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# 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 and estimating 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 interest-rate risk. Precautionary motives are stronger in small, high-volatility, and R&D-intensive firms.

## 1. Introduction

Why do non-financial firms invest in risky financial assets? A recent study by Duchin et al. (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 (2024, 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

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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 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 estimate the structural parameters of the model by Simulated Method of Moments (SMM) and 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. Our final sample contains 19,367 observations from 2009 – when the Financial Accounting Standard Board's Statement of Financial Accounting Standards (SFAS) No. 157 became implemented – to 2018 for 2886 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 0.81% higher corporate risky financial asset holdings as a fraction of total assets, an increase that represents about 20% of the average risky financial asset holdings in our sample (4.2% of total assets).

Next, 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 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 statistically significant coefficients at the 5% level only for the financing deficit betas based on equity and investment-grade corporate bonds. These results suggest that equity market conditions and credit risk also influence corporate savings in risky financial assets, albeit to a lesser extent than interest-rate risk.

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 perform a sample split based on the volatility of firms' financing deficits. In line with the model's predictions, we find that the positive relationship between financing deficit betas and risky financial asset holdings is concentrated among high-volatility firms—those whose investment demand is more sensitive to macroeconomic conditions. For low-volatility firms, this relationship is statistically insignificant. These results support the view that hedging motives play a more prominent role for firms facing greater uncertainty.

In addition, we examine whether firms' decisions to hold risky financial assets depend on the type of capital in which they invest. Splitting the sample by R&D intensity, we find that the financing deficit beta is significantly associated with risky financial asset holdings among high-R&D firms, while the relationship is less statistically significant for low-R&D firms.

Finally, we quantify the value of the firm's option to invest in risky financial assets by performing a counterfactual experiment, restricting firms to invest only in safe financial assets. In response, firms substitute risky assets with safe financial assets, but the overall level of savings declines. Investment, firm size, and profits fall, while reliance on external financing increases. Despite lower trading costs and taxes, cash flows from financial assets decrease, leading to more frequent and larger external financing needs. As a result, firm value declines by 0.35% relative to the benchmark model, and the decline is larger during booms and for small firms, highlighting the importance of risky asset holdings in supporting investment opportunities and mitigating financial frictions.

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 et al. (2021), and Falato et al. (2022).[2] 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.

Some studies highlight the role of agency problems (Nikolov and Whited, 2014) and managerial overconfidence (DGHH) in explaining corporate cash holdings. In contrast, our framework focuses on a different channel: we show that firms may rationally invest in risky financial assets as a hedging tool. This mechanism operates even in the absence of agency frictions or behavioral distortions. Our approach highlights a complementary, rational motive for holding risky financial assets that is distinct from the agency- and behavior-based explanations in the literature.

This hedging motive naturally connects our paper to the broader risk-management literature. The key economic mechanism at work in our model can be traced back to Smith and Stulz (1985) and Froot et al. (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 played by risky financial assets in our model parallels that of credit lines in Acharya et al. (2014) and Nikolov et al. (2019), and more broadly, of state-contingent debt in Rampini and Viswanathan (2010, 2013). In particular, the similarity with credit lines (Nikolov et al., 2019) arises because both instruments enable firms to transfer liquidity across states of the world – risky financial assets in response to aggregate shocks through market returns, and credit lines in response to idiosyncratic shocks through contingent usage – highlighting their potential complementarity in managing different sources of uncertainty.

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; Pinkowitz, Stulz, and Williamson, 2016; Graham and Leary, 2018), as well as economy-wide factors like corporate taxation and interest rates (see, e.g., 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 et al. (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 subsequent fall; and Chen and Duchin (2024) 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 introduces the dynamic model of investment and cash holdings. Section 3 presents the structural estimation results and derives empirical predictions. Section 4 describes the data and reports the empirical analysis. Section 5 presents the counterfactual experiments and additional tests, and Section 6 concludes. The Appendix provides details on the numerical procedure and data collection. The Online Appendix presents further robustness checks.

## 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 et al., 2021), firms can also invest in a risky bond.

We begin by introducing the firm's technology, investment frictions, and the two saving options available to the firm. We then define the firm's cash flows and formulate its dynamic optimization problem. Finally, we discuss the economic mechanism that gives rise to the precautionary motive for holding risky financial assets.

### 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 $\alpha$ 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 $\varepsilon_{jt}^z \sim \mathcal{N}(0,1)$, $\varepsilon_t^x$ is independent of $\varepsilon_{jt}^z$, and $\varepsilon_{jt}^z$ and $\varepsilon_{lt}^z$ are independent for $j \neq l$. The parameters $\rho_x$ and $\rho_z$ capture the persistence, and $\sigma_x$ and $\sigma_z$ 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 $\delta$ is the depreciation rate. Following the literature (e.g., Nikolov et al., 2019; Begenau and Palazzo, 2021), we assume that the firm incurs quadratic capital adjustment costs

$$Adj_{jt}^k = \frac{\psi_i}{2}\left(\frac{k_{jt+1} - (1-\delta)k_{jt}}{k_{jt}}\right)^2 k_{jt}, \tag{5}$$

where the parameter $\psi_i$ captures the severity of 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 $\gamma$ is the risk-aversion parameter.[3] Given this specification of the stochastic discount factor, the risk-free rate is

$$r_f(x_t) = \frac{1}{\mathbf{E}\left[M(x_t, x_{t+1})|x_t\right]} - 1 = \frac{1}{\eta}\exp\left(-\gamma(1-\rho_x)x_t - \frac{\gamma^2\sigma_x^2}{2}\right) - 1. \tag{7}$$

[2] For related models in continuous time, see Bolton et al. (2011), Décamps et al. (2011), and Hugonnier et al. (2015). More broadly, our theoretical framework is also related to recent macroeconomic models that study the aggregate impact of corporate savings (see Ferreira, 2023; Li, 2025).

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

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 of this risk-free security to a fixed rate $\bar{r}_f = r_f(0)$, where $r_f(0)$ is the risk-free rate in the aggregate neutral state ($x = 0$). Given the stochastic discount factor, the price $q^c(x_t)$ of this risk-free security is

$$q^c(x_t) = \mathbf{E}\left[M(x_t, x_{t+1})(1+\bar{r}_f)\right] = \frac{1+\bar{r}_f}{1+r_f(x_t)}. \tag{8}$$

In addition to the risk-free security, we assume that firms can invest in a risky bond.[4] Similar to Gomes et al. (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, $\bar{r}_f$. The parameter $\mu$ determines the fraction of the bond's notional value that matures in every period and, thus, its exposure to interest risk. Indeed, the price $q^s(x_t)$ of the risky bond is given by

$$\begin{aligned} q^s(x_t) =& \mathbf{E}\left[M(x_t, x_{t+1})\left(\mu + \bar{r}_f + (1-\mu)q^s(x_{t+1})\right)|x_t\right] \\ =& \frac{\mu + \bar{r}_f}{1+r_f(x_t)} + (1-\mu)\mathbf{E}\left[M(x_t, x_{t+1})q^s(x_{t+1})|x_t\right]. \end{aligned} \tag{9}$$

The first addend in Eq. (9) represents the value of the fixed component of the bond's payoff, which is the sum of the matured notional value $\mu$ and the coupon payment $\bar{r}_f$, 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. We verify manually, using a subsample of our data, that this pattern holds in our sample as well. 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 Sections 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.[5] Thus, our assumption reduces the dimensionality of the dynamic problem and 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 risk-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

$$(1+\bar{r}_f)c_{jt} + (\mu + \bar{r}_f)s_{jt} + q^s(x_t)(1-\mu)s_{jt}, \tag{10}$$

and the taxable income for the firm is

$$TI_{jt} = \exp(x_t + z_{jt})k_{jt}^{\alpha} - \delta k_{jt} + \bar{r}_f c_{jt} + \bar{r}_f s_{jt}. \tag{11}$$

Notice that, following Gomes et al. (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 trading costs for the firm

$$Adj_{jt}^s = \psi_s \left|s_{jt+1} - (1-\mu)s_{jt}\right|, \tag{12}$$

where the parameter $\psi_s \geq 0$ captures linear trading costs in security transactions. We introduce this parameter because bonds are often traded in illiquid markets, and their trading implies financial frictions such as transaction costs.

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:

$$\begin{aligned} e_{jt} =& (1-\tau)TI_{jt} + \delta k_{jt} + c_{jt} + \mu s_{jt} + q^s(x_t)(1-\mu)s_{jt} \\ &- i_{jt+1} - Adj_{jt}^k - q^c(x_t)c_{jt+1} - q^s(x_t)s_{jt+1} - Adj_{jt}^s. \end{aligned} \tag{13}$$

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 $\Lambda_{jt}$, so that net distributions are:

$$d_{jt} = e_{jt} - \Lambda_{jt}. \tag{14}$$

Following the literature (e.g., Nikolov and Whited, 2014; Nikolov et al., 2019), we specify a linear external financing cost function as

$$\Lambda_{jt} = \xi |e_{jt}| \mathbf{1}_{\{e_{jt}<0\}}, \tag{15}$$

where $\xi$ captures the external financing cost for every dollar raised. 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:

$$\begin{aligned} v(x,z,s,c,k) = \max_{s',c',k'} \; & d(x,z,s,c,k,s',c',k') \\ &+ \mathbf{E}\left[M(x,x')v(x',z',s',c',k')|x,z\right], \end{aligned} \tag{16}$$

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. (16) 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 A for details).

### 2.5. Precautionary motives 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 that Eq. (16) is differentiable with respect to $k'$, the first-order condition for optimal investment yields

$$\underbrace{\left(1+\xi\mathbf{1}_{\{e(\cdot)<0\}}\right)}_{MC\ of\ Financing}\underbrace{\left(1+\psi_i\frac{k'^{*}-(1-\delta)k}{k}\right)}_{MC\ of\ Inv.\ with\ Internal\ Funds} + \kappa^{*} = \underbrace{\mathbf{E}\left[M(x,x')\frac{\partial v(x',z',s',c',k'^{*})}{\partial k'^{*}}\middle| x\right]}_{MV\ of\ Investment}, \tag{17}$$

[4] 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.

[5] A stochastic return $R_{t+1} = q(x_{t+1})/q(x_t)$ satisfies 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.

where $k'^*$ denotes the optimal capital level for next period, and $\kappa^*$ is the Lagrange multiplier associated with the external financing constraint in Eq. (15). The right-hand side of Eq. (17) 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 Fig. 1 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 Fig. 1.

The slope of the marginal cost function, instead, is determined by the marginal capital adjustment cost $\psi_i$ and the cost of external financing $\xi$. 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 $\psi_i$. However, when $e(\cdot) < 0$ the firm starts to tap external financing, so that the slope increases to $(1+\xi)\psi_i$. 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 Fig. 1, 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.

As shown in Eq. (17), the optimal level of investment is determined by the intersection between the marginal value and marginal cost functions. In Panel A of Fig. 1, 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

$$\underbrace{k'^* - (1-\delta)k + Adj^k - (1-\tau)\exp(x+z)k^\alpha - \tau\delta k}_{Financing\ Deficit} > \underbrace{(1+(1-\tau)\bar{r}_f)c - q^c(x)c'}_{Cash\ Flow\ from\ Safe\ Fin\ Assets} + \underbrace{(\mu+(1-\tau)\bar{r}_f)s + (1-\mu)q^s(x)s - q^s(x)s' - Adj^s}_{Cash\ Flow\ from\ Risky\ Fin\ Assets}. \tag{18}$$

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. (18)) will change by

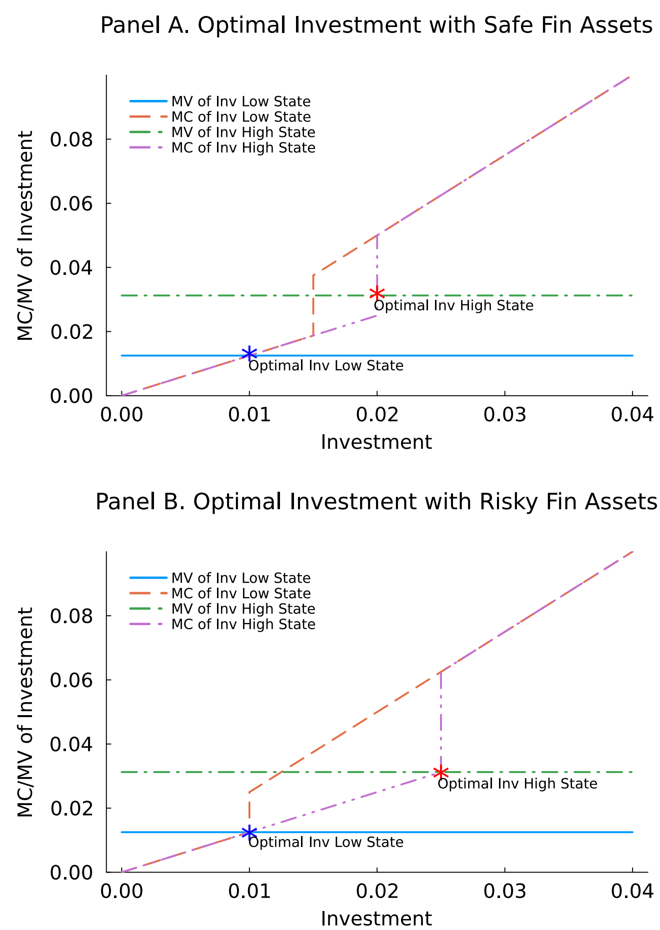


**Fig. 1.** Precautionary motives and risky financial assets. This figure illustrates the first-order conditions for optimal investment to highlight the precautionary role of risky financial assets in the model. Both panels plot the marginal value and marginal cost of investment, defined in Eq. (17) in the simple case of $\alpha = 1$, 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.

$$\underbrace{(1+(1-\tau)\bar{r}_f)(-1)}_{\$1\ Less\ Safe\ Fin\ Assets} + \underbrace{(\mu+(1-\tau)\bar{r}_f) + (1-\mu)q^s(x)}_{\$1\ More\ Risky\ Fin\ Assets} = (1-\mu)(q^s(x)-1). \tag{19}$$

Therefore, if the current-period bond price $q^s(x)$ is greater (less) 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 estimation the risky bond bears positive market risk (see Section 3.1 for details), the bond price $q^s(x)$ is positively correlated with the aggregate profitability shock $x$, so that $q^s(x)$ will be greater (less) 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 $x > 0$ ($x < 0$).

Fig. 1 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

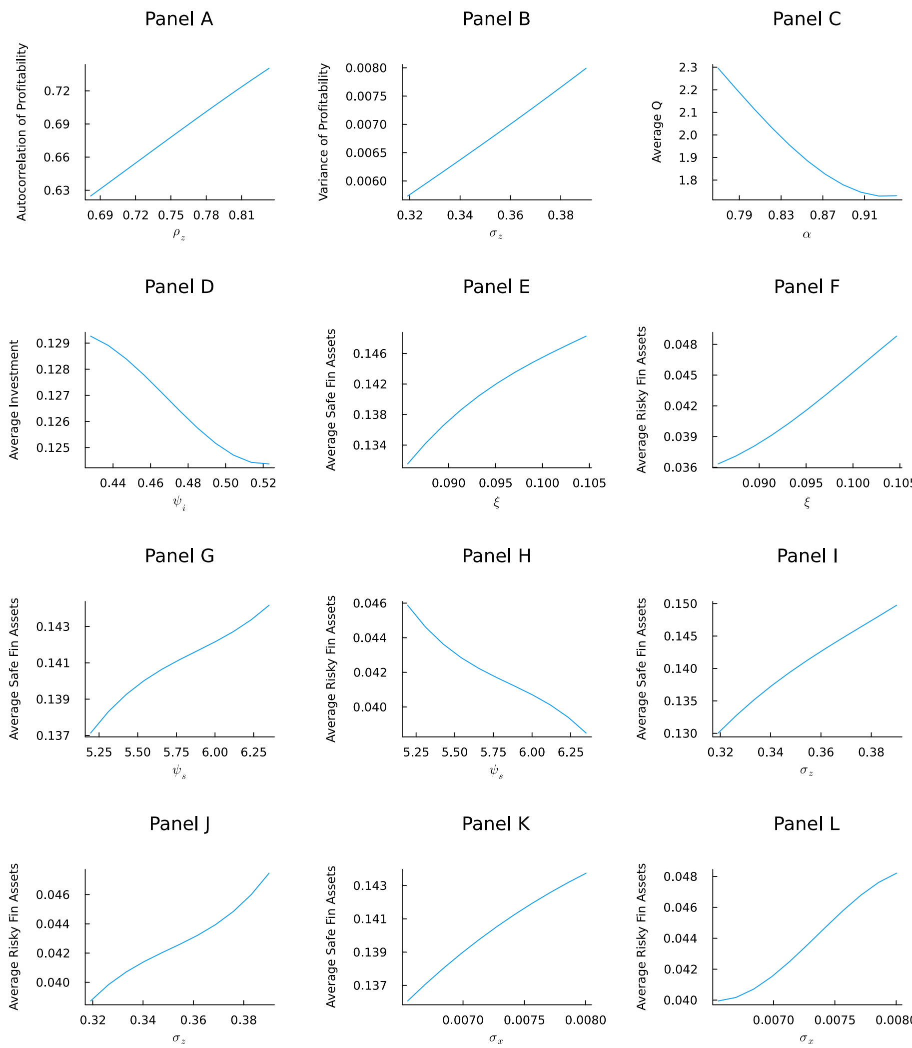


**Fig. 2.** Comparative statics. This figure presents comparative statics showing how key moments respond to changes in underlying structural parameters. For each plot, we set the parameters to the values in Table 1, and only vary the relevant parameter. Panels A, B, C, and D display the autocorrelation of profitability, the variance of profitability, average Tobin's Q, and the average investment rate, respectively, against the persistence of the idiosyncratic profitability shock, $\rho_z$, the conditional standard deviation of the idiosyncratic profitability shock, $\sigma_z$, the curvature of the profit function, $\alpha$, and the capital adjustment cost parameter, $\psi_i$. Panels E through L plot the average safe and risky financial assets, against the external financing cost parameter, $\xi$, in Panels E and F, the trading cost of risky financial assets, $\psi_s$, in Panels G and H, the standard deviation of the conditional idiosyncratic profitability shock, $\sigma_z$, in Panels I and J, and the conditional standard deviation of the aggregate profitability shock, $\sigma_x$, in Panels K and L. Moment definitions are in Table A.3.

