Aggregate Implications of Corporate Bond Holdings by Nonfinancial Firms

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Abstract

This paper explores the impact of risky asset holdings by U.S. nonfinancial firms. From the early 1990s to 2017, the share of risky securities surged from 28% to over 40% of firms' financial assets. Using a business-cycle heterogeneous firms model, I show that declining real interest rates since the 1980s increased the risk premium, driving the increase in risky asset holdings. The model predicts that firms with higher exposure to risky assets experience an investment decline up to 50% more pronounced during large shocks, empirically validated by analyzing the Great Financial Crisis.

Keywords: Risky assets; corporate bonds; firm heterogeneity; firm dynamics; business-cycle
JEL Codes: E22; E44; G11

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1 Introduction

Financial asset holdings by nonfinancial firms almost doubled over the past forty years. In addition to cash, these firms hold a large pool of financial assets, such as corporate and government bonds, equity and asset and mortgage-backed securities, among others. The case of Apple is one of the most striking ones. For example, a recent article published in the *Wall Street Journal* on August 23, 2018, entitled “Apple is a Hedge Fund That Makes Phones" states the following:

> When you buy a share of Apple stock, you do not simply buy into a $1 trillion technology company. You also buy a share of one of the world’s largest investment companies: Braeburn Capital, a wholly owned subsidiary of Apple. Braeburn manages a $244 billion financial portfolio—70% of Apple’s total book assets. Apple acts like a hedge fund by supporting this portfolio with $115 billion of debt.

Out of this $244 billion portfolio of financial assets, $153 billion was invested in corporate bonds making Apple a net lender. Data from the U.S. flow of funds for nonfinancial corporate businesses shows that Apple is not a unique case. Total financial assets held by these corporations by the end of 2017 amounted to more than $21 trillion. Of these financial assets, more than 40% were risky assets.[1] Figure 1 presents the evolution of the share of risky financial asset holdings by U.S. nonfinancial corporate businesses between 1980 and 2017. Beginning in 1990, risky securities grew from representing 28% of financial assets to more than 40% at the end of 2017. Corporate bonds, in particular, represented more than 60% of total risky asset holdings by U.S. publicly listed firms by the end of 2017.

Having documented the large pool of financial assets held by firms, the goal of the paper is to understand whether, and how, the inclusion of diverse savings instruments with different levels of risk affects firms’ investment decisions and

[1] I follow the Federal Reserve’s classification of securities as money-like and nonmoney-like. Securities deemed money-like by the Federal reserve are seen as a store of value, and so I classify them as safe assets. These securities include cash, cash equivalents, deposits, money-market funds, commercial paper, and US treasuries. I consider the nonmoney-like as risky assets, including government bonds excluding treasuries, corporate bonds, equity, mortgage-backed securities, and investment fund shares.

Figure 1: US nonfinancial corporate business risky assets holdings as a percentage of total financial assets. From the end of the 1980s to 2017, the share of risky assets increased from 26% to more than 40%. Source: Flow of Funds, Board of Governors of the Federal Reserve System.

their response to aggregate shocks. More concretely, I assess two different questions: (1) What explains the observed increase in the share of risky asset holdings by nonfinancial firms? (2) How does the savings portfolio affect the propagation of aggregate shocks, more particularly productivity and financial shocks?

To answer these questions, I outline a business-cycle model in which heterogeneous firms can invest in productive capital, issue debt, and save in a risk-free asset and/or in corporate bonds, which are risky and have an unknown return.

First, I argue that the observed decrease in the real interest rate since the 1980s can fully account for the increase in the share of risky asset holdings by nonfinancial corporate businesses. An exogenous decrease in the real interest rate shifts the firm distribution to the right, implying larger firms and a lower percentage of defaulted debt. This generates an endogenous increase in the excess return on corporate bonds in the model, consistent with that observed in the data.[2] In turn, the increase in risky asset's excess return causes firms to alter the composition of their savings portfolio towards accumulating more risky

[2]Excess return is defined as the difference between the realized return on corporate bonds and the risk-free rate.

assets.

