_z,\ \sigma_z,\ \alpha,\ \delta,\ \psi_{i1},\ \psi_{i2}, \xi_0,\ \xi_1,\ \xi_2,\ \psi_{s2},\ \overline{\xi}),$$

we solve the model numerically using the Bellman equation

$$v(x, z, s, c, k|\theta) = \max_{s',c',k'}\ d(\cdot) + \mathbf{E}\left[M(x, x')v(x', z', s', c', k')|x, z\right],$$

and the definitions for net and gross distributions to investors, and for the adjustment cost functions, which are, respectively:

$$\begin{aligned}
d(x, z, s, c, k, s', c', k'|\theta) =& e(\cdot) - \mathbf{1}\left[e(\cdot) < 0\right] \exp(\overline{\xi} - \xi_x x) \left(\xi_0 + \xi_1 \left|e(\cdot)\right| + \frac{\xi_2}{2} e(\cdot)^2\right), \\
e(x, z, s, c, k, s', c', k'|\theta) =& (1 - \tau) \exp(x + z)k^{\alpha} + \tau\delta k - (k' - (1 - \delta)k) - Adj^k(\cdot) \\
&+ (\mu + (1 - \tau)\overline{r}_f)s + (1 - \mu)q^s(x)s - q^s(x)s' - Adj^s(\cdot) \\
&+ (1 + (1 - \tau)\overline{r}_f)c - q^c(x)c', \\
Adj^k(k, k'|\theta) =& \mathbf{1}\left[k' \neq (1 - \delta)k\right] \psi_{i1}k + \frac{\psi_{i2}}{2} \left(\frac{k' - (1 - \delta)k}{k}\right)^2 k, \\
Adj^s(s, k, s'|\theta) =& \frac{\psi_{s2}}{2} \left(\frac{s' - (1 - \mu)s}{k}\right)^2 k.
\end{aligned}$$

To increase the accuracy of the numerical solution, we perform a change in variables, by scaling the state variables for risky and safe assets by physical capital: $\tilde{s} = s/k$ and $\tilde{c} = c/k$. We solve the model by value function iteration and discretization on the following grids:

1. The aggregate and idiosyncratic profitability shocks, x and z, respectively, are discretized on a grid following the method proposed by Rouwenhorst (1995) with $N_x = 3$ and $N_z = 5$ points.

2. We discretize $\log(1 + \tilde{s})$ on $N_s = 15$ grid points evenly distributed between $[0, \log 3]$. $\tilde{s}$ is discretized on log space so there are more points closer to zero. The upper limit for

$\tilde{s}$ is set to 2, which is more than 10 times of the sample mean of risky financial assets over $PPEGT$ in the data. We use the same method to discretize $\log(1+\tilde{c})$ on $N_c = 29$ grid points evenly distributed between $[0, \log 7]$. The upper limit for $\tilde{c}$ is set to 6, which is more than 10 times of the sample mean of safe financial assets over $PPEGT$.[36]

3. Following Riddick and Whited (2009), the grid for physical capital k is defined by

$$\left[(1-\delta)^{36}\overline{k},\ \cdots,\ (1-\delta)\overline{k},\ (1-\delta)^{\frac{1}{2}}\overline{k},\ \overline{k}\right],$$

where the upper bound $\overline{k}$ is set such that the capital stock in the simulated sample never hits the bound. We choose $N_k = 73$ grid points, so that the lower bound of the grid $(1-\delta)^{\frac{N_k-1}{2}}\overline{k} = (1-\delta)^{36}\overline{k}$ is less than $\underline{k}$, the minimum level of the capital stock achievable in our model in the absence of financing frictions.

After discretization, the problem has dimensions of $3 \times 5 \times 15 \times 29 \times 73$, and we solve it by value function iteration:

$$v_n(x, z, \tilde{s}, \tilde{c}, k|\theta) = \max_{\tilde{s}', \tilde{c}', k'} d(x, z, \tilde{s}, \tilde{c}, k, \tilde{s}', \tilde{c}', k'|\theta) + \mathbf{E}\left[M(x, x')v_{n-1}(x', z', \tilde{s}', \tilde{c}', k'|\theta)|x, z\right].$$

To speed up convergence, we use Howard's improvement algorithm to reduce

$$\max|v_n(x, z, \tilde{s}, \tilde{c}, k|\theta) - v_{n-1}(x, z, \tilde{s}, \tilde{c}, k|\theta)|$$

by half before the next policy iteration. The convergence criterion is set to

$$\max|v_n(x, z, \tilde{s}, \tilde{c}, k|\theta) - v_{n-1}(x, z, \tilde{s}, \tilde{c}, k|\theta)| < 10^{-5}.$$