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 $\psi_i$ to $(1+\xi)\psi_i$, 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 Fig. 1 shows how investing in the risky financial asset can alleviate external financing costs for the firm.

## 3. Structural estimation and empirical predictions

In this section, we estimate the structural parameters of the model, describe the equilibrium policy functions that characterize the firm's optimal investment and saving decisions, and derive the empirical predictions on risky financial asset holdings that we test in Section 4.

### 3.1. Structural estimation

Our model is characterized by thirteen parameters. For seven of these, we either use values from the previous literature, or calibrate them to match statistics of macroeconomic variables for our sample period. We follow Gomes and Schmid (2010) and set the persistence $\rho_x$ and conditional standard deviation $\sigma_x$ of the aggregate shock to 0.8140 and 0.0073, respectively, and the risk-aversion parameter $\gamma$ to 15.[6] We set the time-preference parameter $\eta$ to 0.96, which generates an average risk-free rate that matches the average 10-year treasury yield of 3.61% between 1999 and 2018, and the inverse maturity of the bond $\mu = 0.4$ to match a bond beta of 0.2 (similar to the value in Fama and French, 1993) in the neutral aggregate state ($x = 0$). Finally, we set the

[6] 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 with persistence and volatility parameters $\rho_x^M = 0.983$ and $\sigma_x^M = 0.0023$, respectively, from which we derive $\rho_x = \rho_x^{M\,12} = 0.983^{12} = 0.8140$, and $\sigma_x = \sqrt{\frac{1-0.983^{24}}{1-0.983^2}}\,0.0023 = 0.0073$ at yearly frequency.

**Table 1**
Structural estimation results. Panel A reports the sample and simulated moments. Column 1 shows the sample moments targeted in the structural estimation. Column 2 reports the corresponding simulated moments, generated from 50 simulations of 3000 firms over 50 years. Column 3 presents the *t*-statistics for the difference between real and simulated moments. Panel B presents the estimated structural parameters. $\rho_z$ and $\sigma_z$ are the persistence and conditional standard deviation of the idiosyncratic profitability shock, respectively; $\alpha$ is the curvature of the profit function; $\psi_i$ is the capital adjustment cost parameter; $\xi$ is the external financing cost parameter; and $\psi_s$ denotes the bond trading cost. Standard errors are clustered at the firm level. Section 4.1 describes the sample construction. Moment definitions are provided in Table A.3. Appendix A presents the details of the numerical procedure used to solve the model.

Panel A. Moments

| | (1) Data | (2) Model | (3) t-stats |
|---|---|---|---|
| Average Risky Financial Assets | 0.0423 | 0.0418 | 3.24 |
| Average Safe Financial Assets | 0.1432 | 0.1411 | 4.04 |
| Average Investment | 0.1229 | 0.1263 | −2.50 |
| Average Q | 1.8837 | 1.8802 | 1.40 |
| Average Profitability | 0.2196 | 0.1635 | 5.78 |
| Median Distribution | 0.0180 | 0.0037 | 1.23 |
| Variance of Profitability | 0.0082 | 0.0068 | 3.11 |
| Variance of Distribution | 0.0271 | 0.0224 | 4.01 |
| Autocorrelation of Profitability | 0.7691 | 0.6845 | 1.26 |
| Autocorrelation of Investment | 0.6684 | 0.5486 | 2.99 |
| Autocorrelation of Distribution | 0.5533 | 0.4712 | 1.44 |

Panel B. Parameter Estimates

| Parameter | $\rho_z$ | $\sigma_z$ | $\alpha$ | $\psi_i$ | $\xi$ | $\psi_s$ (bps) |
|---|---|---|---|---|---|---|
| Value | 0.7576 | 0.3546 | 0.8552 | 0.4756 | 0.0951 | 5.7723 |
| Standard Error | 0.0151 | 0.0191 | 0.0136 | 0.0418 | 0.0021 | 0.9107 |

corporate tax rate $\tau$ to 0.14, as in Kuehn and Schmid (2014), and the depreciation rate $\delta$ to 0.1, following Gomes et al. (2016).[7]

We estimate the remaining six parameters ($\rho_z$, $\sigma_z$, $\alpha$, $\psi_i$, $\xi$, $\psi_s$) using SMM. This procedure requires matching a set of moments simulated from the model to their empirical counterparts. To compute the real-data moments, we employ a sample of firms for the 2009–2018 period, using standard financial variables from Compustat, as well as information on risky financial asset holdings that we collect from 10-K filings. We describe the sample construction in Section 4.1 and provide details of the SMM procedure in Appendix A. Moment definitions are presented in Table A.3.

To examine how the key target moments used in the estimation respond to changes in individual parameters, we conduct a comparative statics analysis. This exercise helps clarify the sources of identification in the SMM procedure and assess the robustness of the estimates. Fig. 2 plots the results. The persistence ($\rho_z$) and volatility ($\sigma_z$) parameters of the idiosyncratic shocks have a positive impact on the autocorrelation (Panel A) and variance (Panel B) of profitability, respectively. Moreover, average Tobin's Q is highly sensitive to the returns-to-scale parameter $\alpha$ (Panel C), and the capital adjustment cost parameter $\psi_i$ has a negative effect on average investment (Panel D).

Average safe and risky financial asset holdings are key moments that help identify the parameters associated with external financing costs ($\xi$) and trading costs ($\psi_s$). The parameter $\xi$ directly affects firms' incentives to save for precautionary reasons—higher external financing costs lead firms to hold more financial assets, both safe and risky (Panels E and F, respectively). In contrast, the trading costs of risky financial assets, $\psi_s$, influence their cost relative to safe financial assets. As a result, higher values of $\psi_s$ lead firms to substitute risky assets with safe ones (Panels G and H). These differential effects on the target moments facilitate identification of the two parameters, as further illustrated in Table OA.1, which reports the elasticities of moments with respect to the estimated parameters. Finally, for higher values of idiosyncratic volatility ($\sigma_z$), firms hold more safe and risky financial assets (Panels I and J, respectively), reflecting stronger precautionary saving incentives. Similar effects hold for the aggregate volatility parameter ($\sigma_x$; Panels K and L).

Table 1 presents the structural estimation results. Overall, the simulated moments (Column 2 in Panel A) provide a good match to their empirical counterparts (Column 1), even though the differences for some moments remain statistically significant (Column 3). Importantly, the model replicates closely the empirical magnitudes of average investment, Tobin's Q, and safe and risky financial asset holdings.

Panel B reports the structural parameter estimates. The magnitudes of the technology parameters ($\hat{\rho}_z$, $\hat{\sigma}_z$, $\hat{\alpha}$, $\hat{\psi}_i$) are in line with those found in previous studies (e.g., Nikolov and Whited, 2014), as is our estimate of $\hat{\xi}$, which implies external financing costs amounting to 9.51% of proceeds raised. Finally, the estimate for $\hat{\psi}_s$ suggests trading costs on risky financial assets of 5.77 basis points—a level consistent with empirical estimates of bond trading costs following the introduction of the Transaction Reporting and Compliance Engine (TRACE), as discussed in Bessembinder and Maxwell (2008).

### 3.2. Policy functions

We now use the model at the estimated 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 $e/k$; and the notional value of corporate savings in (3) risky $s'/k$ and (4) safe $c'/k$ financial assets. Fig. 3 plots these variables as a function of $s/k$ for three values of the aggregate profitability shock $x$, keeping $k$ constant.

As the aggregate profitability shock is persistent over time, when $x$ is high (dash-dotted green line), investing in physical capital is

[7] The value of $\tau$ is similar to the ratio of Compustat items $TXC/PI$ in our sample (median: 11.7%, mean: 15.4%), and the value of $\delta$ is comparable to the ratio $DP/PPEGT$ (median: 7.9%, mean: 11.5%).

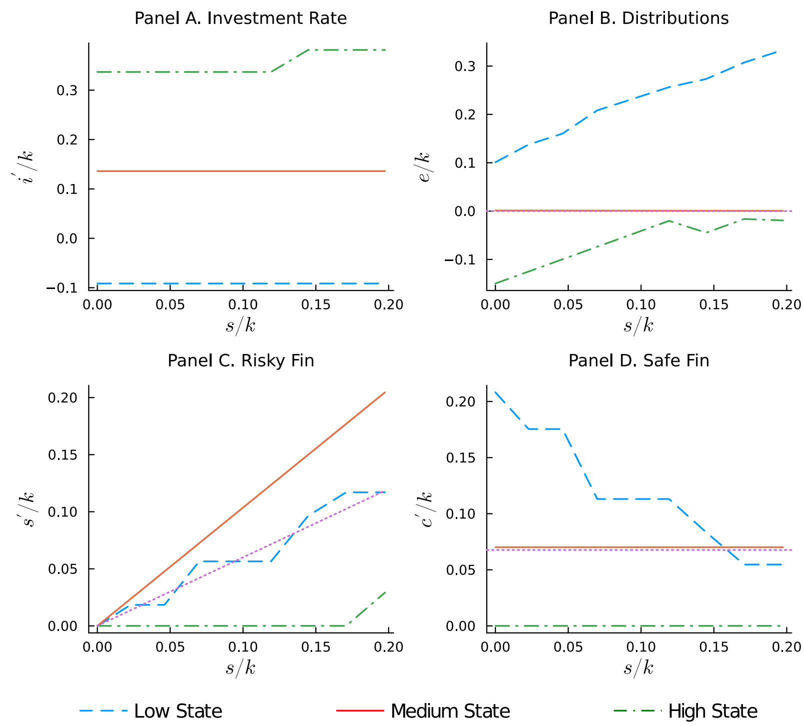


**Fig. 3.** Policy functions. This figure plots the following optimal policy functions for different levels of the aggregate profitability shock $x$: the investment rate $(i'/k)$ in Panel A, distributions/external financing $(e/k)$ in Panel B, risky financial asset holdings $(s'/k)$ in Panel C, and safe financial asset holdings $(c'/k)$ in Panel D against current-period risky financial asset holdings $(s/k)$. The dotted reference lines in Panels B, C, and D represent the loci of points corresponding to zero distributions $(e/k = 0)$, zero trading in risky financial assets $(s'/k = (1-\mu)s/k)$, and zero adjustment in safe financial assets $(c'/k = c/k)$, respectively. The optimal policies are based on the estimated parameters in Table 1.

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, for higher values of $s$, firms prefer to liquidate safe (Panel D) rather than risky financial assets, to avoid incurring bond trading costs. Indeed, as shown in Panel C, risky financial asset holdings are close to the locus of points for which there is no trading in the risky bond, represented by the dotted purple line.

Finally, when the aggregate profitability shock is at its median level (solid red line), the firm rolls over the existing amount of risky (Panel C) and safe (Panel D) financial assets to accommodate future investment opportunities, and uses the operating profits to invest up to the point when the distribution is zero (Panels A and B), so as to avoid costly external financing.

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 Fig. 4 plots the financing deficit scaled by physical capital,

$$FD = \frac{k' - (1-\delta)k + Adj^k - (1-\tau)\pi - \tau\delta k}{k}, \tag{20}$$

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.

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 Fig. 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).

### 3.3. Empirical predictions

As discussed in the previous subsection, the model predicts that the more sensitive a firm's financing deficit is to the risky bond returns, the stronger the firm's incentives to invest in the bond to alleviate external financing costs. To gauge the magnitude of these precautionary incentives, consider the following equation linking the financing deficit to bond returns:

$$FD_{jt+1} = \alpha_{jt} + \beta^D_{jt} R^B_{t+1} + \varepsilon_{jt+1}, \tag{21}$$

where $j$ and $t$ index the firm and year, respectively, and $R^B_{t+1} = q^s(x_{t+1})/q^s(x_t) - 1$ denotes the bond return. Notice that both $FD_{jt+1}$ and $R_{t+1}$ in Eq. (21) are random variables at time $t$, since their realizations at $t+1$ depend on $x_{t+1}$ and $z_{jt+1}$. The term $\alpha_{jt}$ reflects the average realization of $FD_{jt+1}$. The coefficient of interest $\beta^D_{jt}$ – which we refer to as the financing deficit beta – measures the sensitivity of the firm's financing deficit to the bond return, and thus captures the firm's incentives to hold risky financial assets. In the model, this coefficient can be expressed as:

$$\beta^D_{jt} = \frac{\mathbf{Cov}_t[FD_{jt+1}, R_{t+1} | x_t, z_{jt}, s_{jt}, c_{jt}, k_{jt}]}{\mathbf{Var}_t[R_{t+1} | x_t]}, \tag{22}$$

and Appendix A provides the details of its computation.

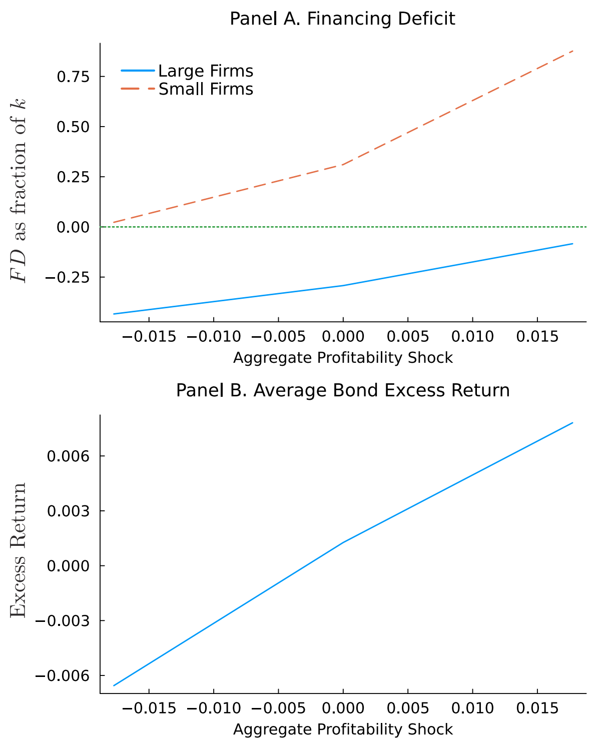


**Fig. 4.** Financing deficit and the incentives to invest in the risky security. Panel A plots the financing deficits, defined in Eq. (20) as $FD = [i' + Adj^k - (1-\tau)\pi - \tau\delta k]/k$, of a small and a large firm, as functions of the aggregate profitability shock $x$. The small (large) firm is defined by setting capital $k$ to a gridpoint below (above) the gridpoint closest to the simulated average $k$: specifically, the third quartile gridpoint below for small firms and the first quartile gridpoint above for large firms, based on the estimated parameters in Table 1. The financing deficit is positively correlated with $x$ for both firms, with a stronger correlation for the small (dashed line) than the large (solid line) firm. 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 when the firm faces large financing deficits.