Second, I show that the riskiness of nonfinancial firms' savings portfolio, measured as the share of risky assets to total savings, can explain heterogeneous cross-sectional firms' investment responses to aggregate shocks, with important implications for aggregate dynamics. In response to an aggregate shock that generates an investment decrease of the same order of magnitude as in the Great Financial Crisis, the savings portfolio can amplify the investment decrease by up to 50% when compared with a canonical heterogeneous firms model, with only cash savings. Firms holding corporate bonds create financial linkages between them, which causes the shocks to propagate from defaulting borrowers to lenders. Some of the lenders end up postponing investment decisions, downsizing, or even defaulting, which explains the larger decrease in investment.[3] For small shocks, which do not trigger a sharp increase in default rates, the return on risky assets is still above the risk-free rate. In this situation, the higher return on the riskier portfolio of savings allows firms to better absorb the shock, and aggregate investment to decrease by less in comparison to a scenario where firms only hold risk-free assets.

I conclude the paper by presenting empirical evidence in support of the model's main mechanism. Using a combination of Compustat and web-scrapped data, I show that firms with a riskier financial portfolio dropped investment significantly more during the Great Financial Crisis.

Related Literature: This paper contributes to several branches of the literature. First, it relates to the literature that builds upon Hopenhayn (1992) to develop theories of the business-cycle and firm dynamics. Papers such as Khan & Thomas (2008), Jermann & Quadrini (2012), Khan & Thomas (2013), Clementi & Palazzo (2016), and Carvalho & Grassi (2019) look into how firm-level dynamics propagate through the aggregate economy. My paper proposes an additional channel, via the propagation from borrowers to nonfinancial lending firms, that helps explain how firm dynamics amplify aggregate shocks.

[3] I abstract from potential propagation from lenders to borrowers, which could happen in the form of demand shortfalls in stress periods, leading to decreases in prices and increases in the cost of debt.

This paper also fits the growing literature exploring how firms' balance sheets affect their decisions and help propagate shocks. On the liabilities side, papers such as Crouzet (2017), Buera & Karmakar (2022) and Begenau & Salomao (2018) illustrate how firms' debt composition (in terms of bonds, loans, equity or debt maturity) may change and be a key determinant of firms' behavior during crises and an important factor in the propagation of shocks. Melcangi (2018) and Ottonello & Winberry (2020) also explore the importance of firms' financial position in determining the elasticity to aggregate shocks. On the asset side, the importance of used capital, liquidity of the firm's balance sheet, and borrowing-to-save mechanism have been shown to be important mechanisms in the propagation of shocks (for more details, see Lanteri (2018), Jeenas (2018), and Xiao (2018)). This paper builds on this literature and explores the implications of the riskiness of the firms' savings portfolio for the macroeconomy.

Lastly, my paper relates to a vast literature on corporate finance focused on exploring the firms' asset-portfolio composition and its evolution through time. A large focus has been on the key determinants of corporate cash holdings and its increase over time. Papers such as Almeida et al. (2004), Bates et al. (2009), Riddick & Whited (2009), Nikolov & Whited (2014), Bigio (2015), Lyandres & Palazzo (2016), Cunha & Pollet (2020), and Gao et al. (2021) argue some of the main determinants of corporate cash holdings are (1) precautionary motives, (2) intertemporal trade-off between taxation on interest on cash holdings and future external financing costs, (3) financial constraints, (4) innovation and market competition, (5) investment opportunities. Other factors contribute to explaining the rapid increase in corporate cash holdings: firm selection, with more R&D-intensive firms with lower initial profits requiring higher cash ratios when entering the market; and the overall increase in profits accompanied by the decline in the labor share while dividends are constant (see Begenau & Palazzo (2021) and Chen et al. (2017) for more details).

Other papers, such as Duchin et al. (2017), Cardella et al. (2015) or Darmouni & Mota (2022), highlight the fact that not all corporate financial asset holdings are in the form of cash or near-cash securities. Studies point to low uncertainty about future liquidity needs, a firm being financially unconstrained, tax incentives, or reaching for yield as some of the major determinants for firms to go from cash to more risky securities with a higher yield. In an environment where firms endogenously choose their savings portfolio, I contribute to this literature by exploring both idiosyncratic and aggregate determinants of the composition of firms' savings across the firm distribution.

The remainder of the paper is organized as follows: In section 2, I describe the model. section 3 presents the calibration strategy and the algorithm to solve the model. In section 4, I inspect the mechanisms and discuss the main results. section 5 presents empirical validation of the model's mechanisms, and section 6 concludes.