We calibrate the parameter vector $\omega = (\psi_{s2},\ \overline{\xi})$ using the following objective function:

$$f(\omega) = (M(\omega) - M)'\, W^{-1}\, (M(\omega) - M)\,,$$

where $M(\omega)$ is the vector of simulated moments, M is the vector of sample moments, and W is the bootstrapped covariance matrix of the sample moments. We simulate 50 samples of 3,000 firms for 500 periods, and we only keep the last 50 periods to eliminate the effect of the initial point in the simulation.

[36]Both $\tilde{s}$ and $\tilde{c}$ are discretized on log space to have a finer grid of points for small values, which at the calibrated parameters are visited in equilibrium more frequently than large values. This grid construction improves numerical accuracy. We have also solved the model on evenly distributed grids for $\tilde{s}$ and $\tilde{c}$ in previous versions, and our results do not hinge on this grid construction.

To obtain the standard errors, we compute the Jacobian matrix at the calibrated parameter vector $\hat{\omega}$

$$\frac{\partial M(\hat{\omega})}{\partial \hat{\omega}^T} = \frac{M(\hat{\omega}^+) - M(\hat{\omega}^-)}{\hat{\omega}^+ - \hat{\omega}^-},$$

where

$$\begin{aligned}\hat{\omega}^+ &= 1.005 \times \hat{\omega} + 0.0005 \times \mathbf{1}[\hat{\omega} = 0] \\ \hat{\omega}^- &= 0.995 \times \hat{\omega} - 0.0005 \times \mathbf{1}[\hat{\omega} = 0],\end{aligned}$$

so the one-side deviation is about 0.5% of the calibrated parameter values, and compute the covariance matrix for $\hat{\omega}$ as

$$Cov(\hat{\omega}) = \left(1 + \frac{1}{S}\right) \left[\left(\frac{\partial M(\hat{\omega})}{\partial \hat{\omega}^T}\right)^T W^{-1} \left(\frac{\partial M(\hat{\omega})}{\partial \hat{\omega}^T}\right) \right].$$

Finally, once we have obtained the calibrated parameter vector $\hat{\omega}$, we solve and simulate the model on a finer grid of points with $N_s = 29$, $N_c = 59$, and $N_k = 361$ on

$$\left[(1-\delta)^{36}\overline{k},\ \cdots,\ (1-\delta)\overline{k},\ (1-\delta)^{\frac{9}{10}}\overline{k},\ \cdots,\ (1-\delta)^{\frac{1}{10}}\overline{k},\ \overline{k}\right],$$

and we use the resulting policy functions to simulate the final sample used in the analysis of section 2.

Table A.1: Baseline Regression in DGHH. This table presents, for different subsamples of firms, the results of the following regression, which uses the same specification as Column 1 of Table III in DGHH:

$$FinComp_{jt} = \alpha_0 + \alpha_1 FinDGHH_{jt} + \beta' X + FE + \varepsilon_{jt},$$

where j and t index firm and year, respectively; the dependent variable ($FinComp$) is risky financial assets scaled by total financial assets; the main independent variable of interest ($FinDGHH$) is total financial assets scaled by total assets; the control variables in X are constructed using the definitions in DGHH, and are reported in the table with the same names as in their paper; and FE are industry and year fixed effects. Column 1 reports the results for the S&P 500 firms in our sample, Column 2 for non-S&P 500 firms, Columns 3 and 4 for large and small firms, defined as firms above and below median size in each year, respectively, and Column 5 for all firms. For each subsample, we report both the number of firm-year observations and the number of firms. The sample construction is described in subsection 3.1. Standard errors in parentheses are clustered at the firm level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