To quantify the effect of the financing deficit beta on firms' saving behavior, we estimate the following regression:

$$FinAssets_{jt} = \zeta_t + \varphi\beta^D_{jt-1} + Controls_{jt-1} + \varepsilon_{jt}, \tag{23}$$

where $FinAssets_{jt}$ is the fair value of risky financial assets, scaled either by total assets or by total financial assets (denoted as $Risky$ and $FinComp$, respectively); $\zeta_t$ captures year fixed effects; $\beta^D_{jt-1}$ denotes the financing deficit beta defined in Eq. (22); and $Controls_{jt-1}$ include lagged Tobin's Q, profitability, size, and a measure of volatility, $FDResiVol$, which we describe below. Variable definitions are provided in Table A.4.

The parameter of interest in Eq. (23) is $\varphi$, which measures the sensitivity of financial asset holdings to the financing deficit beta. However, it is important to note that while $\beta^D_{jt}$ captures the comovement between the financing deficit and the return on the risky bond, it is also influenced by the level of volatility in the economy. We illustrate this point in Figure OA.1, which presents comparative statics of the average financing deficit beta as a function of key model parameters. Specifically, higher levels of idiosyncratic and aggregate volatility ($\sigma_z$ and $\sigma_x$) are associated with higher average values of the financing deficit beta.

To account for all sources of volatility (aggregate and idiosyncratic) in the financing deficit that are not explained by the bond returns, in Eq. (23) we include as a control variable the volatility of residuals from Eq. (21), computed as

$$FDResiVol_{jt} = \sqrt{\mathbf{Var}_t[FD_{jt+1}|x_t, z_{jt}, s_{jt}, c_{jt}, k_{jt}] - \left(\beta^D_{jt}\right)^2 \mathbf{Var}_t[R_{t+1}|x_t]}. \tag{24}$$

Columns 1 and 2 of Table 2 present the estimation results of Eq. (23) 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 total and 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 0.45% of total assets (Column 1) and to a 4.81% increase in the weight of risky financial assets in the financial portfolio (Column 2).[8] Columns 1 and 2 also show that volatility is negatively associated with risky financial asset holdings. This finding is consistent with the idea that, once hedging incentives are accounted for through the financing deficit beta, additional uncertainty leads firms to reduce their exposure to risky financial assets.

Columns 3 to 6 of Table 2 report the estimation results of Eq. (23) for subsamples constructed by splitting simulated firms each year based on the median asset size, as defined in Table A.4. 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) firms. Testing whether these predictions from the model hold in the real data is the main objective of the next sections.

## 4. Empirical results

In this section, we test the empirical predictions of the model. We begin by describing the data sources and sample construction, including a comparison with previous studies on the composition of corporate savings by DGHH and DM. We then construct an empirical measure of the financing deficit beta to quantify firms' incentives to hold risky financial assets. Next, we examine how this measure relates to risky financial asset holdings and the composition of corporate savings in the cross-section of firms. We also explore which risk factors best explain variation in risky financial asset holdings. Finally, we perform a series of sample splits to assess how these relationships vary with firm characteristics such as size, volatility, and R&D intensity.

### 4.1. Data sources and 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. We discuss our definition of risky financial assets in Section 4.2 below. We drop observations for which the value of risky financial assets exceeds total assets, which are likely caused by algorithm errors, and observations with $PPEGT$ or $AT$ lower than 5 million dollars, to eliminate the effect of micro firms on our results. Finally, we complement our dataset with additional

[8] The mean and standard deviation of the simulated financing deficit betas are 4.48 and 0.92, respectively.

**Table 2**

Regressions of risky financial asset holdings using simulated data. This table reports the results of the regression in Eq. (23), $FinAssets_{jt} = \zeta_t + \varphi\beta^D_{jt-1} + Controls_{jt-1} + \epsilon_{jt}$, using the simulated sample from the model. The dependent variable is the value of risky financial assets scaled either by total assets (variable $Risky$ in odd-numbered columns) or total financial assets (variable $FinComp$ in even-numbered columns). The independent variables, $\beta^D_{jt-1}$ and $FDResiVol_{jt-1}$, are the financing deficit beta and residual volatility computed using Eq. (22) and Eq. (24), respectively. The other control variables are $LQ$, $LProf$, $LSize$, and year fixed effects. Columns 1 and 2 report the results for the full simulated sample, Columns 3 and 4 for firms below yearly median firm size, and Columns 5 and 6 for firms above yearly median size. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively. We obtain the simulated sample by solving the model at the estimated parameters in Table 1 and simulating 50 samples of 3000 firms over 50 years. Variable definitions are provided in Table A.4. Appendix A presents the details of the numerical procedure used to solve the model.

| | Full Sample | | < Median Size | | > Median Size | |
|---|---|---|---|---|---|---|
| VARIABLES | (1) Risky | (2) FinComp | (3) Risky | (4) FinComp | (5) Risky | (6) FinComp |
| Beta | 0.634*** | 5.748*** | 1.480*** | 11.639*** | 0.332*** | 7.126*** |
| | (0.007) | (0.049) | (0.013) | (0.065) | (0.008) | (0.080) |
| FDResiVol | −0.446*** | −5.306*** | −0.607*** | −8.972*** | 0.056*** | −2.032*** |
| | (0.002) | (0.018) | (0.004) | (0.023) | (0.003) | (0.028) |
| LQ | 3.306*** | 4.827*** | 3.505*** | 7.696*** | 2.672*** | −13.583*** |
| | (0.010) | (0.036) | (0.014) | (0.051) | (0.027) | (0.178) |
| LProf | −20.854*** | −22.451*** | −32.653*** | −7.065*** | −15.382*** | 3.156*** |
| | (0.038) | (0.231) | (0.082) | (0.389) | (0.077) | (0.437) |
| LSize | −0.190*** | −7.552*** | 1.703*** | −7.752*** | 0.326*** | −8.833*** |
| | (0.007) | (0.051) | (0.023) | (0.111) | (0.008) | (0.083) |
| Observations | 7,500,000 | 7,500,000 | 3,750,000 | 3,750,000 | 3,750,000 | 3,750,000 |
| R-squared | 0.364 | 0.111 | 0.370 | 0.203 | 0.226 | 0.082 |
| Cluster Level | Firm | Firm | Firm | Firm | Firm | Firm |
| Year FEs | Y | Y | Y | Y | Y | Y |

firm-year observations from the sample collected by DM.[9] Variables in ratios are winsorized at the 1st and 99th percentiles. Table A.4 provides the definition of all variables used in the empirical analysis, and their counterparts in the model.

Table 3 presents summary statistics for the final sample, which consists of 19,367 observations for 2886 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 4.2%, while the average ratio of safe financial assets to total assets (*Safe*) is 14.3%.

### 4.2. 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.[10] 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 1727 yearly observations for 446 firms.

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[11]; 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.[12]

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

[9] See Online Appendix E for details. We thank Olivier Darmouni and Lira Mota for making their dataset available.

[10] 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.

[11] 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.

[12] 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.

**Table 3**
Summary statistics. This table reports the summary statistics of the variables used in the empirical analysis of Sections 4 and 5. Variables in Panel A are at the firm-year level, and in Panel B at the firm level. The measures of financial asset holdings used as dependent variables in the main regressions (Eq. (26)) 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 by estimating for each firm the regression in Eq. (25), $FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt}$, where $FD_{jt}$ is the financing deficit of firm $j$ in quarter $t$, and $R_{t-1}^B$ is either the return on the Bloomberg US Aggregate Bond Market Index (for $BetaAgg$) or the reverse change in the 10-year Treasury bond yield (for $BetaTre$) during quarter $t-1$. The financing deficit residual volatilities ($FDResiVolAgg$ and $FDResiVolTre$) are the standard deviations of the residuals from the corresponding regressions. Other control variables are lagged Tobin's Q ($LQ$), profitability ($LProf$), and firm size ($LSize$). $InvTot$ is the sum of tangible and intangible investment and $ExtFin$ measures external financing—these variables are employed for the analysis in Section 5. The sample covers 2886 firms from 2009 to 2018. All variables in ratios are winsorized at the 1% and 99% percentiles. $BetaAgg$ and $BetaTre$ are winsorized at the 5% and 95% percentiles, and $FDResiVolAgg$ and $FDResiVolTre$ at the 95% percentile. Variable definitions are in Table A.4.

Panel A. Firm-Year Level Variables

| | N | Mean | Std. Dev. | P10 | P90 |
|---|---|---|---|---|---|
| Risky | 19 367 | 0.042 | 0.108 | 0.000 | 0.138 |
| Safe | 19 256 | 0.143 | 0.166 | 0.010 | 0.335 |
| FinComp | 19 199 | 0.151 | 0.258 | 0.000 | 0.600 |
| LQ | 19 367 | 1.884 | 1.309 | 0.876 | 3.387 |
| LProf | 19 367 | 0.076 | 0.181 | −0.098 | 0.226 |
| LSize | 19 367 | 6.680 | 2.106 | 3.873 | 9.422 |
| InvTot | 19 352 | 0.323 | 0.615 | 0.026 | 0.763 |
| ExtFin | 19 367 | 0.072 | 0.200 | 0.000 | 0.203 |

Panel B. Firm Level Variables

| | N | Mean | Std. Dev. | P10 | P90 |
|---|---|---|---|---|---|
| BetaAgg | 2886 | 0.409 | 3.208 | −3.741 | 5.178 |
| BetaTre | 2886 | 1.010 | 12.255 | −15.293 | 20.950 |
| FDResiVolAgg | 2886 | 27.580 | 29.428 | 3.872 | 83.861 |
| FDResiVolTre | 2886 | 27.744 | 29.797 | 3.850 | 82.872 |

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. Between 2009 and 2018, the S&P 500 index included 575 firms, and our scraped sample covers 307 of them (53%). Among the 575 firms, 144 are in the finance or utility industry. For the remaining 431 firms, 124 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 we target.[13]

Fig. 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. Online Appendix E provides a detailed comparison between our sample and those used in DGHH and DM.

Fig. 6 illustrates differences in risky and safe financial asset holdings across subsamples defined by firm characteristics and industry. Panel A shows that high-Q firms hold more financial assets – both safe and risky – than low-Q firms. Similar patterns emerge for low-profitability and high-tech firms compared to their high-profitability and low-tech counterparts (Panels B and C, respectively).

### 4.3. Measuring the financing deficit beta

As discussed in Section 3.3, a key determinant of firms' incentives to hold risky financial assets in our model is the financing deficit beta, which measures the sensitivity of the financing deficit to the bond return. While in the model we compute $\beta_{jt}^D$ for each period using the distribution of the financing deficit conditional on the state variables at time $t$ (see Eq. (22)), in the empirical analysis we follow a regression-based approach to obtain firm-level estimates of the financing deficit beta.

We begin by defining the financing deficit, $FD_{jt}$, for firm $j$ in quarter $t$ as the difference between the investment rate and equity cash

[13] 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.

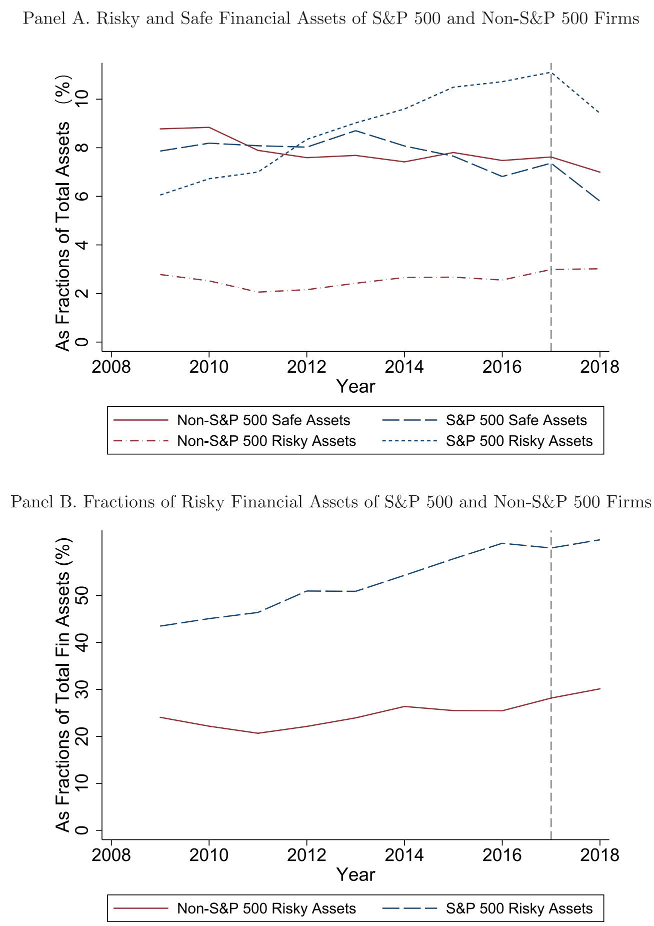


**Fig. 5.** Savings portfolio composition of S&P 500 and non-S&P 500 firms. This figure plots the aggregate value of safe and risky financial assets scaled by aggregate total assets (Panel A), and the fraction of aggregate risky over total financial assets (Panel B) for both S&P 500 and non-S&P 500 firms. The sample covers the years 2009 to 2018.

flows, scaled by capital. We then estimate the financing deficit beta by running firm-level regressions – an empirical analogue to Eq. (22) – for firms with a minimum of ten quarterly observations between 1999 and 2018:

$$FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt}. \tag{25}$$

Here, $R_{t-1}^B$ is measured either as the return on the Bloomberg US Aggregate Bond Market Index (henceforth, "the Agg") or as the reverse change in the 10-year US Treasury bond yield in quarter $t-1$.[14] Using the estimated financing deficit beta, $\hat{\beta}_j^D$, from Eq. (25), we also compute the standard deviation of the residuals (in percentage terms) to construct the empirical analogue of $FDResiVol$ defined in Eq. (24).

Panel B of Table 3 reports the summary statistics of the beta estimates. The financing deficit betas estimated using the Agg and the 10-year Treasury bond have mean values of 0.409 and 1.010, respectively, and the correlation between the two beta measures is

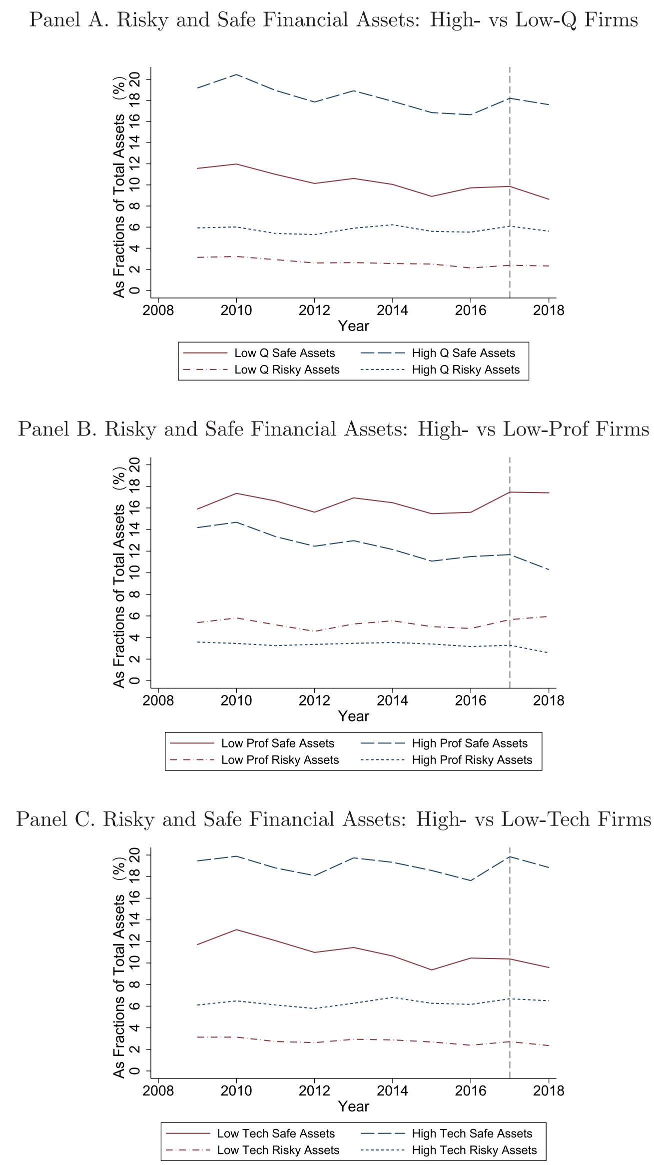


**Fig. 6.** Savings portfolio composition by firm characteristics and industry. This figure shows average safe and risky financial assets as a percentage of total assets, split by firm characteristics: Tobin's Q (Panel A), profitability (Panel B), and industry classification (Panel C). High (Low) Q firms are those above (below) the median Q within each year; high (low) profitability firms are defined similarly. High-tech industries are identified using the classification in Francis and Schipper (1999) based on 2-digit SIC codes. The sample covers the years 2009 to 2018.

0.74. 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 $\hat{\beta}_j^D = 0.409$ means that a one standard deviation (1.7%) increase in the Agg return is associated with an average increase in the financing deficit equal to 0.7% 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.