2 Model

In this section, I embed the savings portfolio decision into a business-cycle heterogeneous firms model. The key agents in the economy are firms facing time-varying idiosyncratic and aggregate productivity shocks, convex capital adjustment costs, and distortions in the credit market, which will generate riskiness for lenders. Firms can decide between investing in productive capital and saving in a risk-free and/or risky asset (bonds issued by other firms)[4]. The distortions in the credit market will cause the returns on loans to depend on the distribution of firms — more specifically, on the defaulted debt — driven by aggregate productivity shocks.

I then use this model to: (1) explore the mechanisms that generate the empirically observed distribution of portfolio composition across firms and its impact on investment decisions, (2) explain the determinants of the aggregate increases in risky asset holdings since the beginning of the 1990s, and (3) explain the aggregate consequences of nonfinancial firms saving in risky assets.

Timing Following evidence by Xiao (2018) that firms adjust the asset side of the balance sheet more often than the liabilities side, I adopt Xiao's assumption that

[4]Is the risky asset class most held by nonfinancial firms. In 2017 accounted for more than 60% of total risky assets held by these firms.

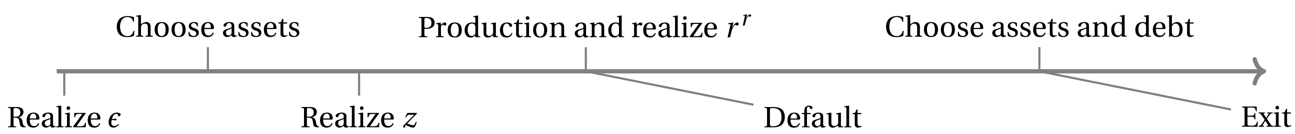

Figure 2: Firms timing in the model

firms can adjust their portfolio of assets both midway through and at the end of the period, whereas they can only adjust debt at the end of the period.[5]

Figure 2 summarizes the timing of the model within a period. At the beginning of each period, firms' idiosyncratic productivity ϵ is realized. Following this realization, but before observing the aggregate productivity z and return on risky savings r^r, firms can reoptimize the asset side: capital ($\hat{k}$), risk-free assets ($\hat{a}_f^{rf}$), and risky assets in the form of loans to other companies ($\hat{a}_f^r$).[6] Firms reoptimize the asset side to maximize the expected discounted value given the amount of debt (b) in place and the just observed idiosyncratic productivity. If firms choose to re-optimize capital, they are subject to convex adjustment costs.

Following this intra-period adjustment, firms observe aggregate productivity z and decide to produce using the reoptimized amount of capital $\hat{k}$ or default, which occurs if the net worth of the firms is below 0, in other words, if firms do not have liquidity to pay back debt and/or the fixed cost of production default happens. The return on the risk asset (r^r) and firms' default are determined at the same time because r^r is a function of the defaulted debt and the firms' default decision is a function of its cash flow and consequently of the realized return on its savings.

After default takes place, exogenous exit occurs.[7] With probability η, a firm will leave the market and all its remaining assets will be distributed to households as dividends. This assumption guarantees not all firms will outgrow financial constraints in the model, and thus results in a firm distribution more in line with

[5]This assumption is motivated by the fact that the variation (measured as the standard deviation divided by the mean) in cash holdings is consistently larger than the variation in leverage ratios. For more details, see Xiao (2018).

[6]All the variables with a hat are intra-period decisions, whereas the non-hat variables are inter-period decisions.

[7]This common assumption in the literature guarantees a firm distribution in line with the data. See, for example, Khan & Thomas (2013).

the data.[8]

Upon surviving the exogenous shock, firms enter the inter-period optimization stage and choose capital k, risk-free assets a_f^{rf}, corporate bond holdings a_f^r, and debt b. The idiosyncratic state of the firm is then characterized as $s = [\epsilon, k, x]$, where x is the cash-on-hand. I define the aggregate state as $S = [z, \mu]$, where μ is the distribution of firms across the idiosyncratic states and z is the aggregate productivity.