VARIABLES	(1) FinComp	(2) FinComp	(3) FinComp	(4) FinComp	(5) FinComp
FinDGHH	1.001***	0.490***	0.673***	0.449***	0.554***
	(0.073)	(0.032)	(0.045)	(0.037)	(0.030)
Market to book	0.006	-0.009***	-0.013***	-0.005	-0.007**
	(0.006)	(0.003)	(0.004)	(0.004)	(0.003)
Size	0.047***	0.007***	0.020***	0.014***	0.012***
	(0.009)	(0.003)	(0.004)	(0.003)	(0.002)
Cash flow	-0.099	0.013	-0.025	0.029	0.023
	(0.112)	(0.020)	(0.030)	(0.023)	(0.020)
Net Working Capital	0.066	-0.044*	-0.043	-0.062**	-0.051**
	(0.074)	(0.023)	(0.033)	(0.026)	(0.022)
Capital expenditure	0.915***	0.184***	0.322***	0.087	0.234***
	(0.265)	(0.058)	(0.078)	(0.069)	(0.057)
Leverage	-0.015	0.070***	0.074***	0.068***	0.061***
	(0.057)	(0.018)	(0.022)	(0.023)	(0.017)
Cash flow volatility	-0.351**	-0.052***	-0.076***	-0.042***	-0.055***
	(0.153)	(0.015)	(0.024)	(0.016)	(0.015)
Dividend dummy	-0.049**	0.016*	0.010	0.012	0.005
	(0.019)	(0.008)	(0.010)	(0.011)	(0.008)
R&D expenditures	0.464*	-0.081	0.066	-0.152***	-0.095*
	(0.272)	(0.053)	(0.089)	(0.059)	(0.053)
Acquisition expenditures	0.232***	-0.019	0.124**	-0.109**	0.014
	(0.065)	(0.037)	(0.048)	(0.046)	(0.034)
Observations	3,113	14,822	8,824	8,359	17,935
R-squared	0.377	0.102	0.156	0.107	0.127
Cluster Level	Firm	Firm	Firm	Firm	Firm
Firm Type	S&P	Non-S&P	Large	Small	Full
Number of Firms	396	2,470	2,248	2,124	2,866
Ind FEs	Y	Y	Y	Y	Y
Year FEs	Y	Y	Y	Y	Y

Table A.2: Risky Financial Asset Holdings—Fama and MacBeth (1973) Regressions. This table reports the Fama and MacBeth (1973) regression results of the following model:

$$FinAssets_{jt} = \zeta_{sic,t} + \phi \hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt},$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ is the fair value of risky financial assets over total assets ($Risky$, Columns 1 and 2), or the fair value of risky financial assets over total financial assets ($FinComp$, Columns 3 and 4); $\zeta_{sic,t}$ are industry×year fixed effects; the control variables are LQ, $LProf$, and $LSize$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated from the following time-series regression for each firm j:

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt},$$

where j and t index firm and quarter, respectively; FD_{jt} is the financing deficit of firm j in quarter t; and R_{t-1}^B is either the Bloomberg US Aggregate Bond Market Index return ("Agg Bond") or the reverse change in the 10-year Treasury bond yield ("Treasury") during quarter $t-1$. The "Number of groups" reported in the table corresponds to the number of cross-sectional regressions, one for each year in our 2009-2018 sample. Table 5 presents the definitions of the variables, and subsection 3.1 describes the sample construction. Standard errors robust to heteroskedasticity and autocorrelation are reported in parentheses. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

VARIABLES	(1) Risky	(2) Risky	(3) FinComp	(4) FinComp
Beta	0.263***	0.068***	0.531***	0.145***
	(0.045)	(0.008)	(0.066)	(0.017)
LQ	1.399***	1.420***	1.149***	1.192***
	(0.111)	(0.106)	(0.183)	(0.175)
LProf	-2.184**	-2.376**	-0.558	-0.909
	(0.806)	(0.765)	(1.430)	(1.339)
LSize	0.268***	0.261***	1.214***	1.197***
	(0.051)	(0.052)	(0.100)	(0.103)
Observations	19,163	19,163	18,921	18,921
R-squared	0.038	0.038	0.017	0.017
Number of groups	10	10	10	10
Beta Type	Agg Bond	Treasury	Agg Bond	Treasury
Ind×Year FEs	Y	Y	Y	Y

Table A.3: Regressions of Risky Financial Asset Holdings Measured Using Compustat Item IVST. This table reports the results of the following regression:

$$FinAssets_{jt} = \zeta_{sic,t} + \phi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt},$$

where j and t index firm and year, respectively; $FinAssets_{jt}$ is the ratio of Compustat items $IVST$ and AT (Columns 1 and 2), or the ratio of Compustat items $IVST$ and CHE (Columns 3 and 4); $\zeta_{sic,t}$ are industry×year fixed effects; the control variables are LQ, $LProf$, and $LSize$, defined in Table 5; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated from the following time-series regression for each firm j:

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt},$$

where j and t index firm and quarter, respectively; FD_{jt} is the financing deficit of firm j in quarter t; and R_{t-1}^B is either the Bloomberg US Aggregate Bond Market Index return ("Agg Bond") or the reverse change in the 10-year Treasury bond yield ("Treasury") during quarter $t-1$. The sample period is 1999-2018. Standard errors in parentheses are clustered at the industry level. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)
VARIABLES	IVST/AT	IVST/AT	IVST/CHE	IVST/CHE
Beta	0.251***	0.060***	0.529***	0.124***
	(0.055)	(0.012)	(0.121)	(0.024)
LQ	1.743***	1.759***	1.835***	1.870***
	(0.248)	(0.249)	(0.380)	(0.381)
LProf	-5.629***	-5.784***	-8.483***	-8.821***
	(1.785)	(1.797)	(1.705)	(1.690)
LSize	0.103	0.095	0.903***	0.886***
	(0.107)	(0.105)	(0.293)	(0.291)
Observations	35,356	35,356	35,187	35,187
R-squared	0.222	0.222	0.170	0.170
Beta Type	Agg Bond	Treasury	Agg Bond	Treasury
Cluster Level	Industry	Industry	Industry	Industry
Ind×Year FEs	Y	Y	Y	Y

Table A.4: Summary Statistics of Financing Deficit Betas Based on Alternative Measures of Investment. This table presents the summary statistics of financing deficit betas based on different types of investment (Panel A), and their pairwise correlations (Panel B). The betas in this table correspond to the ones used in Table 13. Betas estimated using the Bloomberg US Aggregate Bond Market Index return and the reverse change in the 10-year Treasury bond yield are indicated by the suffixes "Agg" and "Tre", respectively. Betas estimated using investment in both tangible and intangible capital ($InvTot$), tangible capital only ($InvTan$), and intangible capital only ($InvInt$) are indicated by the suffixes "Tot", "Tan", and "Int", respectively. Panel A reports summary statistics for these different investment measures, and their definitions are provided in Table 5. Notice that, for comparison purposes, the summary statistics in Panel A use investment rates at an annual frequency, while we employ investment rates at a quarterly frequency to compute the financing deficit betas.

Panel A. Summary Statistics

	N	Mean	St. Dev.	Min	Max
BetaAggTot	2,921	-0.037	1.473	-3.902	3.047
BetaAggTan	2,908	0.308	3.158	-6.880	8.664
BetaAggInt	2,632	0.070	8.130	-21.907	19.912
BetaTreTot	2,921	-0.354	6.297	-17.459	14.255
BetaTreTan	2,908	0.742	13.071	-27.873	36.650
BetaTreInt	2,632	-0.614	34.209	-95.788	86.648
InvTot	19,571	0.105	0.121	0.000	0.847
InvTan	19,562	0.063	0.083	0.000	0.640
InvInt	19,571	0.040	0.086	0.000	0.627

Panel B. Correlations Between Alternative Financing Deficit Beta Measures

	BetaAggTot	BetaAggTan	BetaAggInt	BetaTreTot	BetaTreTan	BetaTreInt
BetaAggTot	1.000					
BetaAggTan	0.650	1.000				
BetaAggInt	0.451	0.377	1.000			
BetaTreTot	0.773	0.493	0.384	1.000		
BetaTreTan	0.482	0.714	0.319	0.640	1.000	
BetaTreInt	0.370	0.314	0.756	0.459	0.391	1.000

Table B.1: Typical Structure of Target Tables. This table presents the standard structure of the tables targeted by our algorithm in the 10-K filings retrieved from the SEC's EDGAR system. Details of the algorithm are reported in Appendix B. The information enclosed in brackets is not necessary for the table to become a target, but it is sometimes helpful for later information extraction and data construction.

			(**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)		(⋯)	⋯	⋯	⋯

Table B.2: Out-of-Sample Accuracy Test. This table reports the results of an out-of-sample accuracy test of the algorithm used to collect information on the fair value of risky financial assets reported in 10-K filings from the SEC's EDGAR system. The original testing sample of 500 10-K filings is selected randomly, and contains 112 target tables. The algorithm accurately scrapes 94 firm-year observations out of the 112 testing observations. The algorithm makes 10 mistakes determining whether a table is the one containing relevant information, 6 mistakes determining whether a specific type of security is risky or not, and 2 mistakes are due to unforeseen table structures. The details of the data extraction algorithm are in Appendix B.

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		