[14] 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 Section 4.6.

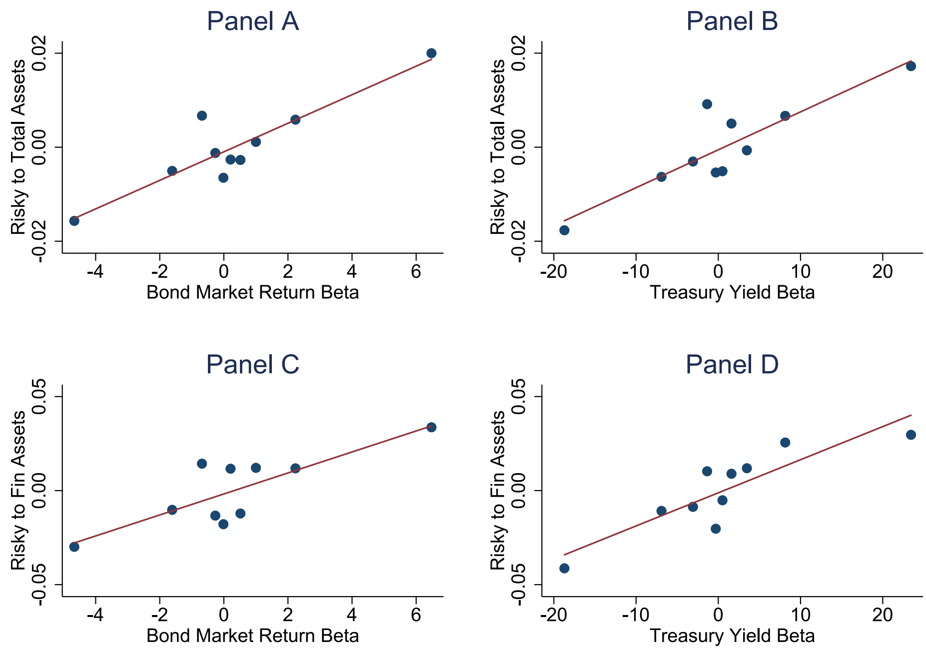


**Fig. 7.** Financing deficit beta and corporate financial assets. This figure plots the relationship between the financing deficit beta and risky financial asset holdings. The figure is constructed using a two-step sorting procedure. For each firm, we estimate the time-series regression in Eq. (25), $FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt}$, where $FD_{jt}$ is the financing deficit of firm $j$ in quarter $t$, and $R_{t-1}^B$ is either the return on the Bloomberg US Aggregate Bond Market Index (for $BetaAgg$) or the reverse change in the 10-year Treasury bond yield (for $BetaTre$) in quarter $t-1$. The financing deficit residual volatilities ($FDResiVolAgg$ and $FDResiVolTre$) are the standard deviations of the residuals from the corresponding regressions. In the first step, each year we sort firms into deciles based on $FDResiVolAgg$ (Panels A and C) or $FDResiVolTre$ (Panels C and D), and we compute, by subtracting the year-decile mean, the residuals in firms' risky financial asset holdings. This step teases out the effects of volatility on saving behavior. The second step is to sort firms each year into deciles based on $BetaAgg$ (Panels A and C) or $BetaTre$ (Panels B and D), and compute the decile means of the residuals from the first step. The graphs plot the decile means from the second step. 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.

### 4.4. Bivariate sorts of risky financial assets

We begin our analysis of the relationship between the financing deficit beta and the level and composition of risky financial assets with a bivariate sorting approach, implemented in two steps. First, for each year, we sort firms into deciles based on $FDResiVol$ and compute residuals in risky financial asset holdings by subtracting the year-decile mean. Since the financing deficit beta is positively correlated with volatility (see Section 3.3), this step removes the volatility-driven component of asset holdings and allows us to isolate the impact of beta in the second step. We then sort firms into deciles based on the financing deficit beta and compute the mean of the residuals from the first step within each beta decile. We conduct this analysis using two measures of risky financial assets: scaled by total assets, and scaled by total financial assets.

Fig. 7 presents the results.[15] 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.

[15] Online Appendix F.3 shows that the results are robust to sorting in the first stage by total financing deficit volatility, instead of $FDResiVol$.

### 4.5. Cross-sectional analysis of risky financial assets

We now extend the empirical results by moving from the bivariate sorting analysis to a multivariate regression framework that assesses the relationship between the financing deficit beta and financial asset holdings:

$$FinAssets_{jt} = \zeta_{sic,t} + \varphi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt}, \tag{26}$$

where $j$ and $t$ index firm and year, respectively; $FinAssets_{jt}$ is measured as the fair value of risky financial assets over total assets, safe financial assets over total assets, or risky over total financial assets (corresponding to the variables *Risky*, *Safe*, or *FinComp*, respectively); $\zeta_{sic,t}$ represents industry-year fixed effects; and $\hat{\beta}_j^D$ is the estimated firm-level financing deficit beta. The control variables include $FDResiVol$ and lagged values of firm profitability, Tobin's Q, and size ($LProf$, $LQ$, and $LSize$, respectively). We include these controls because high-Q and low-profitability firms tend to hold more risky financial assets (Fig. 6) and, at the same time, exhibit higher values of $\hat{\beta}^D$—see Table OA.5 for a regression analysis of the cross-sectional determinants of our beta measures.

It is important to note that our empirical tests follow a two-step procedure: the estimated values of $\beta_j^D$ and $FDResiVol$ from the first-stage regression are used as independent variables in the second-stage regression (Eq. (26)). Accordingly, we adjust the standard errors of the second-stage regression coefficients to account for the presence of generated regressors (Murphy and Topel, 1985; Newey and McFadden, 1994). Online Appendix F.1 provides details on this procedure and reports robustness tests using alternative standard error adjustments.

Table 4 presents the regression results. Consistent with our model predictions in Table 2, we find that risky financial asset holdings (*Risky*) are positively and significantly associated with the financing deficit

**Table 4**
Regressions of corporate financial asset holdings—main results. This table reports the results of the regression in Eq. (26) estimated for the full sample, $FinAssets_{jt} = \zeta_{sic,t} + \varphi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt}$, 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 2-digit SIC code industry × year fixed effects; the control variables are $LQ$, $LProf$, $LSize$, and $FDResiVol$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated for each firm from the time-series regression in Eq. (25), $FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \epsilon_{jt}$, where $FD_{jt}$ is the financing deficit of firm $j$ in quarter $t$; $R_{t-1}^B$ is either the return on the Bloomberg US Aggregate Bond Market Index ("Agg Bond") or the reverse change in the 10-year Treasury bond yield ("Treasury") during quarter $t-1$; and $FDResiVol$ is the standard deviation of the financing deficit residuals, $\hat{\epsilon}_{jt}$, from the corresponding regressions. Standard errors in parentheses are clustered at the industry level and adjusted using the procedure in Murphy and Topel (1985) to account for sampling error in the first stage. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively. Variable definitions are in Table A.4.

| VARIABLES | (1) Risky | (2) Risky | (3) Safe | (4) Safe | (5) FinComp | (6) FinComp |
|---|---|---|---|---|---|---|
| Beta | 0.252*** | 0.072*** | 0.071 | 0.039* | 0.542*** | 0.165*** |
| | (0.040) | (0.013) | (0.091) | (0.021) | (0.126) | (0.035) |
| FDResiVol | 0.034** | 0.035** | 0.042* | 0.041* | 0.037 | 0.039 |
| | (0.016) | (0.016) | (0.021) | (0.021) | (0.027) | (0.027) |
| LQ | 1.534*** | 1.544*** | 3.869*** | 3.866*** | 1.392*** | 1.411*** |
| | (0.267) | (0.268) | (0.304) | (0.304) | (0.422) | (0.415) |
| LProf | −2.828 | −2.828 | −8.814** | −8.766** | −3.982 | −3.973 |
| | (1.795) | (1.778) | (3.376) | (3.355) | (3.009) | (2.959) |
| LSize | 0.297** | 0.295** | −1.146*** | −1.147*** | 1.288*** | 1.282*** |
| | (0.132) | (0.131) | (0.108) | (0.107) | (0.217) | (0.217) |
| Observations | 19,367 | 19,367 | 19,256 | 19,256 | 19,199 | 19,199 |
| R-squared | 0.106 | 0.107 | 0.276 | 0.276 | 0.062 | 0.063 |
| 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 |

beta, using both the measure based on the Agg index (Column 1) and the one based on 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 0.81% (0.88%) higher risky financial asset holdings as a fraction of total assets—an effect that represents 19.3% of the sample average (4.2% of total assets). Overall, these results indicate that the financing deficit beta captures firms' incentives to invest in risky financial assets.

To test whether our measure also proxies for firms' incentives to invest in safe financial assets, we re-estimate the regression in Eq. (26) using as the dependent variable the amount of safe financial assets (*Safe*), measured as the ratio of Compustat items $CH$ to $AT$.[16] The results in Column 3 of Table 4 show that the financing deficit beta based on the Agg index return is not significantly related to the amount of safe financial assets, while Column 4 shows that the coefficient on the beta based on the 10-year Treasury bond is positive but only marginally significant at the 10% level. In contrast to the highly significant coefficients in the regressions for risky financial assets, this weaker relationship suggests that the financing deficit beta better reflects firms' motives for holding risky – as opposed to safe – financial assets.

Columns 5 and 6 of Table 4 show the estimation results for the composition of financial assets. The dependent variable is the fraction of risky to total financial assets (*FinComp*). As predicted by our model, both financing deficit beta measures are positively and significantly (at the 1% level) associated with the share of risky financial assets in firms' savings portfolios. Specifically, a one standard deviation increase in the financing deficit beta based on the Agg index (10-year Treasury bond) is associated with a 1.74% (2.02%) increase in the proportion of risky financial assets. This effect represents 11.5% of the sample average ratio of risky to total financial assets (15.1%).

While the regression results for the financing deficit beta are consistent across the simulated and real data – both yielding coefficients of the same sign – the findings differ for the volatility measure. In the simulated data, $FDResiVol$ has a negative and highly significant coefficient on both $Risky$ and $FinComp$ (cf. Table 2), whereas in the real data, the coefficients are positive and significant only at the 5% level for $Risky$. This suggests that, although the model captures key qualitative patterns, the empirical relationship between volatility and risky asset holdings may reflect additional sources of uncertainty that are excluded from the model for tractability.

Finally, the coefficients on the control variables are largely consistent with the model's predictions and the stylized facts presented in Fig. 6. In particular, Tobin's Q is positively and significantly associated with both $Risky$ and $FinComp$, while the coefficients on profitability are negative, though not statistically significant. The positive relationship between firm size and $Risky$ (Columns 1 and 2) is also in line with the model. However, the model predicts a negative coefficient between size and $FinComp$, whereas the data show a positive association (Columns 5 and 6). This discrepancy may reflect large firms' incentives to invest in risky financial assets for reasons not captured by the model, such as agency problems or tax considerations (e.g., Duchin et al., 2017; Darmouni and Mota, 2024).

### 4.6. Interest-rate risk and financial asset holdings

To better understand the source of risk captured by the financing deficit beta, we compute alternative beta measures by estimating Eq. (25) using several different maturities for the reference bond returns $R_{t-1}^B$: the Fed Funds rate (overnight), and Treasury bonds with maturities of 1, 2, 3, 5, and 10 years.

The regression results in Panel A of Table 5 show that all beta measures are positively and strongly significantly associated with firms' risky financial asset holdings (variable *Risky*). Moreover, the magnitude

[16] 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 Fig. 3 in DM).

**Table 5**
Interest-rate risk and risky financial asset holdings. This table reports the results of the regression in Eq. (26) estimated for the full sample, $FinAssets_{jt} = \zeta_{sic,t} + \varphi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt}$, 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 Panel A), or the fair value of risky financial assets over total financial assets ($FinComp$ in Panel B); $\zeta_{sic,t}$ are 2-digit SIC code industry × year fixed effects; the control variables are $LQ$, $LProf$, $LSize$, and $FDResiVol$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated for each firm from the time-series regression in Eq. (25), $FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt}$, where $FD_{jt}$ is the financing deficit of firm $j$ in quarter $t$; and $R_{t-1}^B$ is the reverse change in the Fed Funds rate (Column 1), and the 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. Standard errors in parentheses are clustered at the industry level and adjusted using the procedure in Murphy and Topel (1985) to account for sampling error in the first stage. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively. Variable definitions are in Table A.4.

Panel A. Risky Financial Assets over Total Assets

| VARIABLES | (1) Risky | (2) Risky | (3) Risky | (4) Risky | (5) Risky | (6) Risky |
|---|---|---|---|---|---|---|
| Beta | 0.023*** | 0.043*** | 0.049*** | 0.057*** | 0.078*** | 0.072*** |
| | (0.006) | (0.007) | (0.008) | (0.008) | (0.010) | (0.013) |
| Observations | 19,367 | 19,367 | 19,367 | 19,367 | 19,367 | 19,367 |
| R-squared | 0.105 | 0.111 | 0.109 | 0.109 | 0.109 | 0.107 |
| 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 | 0.019 | 0.056*** | 0.074*** | 0.090*** | 0.145*** | 0.165*** |
| | (0.013) | (0.015) | (0.018) | (0.020) | (0.029) | (0.035) |
| Observations | 19,199 | 19,199 | 19,199 | 19,199 | 19,199 | 19,199 |
| R-squared | 0.059 | 0.061 | 0.061 | 0.061 | 0.063 | 0.063 |
| 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 |

of the coefficients increases with the maturity of the reference bond used to estimate the beta—from 0.023 using the Fed Funds rate to 0.078 and 0.072 using the 5- and 10-year Treasury bonds, respectively. This pattern suggests that the type of risk firms aim to hedge by investing in risky financial assets is primarily related to medium- to long-term interest-rate risk.

This finding is reinforced by the results in Panel B, where the dependent variable is the fraction of risky to total financial assets (*FinComp*). The regression coefficients increase with the maturity of the reference bond used to compute the financing deficit beta. These results align with the idea that firms can hedge short-term interest-rate risk using a wide range of safe or risky financial assets, while fewer instruments among those we classify as safe are available for hedging long-term interest-rate risk. As a result, betas derived from short-term bonds tend to be positively associated with both safe and risky holdings, weakening their overall correlation with the proportion of risky financial assets in the portfolio. In contrast, betas based on long-term bonds are more strongly and significantly associated with the share of risky financial assets.

### 4.7. Can other risk factors explain saving behavior?

In this section, we explore whether risk factors other than interest-rate risk help explain firms' investment in risky financial assets. To do so, we estimate the financing deficit beta in Eq. (25) using the returns of several alternative reference assets: (1) the quarterly 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.[17]

Table 6 presents the results of the cross-sectional regressions from Eq. (26), where we examine the determinants of risky financial asset holdings. The regressions in the odd-numbered columns include only the alternative beta measures (*BetaAlt*), while those in the even-numbered columns add, as a control, the beta estimated using the reverse change in the yield of the 10-year Treasury bond (*BetaTre*). This variable captures interest-rate risk and serves as one of the standard beta measures in the main analysis (cf. Table 4).

The results reported in the odd-numbered columns show that the only coefficient statistically significant at the 1% level is the one associated with the beta based on equity market returns (Column 1). This beta is negatively associated with both risky financial assets as a share of total assets (variable *Risky*, Panel A) and as a share of total financial assets (*FinComp*, Panel B). The negative coefficients suggest that firms whose financing deficits are highly correlated with equity market returns reduce their holdings of bond-like securities, which

[17] The equity market return is measured using the S&P 500 index. Data on investment-grade and high-yield corporate bond spreads are obtained 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.

**Table 6**

Alternative risk factors and risky financial asset holdings. This table reports the results of the regression in Eq. (26) estimated for the full sample, $FinAssets_{jt} = \zeta_{sic,t} + \varphi\hat{\beta}^{D}_{j} + Controls_{jt-1} + \varepsilon_{jt}$, 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 Panel A), or the fair value of risky financial assets over total financial assets ($FinComp$ in Panel B); $\zeta_{sic,t}$ are 2-digit SIC code industry × year fixed effects; the control variables are $LQ$, $LProf$, $LSize$, and $FDResiVol$; and $\hat{\beta}^{Alt}_{j}$, the alternative financing deficit beta measure, is estimated for each firm from the time-series regression in Eq. (25), $FD_{jt} = \alpha_j + \beta^{Alt}_j R^B_{t-1} + \varepsilon_{jt}$, where $FD_{jt}$ is the financing deficit of firm $j$ in quarter $t$; and $R^B_{t-1}$ is either the return on the S&P 500 index (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), in quarter $t-1$. Even-numbered columns include as a control the financing deficit beta estimated using the reverse change in the 10-year Treasury bond yield, $BetaTre$. Standard errors in parentheses are clustered at the industry level and adjusted using the procedure in Murphy and Topel (1985) to account for sampling error in the first stage. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively. Variable definitions are in Table A.4.