Production Firms produce output (y) using capital and subject to the idiosyncratic (ϵ) and aggregate (z) productivity shocks, according to the following production function:

$$y = \epsilon z k^{\alpha}, \tag{1}$$

where I assume the idiosyncratic shock ϵ follows a Markov chains, $\epsilon \in \mathrm{E} \equiv \left(\epsilon_1, ..., \epsilon_{N_\epsilon}\right)$, where $Pr(\epsilon' = \epsilon_i | \epsilon = \epsilon_j) \equiv \pi_{ij}^{\epsilon} \geq 0$ and $\sum_{j=1}^{N_\epsilon} \pi_{ij}^{\epsilon} = 1$, and aggregate productivity z also follows a Markov chain , $z \in \mathrm{Z} \equiv \left(z, ..., z_{N_z}\right)$, where $Pr(z' = z_i | z = z_j) \equiv \pi_{ij}^{z} \geq 0$ and $\sum_{j=1}^{N_z} \pi_{ij}^{z} = 1$. α is the share of capital and lower that 1.

Capital Accumulation I assume firms are subject to convex adjustment costs, which generate slower convergence to the optimal amount of capital and growth rates more in line with the data. The adjustment costs take on the following form:

$$g(k', \hat{k}) = \frac{F_{k_1,t}}{2} \left(\frac{k' - (1-\delta)\hat{k}}{\hat{k}} \right)^2 \hat{k}, \tag{2}$$

with

$$F_{k_1,t} \equiv p_k^+ \times \mathbb{1}_{[(k'-(1-\delta)\hat{k})>0]} + p_k^- \times \left(1 - \mathbb{1}_{[(k'-(1-\delta)\hat{k})>0]}\right), \tag{3}$$

where k' is the capital for next period, $\hat{k}$ is the intra-period amount of capital chosen by the firm, δ is the depreciation rate, and $\mathbb{1}_{[(k'-(1-\delta)\hat{k})>0]}$ is an indicator

[8] Note exogenous exit does not affect the return on the risky assets, because the firms that exogenously leave the market already paid their debt.

variable equal to 1 if the firm increases capital. Additionally, similar to other papers in the literature (see, e.g. Abel & Eberly (1996) , Begenau & Salomao (2018)), I assume $0 \leq p_k^- < p_k^+$, which captures the costly reversibility of investment. This assumption amplifies the riskiness of capital as a firm cannot invest today without considering the cost of downsizing if a negative shock happens, generating inaction regions.

The firm faces the same type of inter-period adjustment costs, given by

$$g(\hat{k}, k) = \frac{F_{k_1,t}}{2}\left(\frac{\hat{k}-k}{k}\right)^2 k, \tag{4}$$

with

$$F_{k_1,t} \equiv p_k^+ \times \mathbb{1}_{[(\hat{k}-k)>0]} + p_k^- \times \left(1 - \mathbb{1}_{[(\hat{k}-k)>0]}\right). \tag{5}$$

Optimization At the end of the period, if the firm survives the exit shock, it will choose the amount of capital to take to the next period, risk-free and risky savings, and bond issuance. The firm will choose these variables in order to maximize its present discounted expected value. The firm state can be summarized by its level of capital, its idiosyncratic productivity, and cash on hand, defined as

$$\hat{x} = y - C_f - b + (1 + r^{rf})\hat{a}_f^{rf} + (1 + r^r)\hat{a}_f^r, \tag{6}$$

where C_f is the fixed cost of operation. I assume a net-worth default rule — if the liquidation value of the firm's capital plus its cash on hand is smaller than $(1 + r^b)b + C_f$, default occurs. This default rule is similar to Gilchrist et al. (2014) or Xiao (2018).[9]

With this default rule, the default thresholds for aggregate productivity and return on risky savings are easily found. The z lower bound, which guarantees the firm stays in the market, given r^r, and the r^r lower bound, which guarantees

[9] Other type of default rule would be equity based — when the value of equity falls below a given threshold, default occurs (see, e.g., Cooley & Quadrini (2001), Hennessy & Whited (2007)). The reason I adopted the net-worth default rule is computational feasibility, because in this case, I do not need to invert the firm's value function to find the default threshold. Moreover, as Gilchrist et al. (2014) mention, empirically, which default rule is more plausible is unclear.