Panel A. Risky Financial Assets over Total Assets

| VARIABLES | (1) Risky | (2) Risky | (3) Risky | (4) Risky | (5) Risky | (6) Risky | (7) Risky | (8) Risky |
|---|---|---|---|---|---|---|---|---|
| BetaAlt | −1.025*** | −0.656** | −0.424 | −0.305 | 0.010 | 0.046** | −0.077* | 0.018 |
| | (0.260) | (0.252) | (0.421) | (0.448) | (0.021) | (0.019) | (0.045) | (0.044) |
| BetaTre | | 0.057*** | | 0.069*** | | 0.084*** | | 0.074*** |
| | | (0.012) | | (0.014) | | (0.013) | | (0.013) |
| Observations | 19,367 | 19,367 | 19,367 | 19,367 | 19,367 | 19,367 | 19,367 | 19,367 |
| R-squared | 0.106 | 0.109 | 0.103 | 0.108 | 0.103 | 0.109 | 0.103 | 0.108 |
| 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 | −2.499*** | −1.676** | −0.203 | 0.085 | −0.036 | 0.041 | −0.279** | −0.080 |
| | (0.690) | (0.641) | (0.799) | (0.855) | (0.048) | (0.046) | (0.106) | (0.100) |
| BetaTre | | 0.126*** | | 0.165*** | | 0.175*** | | 0.154*** |
| | | (0.030) | | (0.036) | | (0.035) | | (0.034) |
| Observations | 19,199 | 19,199 | 19,199 | 19,199 | 19,199 | 19,199 | 19,199 | 19,199 |
| R-squared | 0.062 | 0.064 | 0.059 | 0.063 | 0.059 | 0.063 | 0.060 | 0.063 |
| 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 |

constitute the largest portion of the financial assets we classify as risky.[18]

Comparing the results in the odd- and even-numbered columns of Table 6, the coefficients on $BetaAlt$ become more positive once $BetaTre$ is included as a control. Since the alternative beta measures are all negatively correlated with $BetaTre$, and $BetaTre$ is positively associated with risky financial asset holdings, omitting it introduces a downward bias in the $BetaAlt$ coefficients.[19] After controlling for $BetaTre$, the coefficients on $BetaAlt$ for equity decline in significance, and the only other coefficient significant at the 5% level is the one associated with the $BetaAlt$ based on the investment-grade bond spread in Panel A. Finally, the coefficients on the Treasury bond beta remain positive and statistically significant across all specifications, with magnitudes similar to those reported in Table 4.

Taken together, these results suggest that interest-rate risk plays a central role in explaining corporate savings in risky financial assets, while factors related to the equity market and credit risk also contribute, albeit to a lesser extent.

### 4.8. Sample splits

In this subsection, we conduct sample splits by firm size, volatility, and R&D intensity. For each subsample, we estimate the structural parameters of the model and then run regressions of the determinants of risky financial asset holdings using both simulated and real data. This analysis allows us to assess how the relationship between the financing deficit beta and risky financial asset holdings varies across key firm characteristics.

#### 4.8.1. Structural estimation by subsample

We construct three subsamples based on firm size, volatility, and R&D intensity. Size-based subsamples are formed by classifying firms in each year as small or large depending on whether lagged total assets

[18] In their samples of large firms, DGHH and DM find that equity securities account for only 1.43% and 2% of the fair value of total financial assets, respectively. While we do not systematically collect information on security types, a check on a subset of firms in our dataset confirms that equity securities represent a minimal fraction of firms' risky financial asset portfolios.

[19] 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 −0.41, −0.10, −0.31, and −0.39, respectively.

**Table 7**
Structural estimation results—small vs large firms. Panel A reports the sample and simulated moments. Columns 1–3 report, for small firms, the empirical moments targeted in the structural estimation, the corresponding simulated moments generated from 50 simulations of 3000 firms over 50 years, and the $t$-statistics for the differences between empirical and simulated moments, respectively. Columns 4–6 report the same set of statistics for large firms. Panels B and C report the estimated structural parameters for small and large firms, respectively. The parameters $\rho_z$ and $\sigma_z$ are the persistence and conditional standard deviation of the idiosyncratic profitability shock, respectively, and they are obtained from an autocorrelation regression of TFP using data from İmrohoroğlu and Tüzel (2014); $\alpha$ is the curvature of the profit function; $\psi_i$ is the capital adjustment cost parameter; $\xi$ is the external financing cost parameter; and $\psi_s$ denotes the bond trading cost. Small and large firms are defined as firms below and above the yearly median of firm size distribution, respectively. Standard errors are clustered at the firm level and adjusted for sampling errors in the first stage. Section 4.1 describes the sample construction. Moment definitions are provided in Table A.3. Appendix A presents details of the numerical procedure used to solve the model and of the estimation approach.

Panel A. Moments

| | Small Firms | | | Large Firms | | |
|---|---|---|---|---|---|---|
| | (1) Data | (2) Model | (3) t-stats | (4) Data | (5) Model | (6) t-stats |
| Average Risky Financial Assets | 0.0505 | 0.0508 | −0.61 | 0.0341 | 0.0390 | −16.04 |
| Average Safe Financial Assets | 0.1840 | 0.1842 | −0.81 | 0.1020 | 0.1087 | −15.14 |
| Average Investment | 0.1328 | 0.1382 | −5.18 | 0.1131 | 0.1318 | −8.75 |
| Average Q | 2.0205 | 2.0209 | −0.05 | 1.7468 | 1.9633 | −24.55 |
| Average Profitability | 0.0626 | 0.1687 | −5.20 | 0.3763 | 0.1571 | 6.62 |
| Median Distribution | 0.0004 | 0.0035 | −0.15 | 0.0398 | 0.0024 | 4.19 |
| Variance of Profitability | 0.0119 | 0.0074 | 1.97 | 0.0038 | 0.0055 | −0.82 |
| Variance of Distribution | 0.0379 | 0.0261 | 2.82 | 0.0140 | 0.0372 | −13.83 |
| Autocorrelation of Profitability | 0.7454 | 0.6399 | 1.48 | 0.9242 | 0.7258 | 1.13 |
| Autocorrelation of Investment | 0.6388 | 0.4865 | 2.36 | 0.7702 | 0.5683 | 1.54 |
| Autocorrelation of Distribution | 0.6047 | 0.4308 | 2.95 | 0.3860 | 0.5221 | −0.64 |

Panel B. Small Firms

| Parameter | $\rho_z$ | $\sigma_z$ | $\alpha$ | $\psi_i$ | $\xi$ | $\psi_s$ (bps) |
|---|---|---|---|---|---|---|
| Value | 0.7410 | 0.3783 | 0.8141 | 0.2677 | 0.1016 | 6.6538 |
| Standard Error | 0.0161 | 0.0116 | 0.0185 | 0.0395 | 0.0061 | 0.6099 |

Panel C. Large Firms

| Parameter | $\rho_z$ | $\sigma_z$ | $\alpha$ | $\psi_i$ | $\xi$ | $\psi_s$ (bps) |
|---|---|---|---|---|---|---|
| Value | 0.7944 | 0.3026 | 0.8801 | 0.4851 | 0.0693 | 3.4985 |
| Standard Error | 0.0212 | 0.0110 | 0.2325 | 0.4114 | 0.0054 | 8.6933 |

fall below or above the annual median. Volatility-based subsamples are defined using the median firm-level volatility of the financing deficit. Finally, R&D-based subsamples distinguish firms with positive versus zero average R&D expenditures, with each group representing approximately half of the sample.

To estimate the structural parameters for each subsample, we proceed as follows. First, we estimate the parameters ($\rho_z$, $\sigma_z$) by running an autocorrelation regression of total factor productivity (TFP). We obtain firm-year TFP data from Şelale Tüzel's website, which provides estimates for the Compustat sample (see İmrohoroğlu and Tüzel, 2014, for details). We then estimate the remaining parameters ($\alpha$, $\psi_i$, $\xi$, $\psi_s$) using the SMM procedure described in Section 3.1. This two-step approach follows the estimation strategy in Gao et al. (2021) and has the advantage of improving the precision of the subsample-specific estimates of the parameters governing the idiosyncratic productivity process. We report the estimates of ($\rho_z$, $\sigma_z$) together with the remaining parameters in the tables and adjust second-stage standard errors to account for sampling error in the first stage. Additional details are provided in Appendix A.

Tables 7, 8, and 9 report the real and simulated moments (Panel A) and the estimated structural parameters (Panels B and C) for the subsamples based on firm size, volatility, and R&D intensity, respectively. Across the three subsample dimensions, the data exhibit systematic differences in savings and operating behavior. Small firms, high-volatility firms, and firms with positive R&D expenditures hold significantly larger amounts of both risky and safe financial assets relative to total assets and exhibit higher Tobin's Q and investment rates. Differences in the corresponding data moments are statistically significant across subsamples, at least at the 5% level.

The structural parameter estimates capture these patterns primarily through variation in the strength of precautionary savings motives. Subsamples characterized by higher uncertainty or greater exposure to financing frictions – small firms, high-volatility firms, and R&D-active firms – are associated with higher estimates of the external financing cost parameter $\xi$ and idiosyncratic volatility $\sigma_z$, indicating stronger incentives to accumulate financial assets. Higher values of $\xi$ lead to greater overall financial asset accumulation, while cross-subsample differences in the bond trading cost parameter $\psi_s$ primarily affect the composition of savings between risky and safe assets, with large firms displaying a higher tilt toward risky financial assets. Finally, subsamples with higher Tobin's Q are associated with lower estimates of the returns-to-scale parameter $\alpha$, whereas higher investment rates are generally reflected in lower estimates of the adjustment cost parameter $\psi_i$. Overall, these results are consistent with the identification arguments in Section 3.1 and the comparative statics illustrated in Fig. 2.

#### 4.8.2. Regressions of risky financial asset holdings by subsample

We now analyze differences in saving behavior across subsamples. Using the subsample-specific parameter estimates reported in Tables 7, 8, and 9, we generate panels of simulated firms. For each simulated sample, we estimate the regression of risky financial asset holdings specified in Eq. (23) and compare the resulting coefficients with those

**Table 8**
Structural estimation results—high vs low volatility firms. Panel A reports the sample and simulated moments. Columns 1-3 report, for high volatility firms, the empirical moments targeted in the structural estimation, the corresponding simulated moments generated from 50 simulations of 3000 firms over 50 years, and the $t$-statistics for the differences between empirical and simulated moments, respectively. Columns 4–6 report the same set of statistics for low volatility firms. Panels B and C report the estimated structural parameters for high and low volatility firms, respectively. The parameters $\rho_z$ and $\sigma_z$ are the persistence and conditional standard deviation of the idiosyncratic profitability shock, respectively, and they are obtained from an autocorrelation regression of TFP using data from İmrohoroğlu and Tüzel (2014); $\alpha$ is the curvature of the profit function; $\psi_i$ is the capital adjustment cost parameter; $\xi$ is the external financing cost parameter; and $\psi_s$ denotes the bond trading cost. High and low volatility firms are defined as firms above and below the median of firm-level financing deficit volatility, respectively. Standard errors are clustered at the firm level and adjusted for sampling errors in the first stage. Section 4.1 describes the sample construction. Moment definitions are provided in Table A.3. Appendix A presents details of the numerical procedure used to solve the model and of the estimation approach.

Panel A. Moments

| | High Volatility Firms | | | Low Volatility Firms | | |
|---|---|---|---|---|---|---|
| | (1) Data | (2) Model | (3) t-stats | (4) Data | (5) Model | (6) t-stats |
| Average Risky Financial Assets | 0.0554 | 0.0576 | −43.78 | 0.0293 | 0.0292 | 0.57 |
| Average Safe Financial Assets | 0.1755 | 0.1837 | −28.96 | 0.1111 | 0.1128 | −15.33 |
| Average Investment | 0.1479 | 0.1278 | 8.19 | 0.0980 | 0.1180 | −11.79 |
| Average Q | 2.0998 | 2.2044 | −17.21 | 1.6678 | 1.7820 | −9.99 |
| Average Profitability | 0.2348 | 0.1694 | 2.79 | 0.2044 | 0.1629 | 5.17 |
| Median Distribution | 0.0025 | 0.0035 | −0.05 | 0.0250 | 0.0042 | 4.73 |
| Variance of Profitability | 0.0105 | 0.0090 | 0.57 | 0.0059 | 0.0058 | 0.07 |
| Variance of Distribution | 0.0423 | 0.0191 | 9.93 | 0.0120 | 0.0198 | −8.61 |
| Autocorrelation of Profitability | 0.7731 | 0.7054 | 0.93 | 0.6909 | 0.7514 | −0.41 |
| Autocorrelation of Investment | 0.6791 | 0.5548 | 1.82 | 0.6086 | 0.5723 | 0.46 |
| Autocorrelation of Distribution | 0.5621 | 0.4438 | 2.46 | 0.3182 | 0.4832 | −1.17 |

Panel B. High Volatility Firms

| Parameter | $\rho_z$ | $\sigma_z$ | $\alpha$ | $\psi_i$ | $\xi$ | $\psi_s$ (bps) |
|---|---|---|---|---|---|---|
| Value | 0.8058 | 0.3762 | 0.8079 | 0.4726 | 0.1318 | 6.9397 |
| Standard Error | 0.0166 | 0.0148 | 0.0317 | 0.1216 | 0.0141 | 1.2929 |

Panel C. Low Volatility Firms

| Parameter | $\rho_z$ | $\sigma_z$ | $\alpha$ | $\psi_i$ | $\xi$ | $\psi_s$ (bps) |
|---|---|---|---|---|---|---|
| Value | 0.8013 | 0.3006 | 0.8974 | 0.8822 | 0.0965 | 7.0583 |
| Standard Error | 0.0200 | 0.0086 | 0.0218 | 0.0576 | 0.0031 | 4.0444 |

obtained from the corresponding regressions estimated on the real-data subsamples, as defined in Eq. (26). The objective of this analysis is to assess the relevance of precautionary motives for portfolio decisions across different groups of firms, both in the model and in the data.

Table 10 reports the regression results for the simulated subsamples. In Panel A, where risky financial assets are scaled by total assets, the coefficient on the financing deficit beta is larger for small firms (Columns 1 versus 2), high-volatility firms (Columns 3 versus 4), and R&D-intensive firms (Columns 5 versus 6). Panel B, which scales risky financial assets by total financial assets, exhibits similar patterns, although the differences in coefficients across subsamples are smaller. Overall, these results indicate stronger hedging incentives for subsamples of firms characterized in the model by higher estimated values of $\sigma_z$ and $\xi$, as well as lower $\psi_i$ (cf. Tables 7–9). Higher $\sigma_z$ and lower $\psi_i$ increase the sensitivity of investment and financing needs to aggregate conditions, while higher $\xi$ amplifies the value of hedging through financial assets.

Table 11 presents the regression results from Eq. (26) for the real-data subsamples based on firm size (Panel A), volatility (Panel B), and R&D intensity (Panel C). All regressions include the standard set of control variables—*FDResiVol*, *LProf*, *LQ*, and *LSize*—along with industry-year fixed effects.

Consistent with the model's prediction that small firms have stronger precautionary incentives to invest in risky financial assets (cf. Table 10), the financing deficit beta is significantly and positively associated with risky asset holdings as a fraction of total assets for small firms (Columns 1 and 2 in Panel A). In contrast, the coefficients for large firms are smaller and less statistically significant (Columns 5 and 6 in Panel A). 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 increase in risky financial asset holdings of 1% (0.86%) as a fraction of total assets.

Columns 3 and 4 in Panel A report the results for small firms using the ratio of risky to total financial assets as the dependent variable. A one standard deviation increase in the financing deficit beta based on the Agg index (Treasury bond) is associated with a 1.75% (1.77%) increase in the share of risky financial assets in the savings portfolios of small firms. For large firms (Columns 7 and 8), the coefficients are of similar magnitude, although statistical significance at the 5% level is present only for the regression using $BetaTre$.

Overall, these results highlight the importance of precautionary motives in small firms' decisions to invest in risky financial assets, while their relevance appears to diminish for large firms. This pattern is consistent with the findings of DGHH and DM, who show that other factors – such as managerial overconfidence, corporate governance issues, and tax considerations – are more closely associated with the savings portfolio choices of very large firms.

Panel B of Table 11 presents the regression results from Eq. (26) for high- and low-volatility firms. The results show that the financing deficit beta is positively and significantly associated with risky financial asset holdings only among high-volatility firms. For these firms, a one

**Table 9**
Structural estimation results—high vs low R&D firms. Panel A reports the sample and simulated moments. Columns 1–3 report, for high R&D firms, the empirical moments targeted in the structural estimation, the corresponding simulated moments generated from 50 simulations of 3000 firms over 50 years, and the $t$-statistics for the differences between empirical and simulated moments, respectively. Columns 4–6 report the same set of statistics for low R&D firms. Panels B and C report the estimated structural parameters for high and low R&D firms, respectively. The parameters $\rho_z$ and $\sigma_z$ are the persistence and conditional standard deviation of the idiosyncratic profitability shock, respectively, and they are obtained from an autocorrelation regression of TFP using data from İmrohoroğlu and Tüzel (2014); $\alpha$ is the curvature of the profit function; $\psi_i$ is the capital adjustment cost parameter; $\xi$ is the external financing cost parameter; and $\psi_s$ denotes the bond trading cost. High and low R&D firms are defined as firms with positive and zero R&D expenditures during the sample period, respectively. Standard errors are clustered at the firm level and adjusted for sampling errors in the first stage. Section 4.1 describes the sample construction. Moment definitions are provided in Table A.3. Appendix A presents details of the numerical procedure used to solve the model and of the estimation approach.

Panel A. Moments

| | High R&D Firms | | | Low R&D Firms | | |
|---|---|---|---|---|---|---|
| | (1) Data | (2) Model | (3) t-stats | (4) Data | (5) Model | (6) t-stats |
| Average Risky Financial Assets | 0.0599 | 0.0600 | −0.48 | 0.0246 | 0.0356 | −113.30 |
| Average Safe Financial Assets | 0.1880 | 0.1888 | −2.81 | 0.0981 | 0.1292 | −102.82 |
| Average Investment | 0.1253 | 0.1274 | −2.66 | 0.1205 | 0.1382 | −6.08 |
| Average Q | 2.1271 | 2.1670 | −19.71 | 1.6376 | 2.1225 | −140.93 |
| Average Profitability | 0.2015 | 0.1706 | 1.41 | 0.2379 | 0.1579 | 5.63 |
| Median Distribution | 0.0196 | 0.0039 | 0.74 | 0.0170 | 0.0026 | 1.57 |
| Variance of Profitability | 0.0070 | 0.0082 | −0.47 | 0.0093 | 0.0059 | 2.19 |
| Variance of Distribution | 0.0322 | 0.0183 | 3.52 | 0.0220 | 0.0437 | −6.25 |
| Autocorrelation of Profitability | 0.7978 | 0.7083 | 1.05 | 0.6986 | 0.7123 | −0.14 |
| Autocorrelation of Investment | 0.6412 | 0.5543 | 1.02 | 0.6982 | 0.5662 | 1.95 |
| Autocorrelation of Distribution | 0.5450 | 0.4280 | 1.36 | 0.5786 | 0.5077 | 0.74 |

Panel B. High R&D Firms

| Parameter | $\rho_z$ | $\sigma_z$ | $\alpha$ | $\psi_i$ | $\xi$ | $\psi_s$ (bps) |
|---|---|---|---|---|---|---|
| Value | 0.8086 | 0.3552 | 0.8063 | 0.4429 | 0.1397 | 6.8493 |
| Standard Error | 0.0154 | 0.0128 | 0.0284 | 0.1061 | 0.0099 | 1.1019 |

Panel C. Low R&D Firms

| Parameter | $\rho_z$ | $\sigma_z$ | $\alpha$ | $\psi_i$ | $\xi$ | $\psi_s$ (bps) |
|---|---|---|---|---|---|---|
| Value | 0.7971 | 0.3176 | 0.8585 | 0.3807 | 0.0679 | 4.7340 |
| Standard Error | 0.0220 | 0.0111 | 0.0161 | 0.0507 | 0.0012 | 1.0004 |

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 of 0.85% (0.83%) as a fraction of total assets, or 1.82% (1.95%) as a fraction of total financial assets. In contrast, for low-volatility firms, the coefficients are statistically insignificant across most specifications. These findings support the notion that hedging motives for holding risky financial assets are stronger in firms whose investment demand is more sensitive to macroeconomic conditions. For firms with more stable financing deficits, these incentives appear to play a less prominent role in shaping portfolio choices.

Finally, firms that invest heavily in innovation may face different incentives to hedge factors related to interest-rate risk, given the higher cost of external financing for investments in intangible assets (see, e.g., Hall and Lerner, 2010). Panel C of Table 11 shows that the regression coefficients on the financing deficit beta are positive for both high- and low-R&D firms. These results suggest that hedging motives are present in both groups, although statistical significance is somewhat lower among low-R&D firms.

### 4.9. Additional robustness tests

The Online Appendix reports several robustness checks of our empirical findings. First, we show that the main results on the cross-section of financial asset holdings in Table 4 are both qualitatively and quantitatively robust to using time-varying estimates of the financing deficit beta based on rolling windows, $\hat{\beta}^D_{jt}$, instead of constant firm-specific betas, $\hat{\beta}^D_j$ (see Table OA.6). Second, we replicate the baseline analysis using alternative measures of volatility. Specifically, we replace the residual-based volatility measure $FDResiVol$ from Eq. (25) with total financing deficit volatility, $FDVol$, and with cash flow volatility, $CFVol$, defined following Duchin et al. (2017). As shown in Table OA.7 through Table OA.9, the main results remain robust to these alternative volatility measures.

We further verify that our findings are not driven by outliers in the financing deficit beta estimates. In particular, we re-estimate the main regressions after winsorizing betas at the 10th and 90th percentiles, rather than at the 5th and 95th percentiles, and after transforming beta estimates into percentiles, which preserves only their relative ranking and abstracts from their magnitude. The results based on these alternative beta transformations, reported in Table OA.10 and Table OA.11, confirm the robustness of our conclusions.

Next, we test the robustness of our results by measuring the value of risky financial asset holdings using Compustat item $IVST$ (short-term investments). Specifically, we replace $Risky$ and $FinComp$ with $IVST/AT$ and $IVST/CHE$, respectively, as the dependent variables in Eq. (26). While our measures of risky financial asset holdings are more precise than those based on $IVST$ (see Online Appendix F.5 for a detailed discussion), we conduct this test to verify our results using widely available proxies that extend over a longer sample period. The results, reported in Table OA.12, show that the estimated coefficients are similar to those obtained using $Risky$ and $FinComp$ in Table 4.

Previous studies have shown that intangible capital plays an important role in firms' cash-holding decisions (e.g., Begenau and Palazzo,

**Table 10**
Regressions of risky financial asset holdings—simulated subsamples. This table reports the results of the regression in Eq. (23), $FinAssets_{jt} = \zeta_t + \varphi\beta^D_{jt-1} + Controls_{jt-1} + \varepsilon_{jt}$, using the simulated samples from the model. The dependent variable is the value of risky financial assets scaled either by total assets (variable $Risky$ in Panel A) or total financial assets (variable $FinComp$ in Panel B). The independent variable $\beta^D_{jt-1}$ is the financing deficit beta computed using Eq. (22). Control variables include $LQ$, $LProf$, $LSize$, *FDResiVol* computed using Eq. (24), and year fixed effects. In both panels, Columns 1 to 6 report the regression results using subsamples simulated from the structural estimates for small (Panel B in Table 7), large (Panel C in Table 7), high volatility (Panel B in Table 8), low volatility (Panel C in Table 8), high R&D (Panel B in Table 9), and low R&D (Panel C in Table 9) firms, respectively. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively. We obtain the simulated samples by solving the model at the estimated parameters and simulating 50 samples of 3000 firms over 50 years. Variable definitions are provided in Table A.4. Appendix A presents the details of the numerical procedure used to solve the model.

Panel A. Risky Financial Assets over Total Assets

| VARIABLES | Small (1) Risky | Large (2) Risky | High-Vol (3) Risky | Low-Vol (4) Risky | High-R&D (5) Risky | Low-R&D (6) Risky |
|---|---|---|---|---|---|---|
| Beta | 1.119*** | 0.381*** | 2.117*** | 0.267*** | 2.405*** | 0.924*** |
| | (0.007) | (0.007) | (0.008) | (0.006) | (0.008) | (0.006) |
| Observations | 7,500,000 | 7,500,000 | 7,500,000 | 7,500,000 | 7,500,000 | 7,500,000 |
| R-squared | 0.389 | 0.339 | 0.388 | 0.347 | 0.402 | 0.345 |
| Cluster Level | Firm | Firm | Firm | Firm | Firm | Firm |
| Controls | Y | Y | Y | Y | Y | Y |
| Year FEs | Y | Y | Y | Y | Y | Y |

Panel B. Risky Financial Assets over Total Financial Assets

| VARIABLES | Small (1) FinComp | Large (2) FinComp | High-Vol (3) FinComp | Low-Vol (4) FinComp | High-R&D (5) FinComp | Low-R&D (6) FinComp |
|---|---|---|---|---|---|---|
| Beta | 3.549*** | 3.005*** | 5.669*** | 7.827*** | 7.530*** | 6.862*** |
| | (0.035) | (0.048) | (0.043) | (0.050) | (0.039) | (0.044) |
| Observations | 7,500,000 | 7,500,000 | 7,500,000 | 7,500,000 | 7,500,000 | 7,500,000 |
| R-squared | 0.149 | 0.137 | 0.104 | 0.127 | 0.115 | 0.093 |
| Cluster Level | Firm | Firm | Firm | Firm | Firm | Firm |
| Controls | Y | Y | Y | Y | Y | Y |
| Year FEs | Y | Y | Y | Y | Y | Y |

2021; Falato et al., 2022; Li, 2025). To test whether investment in intangible capital leads to different incentives to hold risky financial assets compared to tangible investment, in Online Appendix F.6 we re-estimate the financing deficit beta using the measure of intangible capital proposed by Peters and Taylor (2017). The second-stage regression results from Eq. (26), reported in Table OA.14, show that while the coefficients associated with the financing deficit beta are larger for tangible investment, they remain positive and significant for both types of capital.

## 5. Risky financial assets and firm value

In this section, we analyze the effects of risky financial assets on firm value, investment, and financing activities. We do so by first performing a counterfactual experiment based on the estimated model, and then by running regressions on the real data sample that relate financial asset holdings to corporate investment and external financing.

### 5.1. Counterfactuals

What is the value to the firm of the option to trade risky financial assets? To address this question, we conduct two counterfactual experiments using the model estimated in Section 3.1. First, we perform comparative statics by varying the trading cost of risky financial assets, $\psi_s$. This parameter directly affects firms' incentives to invest in risky financial assets but has no direct impact on their technology, external financing cost, or the economic environment they face. Fig. 8 shows that as $\psi_s$ increases, the firm increases its holdings of safe financial assets (Panel A) as a substitute for risky financial assets (Panel B). In turn, average investment declines (Panel C), as the firm's ability to hedge external financing costs is reduced. Consequently, firm value decreases with higher values of $\psi_s$ (Panel D).

The results in Fig. 8 suggest that while the impact of $\psi_s$ on the composition of savings is substantial, its effects on investment and firm value are quantitatively modest. This is because risky and safe financial assets are, to a large extent, substitutes. As $\psi_s$ increases, the firm shifts from risky to safe financial assets in equilibrium, which largely offsets the negative effects of higher trading costs on investment and firm value.

To quantify the overall effects of firms' ability to access risky financial assets, our second counterfactual experiment solves the model at the estimated parameters while restricting both $s$ and $s'$ to zero. This allows us to compute optimal policies and firm value under the assumption that the firm cannot invest in the risky security. We then simulate samples from both the full and counterfactual models based on the full-sample estimates in Table 1 and, for each, compute the average

**Table 11**

Regressions of risky financial asset holdings—sample splits. This table reports—for the subsample splits by firm size (Panel A), volatility (Panel B), and R&D (Panel C)—the results of the regression in Eq. (26), $FinAssets_{jt} = \zeta_{sic,t} + \varphi\hat{\beta}_j^D + Controls_{jt-1} + \varepsilon_{jt}$, 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, 2, 5 and 6), or the fair value of risky financial assets over total financial assets ($FinComp$ in Columns 3, 4, 7 and 8); $\zeta_{sic,t}$ are 2-digit SIC code industry × year fixed effects; the control variables are $LQ$, $LProf$, $LSize$, and $FDResiVol$; and $\hat{\beta}_j^D$, the financing deficit beta, is estimated for each firm from the time-series regression in Eq. (25), $FD_{jt} = \alpha_j + \beta_j^D R_{t-1}^B + \varepsilon_{jt}$, where $FD_{jt}$ is the financing deficit of firm $j$ in quarter $t$; $R_{t-1}^B$ is either the return on the Bloomberg US Aggregate Bond Market Index ("Agg Bond") or the reverse change in the 10-year Treasury bond yield ("Treasury") during quarter $t-1$; and $FDResiVol$ is the standard deviation of the financing deficit residuals, $\hat{\varepsilon}_{jt}$, from the corresponding regressions. Firms are split by yearly median size in Panel A, median financing deficit volatility in Panel B, and positive and zero R&D in Panel C. Standard errors in parentheses are clustered at the industry level and adjusted using the procedure in Murphy and Topel (1985) to account for sampling error in the first stage. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively. Variable definitions are in Table A.4.

Panel A. Split by Size

| | Small Firms | | | | Large Firms | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLES | Risky | Risky | FinComp | FinComp | Risky | Risky | FinComp | FinComp |
| Beta | 0.310*** | 0.070*** | 0.544*** | 0.144*** | 0.091 | 0.064** | 0.458 | 0.197** |
| | (0.057) | (0.014) | (0.107) | (0.030) | (0.109) | (0.027) | (0.319) | (0.076) |
| Observations | 9652 | 9652 | 9590 | 9590 | 9646 | 9646 | 9540 | 9540 |
| R-squared | 0.113 | 0.112 | 0.067 | 0.067 | 0.155 | 0.158 | 0.118 | 0.121 |
| Beta Type | Agg Bond | Treasury | Agg Bond | Treasury | Agg Bond | Treasury | Agg Bond | Treasury |
| 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. Split by Volatility

| | High Volatility Firms | | | | Low Volatility Firms | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLES | Risky | Risky | FinComp | FinComp | Risky | Risky | FinComp | FinComp |
| Beta | 0.264*** | 0.068*** | 0.566*** | 0.159*** | −0.202 | 0.095 | 0.099 | 0.314* |
| | (0.043) | (0.014) | (0.131) | (0.038) | (0.237) | (0.064) | (0.643) | (0.157) |
| Observations | 9625 | 9625 | 9518 | 9518 | 9643 | 9643 | 9582 | 9582 |
| R-squared | 0.121 | 0.121 | 0.080 | 0.081 | 0.100 | 0.101 | 0.089 | 0.090 |
| Beta Type | Agg Bond | Treasury | Agg Bond | Treasury | Agg Bond | Treasury | Agg Bond | Treasury |
| 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 C. Split by R&D

| | High R&D Firms | | | | Low R&D Firms | | | |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| VARIABLES | Risky | Risky | FinComp | FinComp | Risky | Risky | FinComp | FinComp |
| Beta | 0.283*** | 0.064*** | 0.444*** | 0.135*** | 0.150 | 0.069*** | 0.636** | 0.199*** |
| | (0.045) | (0.016) | (0.132) | (0.037) | (0.094) | (0.024) | (0.244) | (0.068) |
| Observations | 9663 | 9663 | 9581 | 9581 | 9618 | 9618 | 9532 | 9532 |
| R-squared | 0.115 | 0.114 | 0.075 | 0.076 | 0.082 | 0.087 | 0.091 | 0.092 |
| Beta Type | Agg Bond | Treasury | Agg Bond | Treasury | Agg Bond | Treasury | Agg Bond | Treasury |
| 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 |

value of several variables of interest. Table 12 reports the differences in averages between the two models, expressed as percentages of average capital in the full model.[20] Compared to the full model, restricting the firm from using risky securities as a hedging instrument leads to lower investment, smaller firm size, and reduced profits (Column 1). In terms of savings behavior, the firm shifts from risky to safe financial assets, but the overall level of savings declines. While the firm saves on taxes and trading costs, the cash flows generated by financial assets fall. The combined effect of reduced operating and financial cash flows lowers distributions, prompting the firm to rely more frequently – and more heavily – on external financing. Ultimately, these effects reduce firm value by 0.35% relative to the full model.

To investigate when and for which firms the option to save in risky financial assets is most valuable, we perform time-series and cross-sectional sample splits. First, we find that the loss in firm value is

[20] We scale by capital to maintain comparability in terms of magnitude across variables. For ease of interpretation, however, issuance frequency and firm value are scaled by their respective average values in the full model.