the firm stays in the market given z, are defined by

$$\underset{\sim}{z} = \frac{C_f + b - (1+r^{rf})\hat{a}_f^{rf} - (1+r^r)\hat{a}_f^r - p_k^-(1-\delta)\hat{k}}{\epsilon \hat{k}^\alpha}, \tag{7}$$

$$\underset{\sim}{r}^r = \frac{C_f + b - (1+r^{rf})\hat{a}_f^{rf} - p_k^-(1-\delta)\hat{k} - y(z)}{\hat{a}_f^r} - 1. \tag{8}$$

Conditional on surviving the default and exogenous exit stages, firms continue to the next period. Formally, the firm's problem at the end of the period, after the exit shock, consists of the choice of capital, risk-free and risky asset holdings, and debt. The firm chooses in order to maximize its present discounted value $V^1(\epsilon, \hat{k}, \hat{x}, S)$. At this stage, the idiosyncratic state of the firm is characterized by its productivity ϵ, the capital from the intra-period optimization stage $\hat{k}$, and its cash on hand $\hat{x}$. The aggregate state is summarized by S, which includes aggregate productivity z and the distribution of firms μ. $\hat{V}^0(\epsilon', k', x', S')$ is the firm's value in the intra-period optimization stage. Thus, the end of period firms problem takes the following form

$$\begin{aligned} V^1(\epsilon, \hat{k}, \hat{x}, S) = \max_{k', b', a_f^{rf'}, a_f^{r'}} \quad & \beta E[\hat{V}^0(\epsilon', k', x', b', S)] \\ s.t: \quad x' \equiv a_f^{rf'} + a_f^{r'} &= \hat{x} - g(k', \hat{k}) + q^r b' \\ g(k', \hat{k}) &= \frac{F_{k_1,t}}{2}\left(\frac{k' - (1-\delta)\hat{k}}{\hat{k}}\right)^2 \hat{k}. \end{aligned} \tag{9}$$

In the next period, after observing the idiosyncratic productivity, the firm enters the intra-period adjustment stage. In this stage, the firm can reoptimize its assets by choosing capital $\hat{k}'$, risk-free $\hat{a}_f^{rf'}$, and risky $\hat{a}_f^{r'}$ savings. The intra-period problem is formally given by

$$\hat{V}^0(\epsilon', k', x', b', S) = \max_{\hat{k}', \hat{a}_f^{rf'}, \hat{a}_f^{r'}} \int_{\underline{r}^{r'}} \int_{\underline{z}'} V^0(\epsilon', \hat{k}', \hat{x}', S') dF(z) dF(\mu) \tag{10}$$

$$\begin{aligned} s.t: \quad & \hat{a}_f^{r'} + \hat{a}_f^{rf'} + g(\hat{k}', k') \leq a_f^{r'} + a_f^{rf'} \\ & \hat{x}' = y' - C_f - b' + (1 + r^{rf'})\hat{a}_f^{rf'} + (1 + E(r^{r'}))\hat{a}_f^{r'} \\ & g(\hat{k}', k') = \frac{F_{k_1,t}}{2} \left(\frac{\hat{k}' - k}{k'} \right)^2 k' \\ & S' = \Gamma^{S'}(S) \\ & E(r^{r'}) = \Gamma^{r^r}(S'). \end{aligned}$$

where $S' = \Gamma^{S'}(S)$ is the aggregate law of motion, which the firms then use to form expectations for the return on risky assets tomorrow, according to $E(r^{r'}) = \Gamma^{r^r}(S')$. V^0 is the value of the firm after the debt settlement and production stage but before the exit shock, defined as

$$V^0(\epsilon', \hat{k}', \hat{x}', S') = (1 - \eta) V^1(\epsilon', \hat{k}', \hat{x}', S') + \eta(\hat{x}' + p_k^-(1 - \delta)\hat{k}'), \tag{11}$$

where η is the probability of exit and $(\hat{x}' + p_k^-(1 - \delta)\hat{k}')$ is the liquidation value of the firm.

Entrants Entry in this model is exogenous. I follow Arellano et al. (2019) and assume there is a fixed measure, μ_e , of entrants equal to the mass of firms exiting. Entrants are endowed with an initial amount of capital k_0, which is targeted to be a given percentage of incumbents' average capital, and 0 cash on hand. Entrants draw a signal for their productivity tomorrow ϵ_0, which will follow the same Markov chain as incumbents' productivity. Firm entry takes place at the end of the period, and entrants start operating the following period, with their initial state being $(\epsilon_0, k_0, 0)$.

Financial Intermediary The financial intermediary collects the risky savings from firms a_f^r and uses these savings to finance firms' debt. Next period, the intermediary receives back the bond payments and distributes the proceedings among firms that had risky savings.

Three key assumptions generate the risk associated with firms' bonds. First, because I am modeling the bonds market and not bank loans, I assume firms do not need to provide capital as collateral to issue a bond. This assumption is backed by the empirical study by Rauh & Sufi (2010), who highlight that one of the main differences between bank loans and bonds is that the former is usually backed by collateral whereas the later is not. Second, similar to other papers in the literature (see, e.g., Khan & Thomas (2013), Khan et al. (2017), Ottonello & Winberry (2020)), I assume a deadweight loss in the default process, which means the lender can only recover a share χ of the firm's remaining resources. Third, the financial intermediary does not observe the idiosyncratic state of the borrower, only the aggregate state of the economy – this assumption is consistent with the literature on theories of financial intermediation, which have proven financial markets are less efficient than banks in screening and monitoring borrowers. Some reasons are provided in the literature: banks have access to inside information, whereas markets only have access to publicly available information; banks have economies of scale in the screening and monitoring process; and banks have better incentives to invest in screening and monitoring technology. For more details see, for example, Diamond (1984), Fama (1985), Boot et al. (2010), De Fiore & Uhlig (2011) and Gande & Saunders (2012).

Whereas the last assumption generates the risk because the intermediary cannot design firm-specific contracts that eliminate the risk and, on expectations, guarantee a return equal to the risk-free return rate, the first two assumptions drive up the riskiness of the bond because, in case of default, the return is lower than under a collateral constraint or no-default loss scenario.

Therefore, the firms' bond price is equal to the risk-free bond price minus an exogenous risk premium ω:

$$q^r = q^{rf} - \omega. \tag{12}$$

The actual return on the bonds is going to depend on the fraction of defaulted debt and on the recovery rate on the defaulted debt χ. If no default happens, the actual return on bonds is just $\frac{1}{q^r}$. With default, the return will be increasing in the recovery rate and diminishing in the default rate. The return is given by

$$1 + r^r = \frac{\frac{1}{q^r}\int b d\mu_{ND} + \int \min(b, \chi((\hat{x} + p_k^- \hat{k}))) d\mu_D}{\int b d\mu}, \tag{13}$$

where μ_{ND} and μ_D are respectively the distributions of non-defaulting and defaulting firms. Because the return on firms' bonds is uncertain at the time agents make savings-portfolio decisions, agents form rational expectations about the return on this risky asset, which are fully characterized by the mapping $E(r^{r'}) = \Lambda(S')$.

Formally, given firms decision on risky savings, the financial-intermediary determines new bond holdings ϕ' to maximize the next-period payment to the agents with risky assets:

$$\begin{aligned} W^f(\phi, S) =& \max_{\phi'} D^f + \beta E[W^f(\phi', S')] \qquad (14) \\ s.t: \quad D^f =& \int (1 - \mathbb{1}_{[default]}(\epsilon, k, x, b, S))\phi d[\epsilon \times k \times x \times b] \\ &+ \int \mathbb{1}_{[default]}(\epsilon, k, x, b, S) \min(\chi(x' + p_k^- k), \phi) d[\epsilon \times k \times x \times b]. \end{aligned}$$

Let $\Phi(\phi, S)$ describe the decision rule for bonds. $\mathbb{1}_{[default]}(\epsilon, k, x, S)$ is an indicator function equal to 1 if firm in state (ϵ, k, x, S) defaulted on the bond, and $\min(\chi(x' + p_k^- k), \phi)$ is the amount the financier is able to recover in case of default, where χ is the recovery rate on the remaining value of the firm.