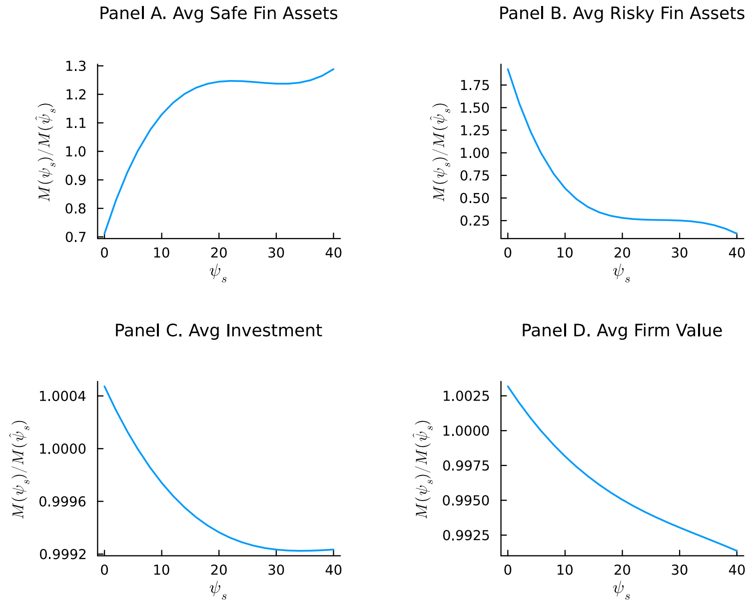


**Fig. 8.** Trading costs, financial assets, and firm value. This figure reports comparative statics with respect to the trading cost parameter $\psi_s$. All other parameters are held fixed at their estimated values from Table 1. Each panel plots the ratio $M(\psi_s)/M(\hat{\psi}_s)$, where $M(\cdot)$ denotes the corresponding simulated moment and $\hat{\psi}_s$ is the estimated value reported in Table 1. Thus, a value of one corresponds to the benchmark economy at $\hat{\psi}_s$, and deviations from one indicate proportional changes in the corresponding moment, rather than levels or percentages. Panel A corresponds to the moment of average safe financial asset holdings, Panel B to average risky financial asset holdings, Panel C to average investment, and Panel D to average firm value.

**Table 12**
Risky financial assets and firm value. This table reports the results of a counterfactual experiment based on the model to evaluate the effects and value of the option to invest in risky financial assets. We compare the full model to a counterfactual version in which firms are restricted from holding risky financial assets. Both models are solved using the estimated parameters reported in Table 1. We simulate two samples of firms from the full and counterfactual models and compare their outcomes across operating performance, financing behavior, and firm value. Column 1 reports the mean differences in each outcome, scaled by average capital in the full model—except for issuance frequency and firm value, which are scaled by their respective means. Columns 2 to 5 report analogous differences for subsamples defined by business cycle conditions and firm size, using the same scaling relative to conditional means. Boom and bust periods are defined by positive and negative aggregate profitability shocks, respectively; below and above median size firms are defined relative to the yearly median of total assets.

| | % Differences No Risky vs Full Model | | | | |
|---|---|---|---|---|---|
| | (1) Full Sample | (2) Boom Periods | (3) Bust Periods | (4) < Median Size | (5) > Median Size |
| Capital | −0.1685 | −0.1617 | −0.1233 | −0.2289 | −0.1501 |
| Investment | −0.0165 | −0.0170 | 0.0150 | −0.0398 | −0.0093 |
| Profits | −0.0250 | −0.0213 | −0.0210 | −0.0305 | −0.0233 |
| Financial Assets | −0.3566 | −0.2282 | −0.3305 | −0.6704 | −0.2610 |
| Tax Costs on Financial Assets | −0.0018 | −0.0011 | −0.0016 | −0.0033 | −0.0013 |
| Trading Costs | −0.0008 | −0.0006 | −0.0006 | −0.0016 | −0.0006 |
| Cash Flows from Financial Assets | −0.0110 | −0.0385 | −0.0824 | −0.0207 | −0.0080 |
| Distributions | −0.0176 | −0.0439 | −0.1156 | −0.0086 | −0.0203 |
| Issuance Amount | 0.0471 | 0.0879 | 0.0008 | 0.0997 | 0.0311 |
| Issuance Costs | 0.0045 | 0.0084 | 0.0001 | 0.0095 | 0.0030 |
| Issuance Frequency | 4.6964 | 1.2243 | 19.2459 | 5.0150 | 4.2484 |
| Firm Value | −0.3499 | −0.3089 | −0.2143 | −0.4594 | −0.3008 |

larger during booms than in busts (Columns 2 and 3). In the model, the risky security allows firms to transfer liquidity from bad times – when investment needs are low – to good times, when the firm seeks to grow. Accordingly, firm investment is lower in booms when the risky asset is not available, while in busts, firms divest less. Second, we perform a cross-sectional split of the simulated sample every year based on the median asset size. The comparison between Columns 4 and 5 shows that the option to invest in the risky security is more valuable when firms are small. In the counterfactual, small firms reduce investment more sharply and rely more heavily on external financing than large firms.

In summary, the counterfactual experiment shows that losing access to risky financial assets reduces firm value by 0.35%, with larger losses observed for small firms and during economic booms. Online Appendix F.7 presents the results of additional counterfactual experiments based on the sample splits described in Section 4.8.

### *5.2. Risky financial assets, investment, and financing*

The discussion in the previous section highlights that, in the model, risky financial assets affect firm value through their impact on investment and external financing policies. To provide empirical support for this mechanism, we estimate the following regression using our data

**Table 13**
Risky financial assets, investment, and external financing. This table reports the results of the regression in Eq. (27),
$Y_{jt} = \varphi_1 Risky_{jt-1} + \varphi_2 Safe_{jt-1} + Controls_{jt-1} + \alpha_j + \zeta_t + \varepsilon_{jt}$,
where $j$ and $t$ index firm and year, respectively; the dependent variable is either the investment rate ($InvTot$ in Panel A) or external financing ($ExtFin$ in Panel B); $LRisky$ and $LSafe$ are lagged risky and safe financial assets; control variables are $LQ$, $LProf$, and $LSize$; and firm and year fixed effects are included. Column 1 reports results for the full sample. Columns 2 and 3 report results for small and large firms, defined by whether total assets in the previous year fall below or above the annual median, respectively. Columns 4 and 5 report results for high- and low-volatility firms, based on whether financing deficit volatility is above or below the median. Columns 6 and 7 report results for high- and low-R&D firms, defined by whether average R&D expenditure is positive or zero, respectively. Standard errors are clustered at the industry level defined by 2-digit SIC code. Significance levels at 10%, 5%, and 1% are denoted by *, **, and ***, respectively. Variable definitions are in Table A.4.

Panel A. Investment

| VARIABLES | Full (1) InvTot | Small (2) InvTot | Large (3) InvTot | High-Vol (4) InvTot | Low-Vol (5) InvTot | High-R&D (6) InvTot | Low-R&D (7) InvTot |
|---|---|---|---|---|---|---|---|
| LRisky | 0.186*** | 0.298*** | 0.012 | 0.222*** | 0.129* | 0.240*** | 0.085* |
| | (0.061) | (0.102) | (0.049) | (0.067) | (0.072) | (0.078) | (0.046) |
| LSafe | 0.439*** | 0.463*** | 0.301*** | 0.549*** | 0.140*** | 0.468*** | 0.400*** |
| | (0.062) | (0.076) | (0.090) | (0.083) | (0.030) | (0.087) | (0.102) |
| Observations | 16,946 | 8396 | 8428 | 8409 | 8537 | 8516 | 8430 |
| R-Squared | 0.070 | 0.062 | 0.106 | 0.073 | 0.091 | 0.068 | 0.116 |
| Cluster Level | Industry | Industry | Industry | Industry | Industry | Industry | Industry |
| Controls | Y | Y | Y | Y | Y | Y | Y |
| Firm FEs | Y | Y | Y | Y | Y | Y | Y |
| Year FEs | Y | Y | Y | Y | Y | Y | Y |

Panel B. External Financing

| VARIABLES | Full (1) ExtFin | Small (2) ExtFin | Large (3) ExtFin | High-Vol (4) ExtFin | Low-Vol (5) ExtFin | High-R&D (6) ExtFin | Low-R&D (7) ExtFin |
|---|---|---|---|---|---|---|---|
| LRisky | −0.123*** | −0.189*** | −0.004 | −0.160*** | −0.054 | −0.156*** | −0.063** |
| | (0.027) | (0.039) | (0.032) | (0.037) | (0.043) | (0.038) | (0.030) |
| LSafe | −0.154*** | −0.193*** | −0.018 | −0.202*** | −0.033 | −0.181*** | −0.089 |
| | (0.042) | (0.043) | (0.055) | (0.048) | (0.058) | (0.045) | (0.074) |
| Observations | 16,959 | 8401 | 8435 | 8416 | 8543 | 8518 | 8441 |
| R-Squared | 0.126 | 0.134 | 0.072 | 0.153 | 0.064 | 0.143 | 0.115 |
| Cluster Level | Industry | Industry | Industry | Industry | Industry | Industry | Industry |
| Controls | Y | Y | Y | Y | Y | Y | Y |
| Firm FEs | Y | Y | Y | Y | Y | Y | Y |
| Year FEs | Y | Y | Y | Y | Y | Y | Y |

sample:

$$Y_{jt} = \varphi_1 Risky_{jt-1} + \varphi_2 Safe_{jt-1} + Controls_{jt-1} + \alpha_j + \zeta_t + \varepsilon_{jt}, \tag{27}$$

where $j$ and $t$ index firm and year, respectively; the dependent variable $Y_{jt}$ is either the investment rate ($InvTot$) or external financing ($ExtFin$); $Risky$ and $Safe$ denote risky and safe financial asset holdings; control variables include lagged values of Tobin's Q, profitability, and firm size; and $\alpha_j$ and $\zeta_t$ are firm and year fixed effects. Variable definitions are provided in Table A.4.

Table 13 presents the estimation results of Eq. (27) for investment (Panel A) and external financing (Panel B). Column 1 shows that $Risky$ is positively associated with the investment rate and negatively associated with external financing. Moreover, the coefficients on $Risky$ and $Safe$ have the same sign, consistent with the idea that these two liquidity tools function as substitutes. To examine whether these effects vary across firm types, we perform a series of sample splits. Columns 2 and 3 show that the relationship between $Risky$ and the investment rate is statistically significant only for small firms, and the same pattern holds for external financing. Similar results emerge when comparing high- and low-volatility firms (Columns 4 and 5) as well as high- and low-R&D firms (Columns 6 and 7). In particular, the coefficients on $Risky$ are significant at the 1% level for high-volatility and high-R&D firms, while significance weakens in the low-volatility and low-R&D subsamples.

Overall, the empirical evidence aligns with the economic channel highlighted in the model, linking risky financial assets to investment and external financing. This relationship appears to be particularly relevant for small, high-volatility, and high-R&D firms.

## 6. 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 gain a better understanding of 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 stronger incentives to invest in risky financial assets when their financing deficit – defined as the gap between investment needs and internal funds – is more sensitive to the returns on those assets.

To empirically test the model's predictions, we construct the most comprehensive sample to date of US firms' risky financial asset holdings. Our main finding is that the financing deficit beta – our empirical measure of the sensitivity of the financing deficit to risky financial asset returns – estimated using bond market data, is positively correlated with corporate risky financial asset holdings, consistent with the model. When we explore alternative risk factors, we find that beta measures linked to medium- to long-term interest-rate risk best explain the cross-sectional variation in risky financial asset holdings. Moreover, these precautionary motives are most relevant for small, high-volatility, and R&D-intensive firms.

The findings from this study open several avenues for future research. First, while we focus on two broad categories of financial assets – "safe" and "risky" – a more granular examination of the specific securities held by firms could shed light on the distinct drivers of corporate portfolio decisions. Such an analysis may reveal how different asset classes contribute to firms' hedging strategies. Second, it would be valuable to explore how firms combine multiple liquidity tools – such as cash holdings, credit lines, and risky financial assets – to manage uncertainty. While our model emphasizes aggregate risk and the role of risky financial assets as a source of state-contingent liquidity, credit lines can play a similar role in response to idiosyncratic shocks (Nikolov et al., 2019). In this sense, the two instruments may be complementary. Empirical analysis of how firms balance these tools in practice could shed light on the interaction between different sources of liquidity.

## CRediT authorship contribution statement

**Teng Huang:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Resources, Project administration, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Stefano Sacchetto:** Writing – review & editing, Writing – original draft, Visualization, Validation, Supervision, Software, Resources, Project administration, Methodology, Investigation, Funding acquisition, Formal analysis, Data curation, Conceptualization.

## Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

## Appendix A. Numerical details

This appendix provides details on the model solution, structural estimation, computation of the financing deficit beta in the model, and counterfactual experiments.

### A.1. Model solution

For a given value of the vector of structural parameters,

$$\vartheta = (\rho_x,\ \sigma_x,\ \gamma,\ \eta,\ \mu,\ \tau,\ \delta,\ \rho_z,\ \sigma_z,\ \alpha,\ \psi_i,\ \xi,\ \psi_s), \tag{28}$$

the Bellman equation characterizing the optimal policy functions is

$$v(x,z,s,c,k|\vartheta) = \max_{s',c',k'}\ d(\cdot) + \mathbf{E}\left[M(x,x')v(x',z',s',c',k'|\vartheta)|x,z\right], \tag{29}$$

and the net and gross distributions to investors, capital adjustment costs, and bond trading costs are determined, respectively, by

$$\begin{aligned} d(x,z,s,c,k,s',c',k'|\vartheta) =& e(\cdot) - \xi\,|e(\cdot)|\,\mathbf{1}_{\{e(\cdot)<0\}},\\ e(x,z,s,c,k,s',c',k'|\vartheta) =& (1-\tau)\exp(x+z)k^{\alpha} + \tau\delta k - (k'-(1-\delta)k) - Adj^k(\cdot)\\ &+ (\mu + (1-\tau)\overline{r}_f)s + (1-\mu)q^s(x)s - q^s(x)s' - Adj^s(\cdot)\\ &+ (1+(1-\tau)\overline{r}_f)c - q^c(x)c',\\ Adj^k(k,k'|\vartheta) =& \frac{\psi_i}{2}\left(\frac{k'-(1-\delta)k}{k}\right)^2 k,\\ Adj^s(s,s'|\vartheta) =& \psi_s\left|s'-(1-\mu)s\right|. \end{aligned} \tag{30}$$

To increase the accuracy of the numerical solution, we perform a change in variables by scaling risky and safe financial assets by physical capital: $\tilde{s} = s/k$ and $\tilde{c} = c/k$. We construct grids for the state variables as follows:

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 $N_s = 19$ grid points evenly distributed in the range $[0, \log(1.5)]$. We use the same method to discretize $\log(1+\tilde{c})$ on $N_c = 29$ grid points evenly distributed in $[0, \log(2.5)]$. The upper limits for $\tilde{s}$ and $\tilde{c}$ are set to 0.5 and 1.5, respectively. These values are more than 10 times the sample mean of risky and safe financial assets over total assets in our sample.[21]
3. We discretize capital $k$ on $N_k = 99$ grid points evenly distributed on log space between $[\log(\underline{k}),\ \log(\overline{k})]$, where $\underline{k}$ and $\overline{k}$ are the minimum and maximum capital levels, respectively, in a frictionless model (i.e., $\psi_i = \psi_s = \xi = 0$).

After discretization, the state space has dimensions $3\times5\times19\times29\times99$, and we solve the model using value function iteration:

$$\begin{aligned} v_n(x,z,\tilde{s},\tilde{c},k|\vartheta) = \max_{\tilde{s}',\tilde{c}',k'} & d(x,z,\tilde{s},\tilde{c},k,\tilde{s}',\tilde{c}',k'|\vartheta)\\ &+ \mathbf{E}\left[M(x,x')v_{n-1}(x',z',\tilde{s}',\tilde{c}',k'|\vartheta)|x,z\right]. \end{aligned} \tag{31}$$

To accelerate convergence, we implement Howard's improvement method: for each policy function iteration, we compute the converging value function while holding the policy fixed. During this step, the convergence criterion is

$$\max|v_n(x,z,\tilde{s},\tilde{c},k|\vartheta) - v_{n-1}(x,z,\tilde{s},\tilde{c},k|\vartheta)| < 10^{-4}. \tag{32}$$

Once the policy function converges, or after completing ten policy function iterations, the final convergence criterion is tightened to

$$\max|v_n(x,z,\tilde{s},\tilde{c},k|\vartheta) - v_{n-1}(x,z,\tilde{s},\tilde{c},k|\vartheta)| < 10^{-5}. \tag{33}$$

### A.2. Estimation procedure

We estimate the parameter vector $\vartheta_e = (\rho_z,\ \sigma_z,\ \alpha,\ \psi_i,\ \xi,\ \psi_s)$ by solving the following SMM minimization problem:

$$\hat{\vartheta}_e = \arg\min_{\vartheta_e}\ \left(M(\vartheta_e) - \hat{M}\right)'\hat{W}\left(M(\vartheta_e) - \hat{M}\right), \tag{34}$$

where $M(\vartheta_e)$ is the vector of simulated moments evaluated at $\vartheta_e$, $\hat{M}$ is the vector of sample moments, and $\hat{W}$ is the weighting matrix. We simulate 50 samples of 3000 firms for 500 periods, discard the first 450 periods to eliminate the influence of initial conditions, and use the final 50 periods to compute the simulated moments $M(\vartheta_e)$.

To obtain the weighting matrix $\hat{W}$, we employ the influence function approach from Erickson and Whited (2000, 2002). Since firms are ex-ante homogeneous in our model, we need to filter out the cross-sectional heterogeneity present in the data. To do so, we compute influence functions for the mean and variance moments using data demeaned at the firm level, following Nikolov and Whited (2014), and estimate the autocorrelation moments by eliminating firm fixed effects through the differencing method in Han and Phillips (2010). The weighting matrix $\hat{W}$ is then calculated as the inverse of the covariance matrix of the stacked influence functions.

[21] Both $\tilde{s}$ and $\tilde{c}$ are discretized in log space to create a finer grid at lower values, which at the estimated parameters are visited more frequently in equilibrium than higher values. This grid construction improves numerical accuracy. We have also solved the model using evenly spaced grids for $\tilde{s}$ and $\tilde{c}$ in previous versions, and our results are not sensitive to the choice of grid method.

The asymptotic distribution of $\hat{\vartheta}_e$ is given by

$$\sqrt{N}(\hat{\vartheta}_e - \vartheta_e) \xrightarrow{d} \mathcal{N}\left(0, \left(1 + \frac{1}{S}\right) \left[J'\hat{W}J\right]^{-1} \left[J'\hat{W}\hat{\Omega}\hat{W}J\right] \left[J'\hat{W}J\right]^{-1}\right), \tag{35}$$

where $S$ denotes the ratio of simulated to actual data observations, $J$ is the Jacobian matrix evaluated at the estimated parameter vector $\hat{\vartheta}_e$, computed numerically as

$$J = \frac{\partial M(\hat{\vartheta}_e)}{\partial \hat{\vartheta}_e^{\top}} = \frac{M(\hat{\vartheta}_e^{+}) - M(\hat{\vartheta}_e^{-})}{\hat{\vartheta}_e^{+} - \hat{\vartheta}_e^{-}}, \tag{36}$$

with $\hat{\vartheta}_e^{+} = 1.01 \times \hat{\vartheta}_e$ and $\hat{\vartheta}_e^{-} = 0.99 \times \hat{\vartheta}_e$ (so the one-side deviation is 1% of the estimated parameter values), and $\hat{\Omega}$ is the clustered covariance matrix of the moments. Following Nikolov and Whited (2014) and Li et al. (2016), we use the data demeaned at the firm level to construct the influence functions for the autocorrelation and variance moments, but undemeaned data for the influence functions of the mean moments. We then covary these influence functions clustered at the firm level (see Eq. (23) in Bazdresch et al., 2018) to obtain $\hat{\Omega}$.

After obtaining the estimated parameter vector $\hat{\vartheta}_e$, we solve and simulate the model on a finer grid with $N_s = 19$, $N_c = 29$, and $N_k = 499$. The resulting policy functions are used to simulate the final sample employed in the empirical analysis in Sections 3 and 5. The comparative statics figures (Fig. 2, 8, and OA.1) are generated using cubic-spline interpolation between grid points.

Finally, we provide details of the estimation procedure for the sample splits in Section 4.8.1. In the first stage, for each subsample we estimate the parameter $\rho_z$ as the coefficient from an autocorrelation regression of log TFP, and $\sigma_z$ as the standard deviation of the regression residuals. We obtain the log TFP data from Şelale Tüzel's website, which covers Compustat firms for our entire sample period. TFP is computed at the firm-year level according to the procedure in İmrohoroğlu and Tüzel (2014), which employ the control function approach of Olley and Pakes (1996) to deal with selection and simultaneity bias in the estimation of the production function parameters, and filter out industry-time fixed effects. Therefore, the log TFP data corresponds to our idiosyncratic productivity shock $z$. In the second stage, for each subsample, we use the estimated ($\hat{\rho}_z$, $\hat{\sigma}_z$) and perform the SMM procedure described above to estimate the remaining parameters ($\alpha$, $\psi_i$, $\xi$, $\psi_s$). We adjust the second-stage standard errors following Gao et al. (2021).

### *A.3. Numerical computation of the financing deficit beta*

In the model, the financing deficit beta is computed as

$$\beta_{jt}^{D} = \frac{\mathbf{Cov}_t\left[FD(x_{t+1}, z_{jt+1}, s_{jt+1}, c_{jt+1}, k_{jt+1})R(x_{t+1})|x_t, z_{jt}, s_{jt}, c_{jt}, k_{jt}\right]}{\mathbf{Var}_t[R(x_{t+1})|x_t]}. \tag{37}$$

In period $t$, the financing deficit $FD(x_{t+1}, z_{jt+1}, s_{jt+1}, c_{jt+1}, k_{jt+1})$, defined in Eq. (20), is a random variable because it depends on the future realizations of $(x_{t+1}, z_{jt+1})$. In contrast, the other state variables $(s_{jt+1}, c_{jt+1}, k_{jt+1})$ are already determined by the firm's decisions at time $t$. The return $R(x_{t+1})$ is also a random variable, but its distribution is determined solely by $x_t$. Therefore, $\mathbf{Cov}_t$ and $\mathbf{Var}_t$ are computed as integrals over the conditional distribution $\mathcal{P}(x_{t+1}, z_{jt+1}|x_t, z_{jt})$. We compute these moments numerically by integrating over the transition matrices of $x$ and $z$, which are constructed using the Rouwenhorst (1995) method. We apply the same numerical approach to compute the model-based residual volatility of the financing deficit, $FDResiVol_{jt}$, as defined in Eq. (24).

### *A.4. Details of the counterfactual experiment*

The model used for the counterfactual experiment in Section 5 is identical to the full model, except for the restriction that the firm cannot invest in the risky bond, i.e., $s = s' = 0$. This constraint effectively reduces the state space to four variables – $x$, $z$, $c$, and $k$ – as the firm has access only to the safe financial asset. To solve this counterfactual model numerically, we set the upper bound for safe financial assets (scaled by total assets) to 2, equal to the sum of the upper bounds for risky (0.5) and safe (1.5) financial assets in the full model. The number of grid points is $N_x = 3$, $N_z = 5$, and $N_k = 499$, consistent with the full model, and $N_c = 49$, which approximately matches the combined number of grid points for risky (19) and safe (29) financial assets in the full model. We solve the counterfactual model using the estimated parameter values from Table 1 to generate the simulated samples used in the counterfactual experiment.

## Appendix B. Details of the data collection algorithm

To collect the fair value of risky financial assets from SEC 10-K filings, we first target all tables with a reporting structure similar to Table A.1. For a table to be considered a target, two basic conditions are necessary:

1. The table contains at least one dollar symbol ($). This symbol is used to distinguish table-content information (i.e., numerical data) from table-header information. All rows above the first appearance of a dollar symbol are classified as table headers.
2. The table header must include fair-value hierarchy information, which firms are required to disclose under SFAS No. 157. Specifically, assets must be classified into three categories: "Level 1" assets have quoted prices in active markets; "Level 2" assets do not have quoted prices in active markets but are valued using other observable inputs (e.g., quoted prices for similar securities); and "Level 3" assets are valued based on unobservable inputs.

Overall, this target table structure is used in approximately 80% of firm-year filings that disclose fair value information, conditional on the disclosure being presented in tabular format. Our algorithm excludes data reported in tables with formats that differ from the one described above, as well as data embedded within text narratives. Additionally, if a firm reports information for multiple years within the same table, the table is still classified as a target.

For all tables with the target structure, we scrape up to six long sentences – defined as those containing more than five words – immediately preceding the table. This text is used to help identify whether the target table contains information on financial asset holdings.[22] We then determine the year and unit of measurement (e.g., thousands, millions) associated with the target table using the following procedure:

1. We first search for this information within the target table itself.
2. If year or unit information is not found in the table, we perform a backward search over the scraped text until we identify the first instance of such information.
3. If it still cannot be identified, we scrape the full text of the filing and use the year or unit that appears most frequently.
4. Finally, for all target tables extracted from the same filing, we retain only those associated with the most recent year.

[22] If the target table is preceded by another table and there are fewer than six long sentences between them, we collect all sentences between the two tables.

**Table A.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** | $ | (3000) | 1000 | 1000 | 1000 |
| … | | (…) | … | … | … |
| (Total Synonyms) | | (…) | … | … | … |

**Table A.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 | | | |

**Table A.3**
Moment definitions. This table presents the definitions of moments from the model, and their empirical counterparts in the real data. The subscripts $j$ and $t$ denote the firm and year, respectively. In the data, $FV_{jt}$ represents the fair value of risky financial assets scraped from the corporate 10-K filings, distributions are defined as $E_{jt} = DVC_{jt} + DVP_{jt} + PRSTKC_{jt} - SSTK_{jt} + XINTD_{jt} + DLTR_{jt} - DLTIS_{jt}$, and all other abbreviations refer to the item names of the variables in Compustat.

| Model | Data |
|---|---|
| Autocorrelation of Profitability $\pi_{jt}/k_{jt}$ | Autocorrelation of $OIBDP_{jt}/PPEGT_{jt}$ |
| Autocorrelation of Investment $i_{jt+1}/k_{jt}$ | Autocorrelation of $CAPEX_{jt}/PPEGT_{jt-1}$ |
| Autocorrelation of Distributions $e_{jt}/k_{jt}$ | Autocorrelation of $E_{jt}/PPEGT_{jt-1}$ |
| Average Profitability $\pi_{jt}/k_{jt}$ | Mean of $OIBDP_{jt}/PPEGT_{jt}$ |
| Average Investment $i_{jt+1}/k_{jt}$ | Mean of $CAPEX_{jt}/PPEGT_{jt-1}$ |
| Median Distributions $e_{jt}/k_{jt}$ | Median of $E_{jt}/PPEGT_{jt-1}$ |
| Average Safe Financial Assets $\left((1+\bar{r}_f)c_{jt}\right) / \left(k_{jt} + (1+\bar{r}_f)(c_{jt}+s_{jt})\right)$ | Mean of $CH_{jt}/AT_{jt-1}$ |
| Average Risky Financial Assets $\left((\mu+\bar{r}_f)s_{jt} + (1-\mu)q_t^s s_{jt}\right) / \left(k_{jt} + (1+\bar{r}_f)(c_{jt}+s_{jt})\right)$ | Mean of $FV_{jt}/AT_{jt-1}$ |
| Average Tobin's Q $v_{jt}/\left(k_{jt} + (1+\bar{r}_f)(c_{jt}+s_{jt})\right)$ | Mean of $(AT_{jt} - CEQ_{jt} + CSHO_{jt} \times PRCC\_F_{jt})/AT_{jt}$ |
| Variance of Profitability $\pi_{jt}/\left(k_{jt} + (1+\bar{r}_f)(c_{jt}+s_{jt})\right)$ | Variance of $OIBDP_{jt}/AT_{jt}$ |
| Variance of Distributions $e_{jt}/\left(k_{jt} + (1+\bar{r}_f)(c_{jt}+s_{jt})\right)$ | Variance of $E_{jt}/AT_{jt-1}$ |

**Table A.4**
Variable definitions. This table presents the definitions of the variables used in the reduced-form analysis of the determinants of risky financial assets in the model (Section 3.3) and in the data (Sections 4 and 5). In the data, $FV$ is the fair value of risky financial assets scraped from the corporate 10-K filings. All other variables are from Compustat, and the table reports their item names.

| Variables | Model | Data |
|---|---|---|
| Risky | $\left((\mu+\bar{r}_f)s_{jt} + (1-\mu)q_t^s s_{jt}\right) / \left(k_{jt} + (1+\bar{r}_f)(c_{jt}+s_{jt})\right)$ | $FV_{jt}/AT_{jt-1}$ |
| Safe | $\left((1+\bar{r}_f)c_{jt}\right) / \left(k_{jt} + (1+\bar{r}_f)(c_{jt}+s_{jt})\right)$ | $CH_{jt}/AT_{jt-1}$ |
| FinComp | $\dfrac{(\mu+\bar{r}_f)s_{jt} + (1-\mu)q_t^s s_{jt}}{(1+\bar{r}_f)c_{jt} + (\mu+\bar{r}_f)s_{jt} + (1-\mu)q_t^s s_{jt}}$, 0 if $s_{jt} = c_{jt} = 0$ | $FV_{jt}/(FV_{jt} + CH_{jt})$ |
| LQ | $\left(v_{jt-1} - (1+\bar{r}_f)c_{jt-1} - (\mu+\bar{r}_f)s_{jt-1} - (1-\mu)q_t^s s_{jt-1}\right)/k_{jt-1}$ | $(AT_{jt-1} - CEQ_{jt-1} + CSHO_{jt-1} \times PRCC\_F_{jt-1})/AT_{jt-1}$ |
| LProf | $\pi_{jt-1}/k_{jt-1}$ | $OIBDP_{jt-1}/AT_{jt-1}$ |
| LSize | $\log\left(k_{jt-1} + (1+\bar{r}_f)(c_{jt-1}+s_{jt-1})\right)$ | $\log(AT_{jt-1})$ |
| FD | $\left(i_{jt+1} + \psi_i/2(i_{jt+1}/k_{jt})^2 k_{jt} - (1-\tau)\pi_{jt}\right)/k_{jt}$ | $\left((CAPEX_{jt} + XRD_{jt} - SPPE_{jt}) - (OIBDP_{jt} - OtherCF_{jt-1})\right)/PPEGT_{jt-1}$ |
| OtherCF | | $TXT_{jt} + CDVC_{jt} + PDVC_{jt} + XINT_{jt} - \Delta DLTTQ_{jt} - \Delta DLCQ_{jt}$ |
| InvTot | | $(CAPEX_{jt} + XRD_{jt} - SPPE_{jt})/PPEGT_{jt-1}$ |
| ExtFin | | $\max\{0,\ (SSTK_{jt} + DLTIS_{jt} - OtherFinAct_{jt})/AT_{jt-1}\}$ |
| OtherFinAct | | $CDVC_{jt} + PDVC_{jt} + PRSTKC_{jt} + XINTD_{jt} + DLTR_{jt}$ |

The target table may be used not only to disclose the fair value of corporate financial assets but also for other purposes, such as reporting the value of pension plan assets, intangible assets (e.g., goodwill), assets held for compensation, and various liabilities. To identify tables that contain relevant information on financial assets, we randomly select 1500 10-K filings to form a training sample for a machine learning algorithm. Within this sample, we identify 527 target tables, of which 333 report fair value information on corporate financial assets. We manually label these tables by reading the six sentences preceding each table, along with the table header. We then use a simple $n$-gram method and an L1-regularized logistic regression model to classify all tables. The regularization parameter is tuned to 0.6 based on performance in the training sample.

Even if a target table is classified as containing relevant information, it may also include additional content that we aim to exclude. Therefore, for all tables classified as reporting corporate financial assets, we drop securities related to restricted cash, pension plan assets, liabilities, assets held for compensation, and hedging activities. This filtering is based on the presence of the subheading "Additional Information" (as shown in Table A.1) and on the security name. We then classify a security as risky if it is not one of the following: cash, bank receivables, bank drafts, bank acceptances, deposits, checks, letters of credit, money orders, commercial paper, treasuries, money market funds, or cash equivalents. Next, we sum the fair value of all risky securities to construct firm-year observations of risky financial asset holdings. Finally, we set the value of risky financial asset holdings to zero in years with missing information for all firms with at least one firm-year observation of the fair value of risky financial assets found between 2009 and 2018, and to Compustat item $IVST$ for remaining missing values.

To evaluate the accuracy of the algorithm, we perform an out-of-sample test using a random sample of 500 10-K filings, which contain 112 target tables. Table A.2 reports an overall accuracy rate of 83.93% in the testing sample. The algorithm correctly scrapes 94 firm-year observations, while it makes 10 errors in identifying whether a table contains relevant information, 6 errors in determining whether a specific security is risky, and 2 errors due to unforeseen table structures.

## Appendix C. Moment and variable definitions

This section provides definitions for the moments used in the structural estimation and the variables used in the empirical analysis. Table A.3 describes the moments matched in the SMM procedure (see Section 3). Table A.4 lists the firm-level variables used in the regression analysis and robustness tests in Section 4.

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