Recursive Competitive Equilibrium The recursive competitive equilibrium in this economy is defined by policy functions $K(\epsilon, \hat{k}, \hat{x}, S)$, $A_f^r(\epsilon, \hat{k}, \hat{x}, S)$, $A_f^{rf}(\epsilon, \hat{k}, \hat{x}, S)$, $B(\epsilon, \hat{k}, \hat{x}, S)$, $\hat{K}(\epsilon, k, x, S)$, $\hat{A}_f^r(\epsilon, k, x, S)$, $\hat{A}_f^{rf}(\epsilon, k, x, S)$, and $\Phi(\phi, S)$ and value functions $W^f(\phi, S)$, $\hat{V}^0(\epsilon', k', x', b', S')$, $V^0(\epsilon', k', x', b', S')$, $V^1(\epsilon, \hat{k}, \hat{x}, S)$, and $V_e(\epsilon_0, k_0, 0, S)$, prices q^r and r^r, such that:

i. Firm value and policy functions solve its optimization problem (9), (10), and (11).

ii. Financier value and policy functions solve the financier problem (14).

iii. Debt price satisfies equation (12) and return on debt satisfies equation (13).

iv. The measure of firms evolves according to

$$\mu' = \eta \int (1 - \mathbb{1}_{[default]}(\epsilon, k, x, b, S))\phi d[\epsilon \times k \times x \times b] + \mu_e. \tag{15}$$

3 Solving and calibrating the model

Algorithm The numerical algorithm I use employs the inner-and-outer loop proposed by Krusell & Smith (1998). I iterate between an inner loop that solves the firms' problem and an outer loop that simulates the economy and updates the forecast rules until convergence of the forecast rules. Here, I provide a brief overview of the algorithm. For more details, check Appendix C.

In the model, the distribution of firms spans over capital, cash on hand and idiosyncratic productivity. Because the distribution is a highly dimensional object, I follow Krusell & Smith (1998) and approximate it with the current levels of aggregate capital K, aggregate corporate debt B_f, and aggregate productivity z. More specifically, I assume agents perceive (K, B, z) as the aggregate state of the economy. Agents then use the log-linearized law of motion of the aggregate state to characterize the mappings for the expected return on the risky assets Γ^{r^r}:

$$\begin{bmatrix} \log B^{f'} \\ \log K' \\ r_r \end{bmatrix} = A + B \begin{bmatrix} \log B^f \\ \log K \end{bmatrix} + C \log(z). \tag{16}$$

I initiate the outer loop by guessing the coefficients A, B and C. I then proceed to the inner loop, where the firms' problem is solved through value-function iteration and policy functions are found. I then proceed to simulate the economy, based on the policy functions found, using Monte Carlo simulation. The equilibrium mappings are then updated using OLS regression on the simulated data. This procedure is repeated until convergence of the equilibrium mappings is achieved.

Calibration The length of each period is one year, in line with the data I use in section 5 to validate model mechanisms. In the calibration of most model parameters, I follow prior work and use common values in the literature. The remaining parameters are split into two groups: the ones that have a direct counterpart in the data and the internally calibrated ones used to match moments of the model's stochastic steady-state to time averages in the data. All the parameter values can be found in table 7 in Appendix A.

Parameters from the literature: Regarding the production side of the economy, I set the share of capital α to 0.66, which is commonly used in the literature when the production technology only employs capital. The price of capital p_k^+ is normalized to 1, whereas the price of sold capital p_k^- is set to 0.57, so it is consistent with the percentage of investment resale loss of 43% estimated by Bloom (2009). The annual depreciation rate δ is set to 6%, a common value for annual frequency in the literature.

For the recovery rate on defaulted debt, I follow Xiao (2018) and set χ to 0.64. The author calibrates this parameter internally to match the corporate-bonds spread in the data. The parameter governing the persistence of the idiosyncratic productivity process ρ_ϵ is taken from Khan & Thomas (2013) and set to 0.6. Lastly, the discount factor is set to 0.96.

Parameters with a direct data counterpart: I set the capital of potential entrants k_0 to be 17.1% of the average incumbents' capital. Given that I am interested in studying firms that issue bonds, the data parallel for entry in the model is the decision of a firm to go public. Therefore, to calibrate the initial capital of entrants, I use Compustat in the 2000-2017 period and compare the capital holding of firms in the first year after going public with the remaining firms in the dataset.

The exogenous probability of exit η is set to 0.065 to match the 6.5% default

Moment	Source	Data	Model
Exit rate all firms	LBD	0.0824	0.0819
Average share risky savings	Flow of Funds	0.2918	0.2925
Standard deviation share risky savings	Compustat	0.3504	0.4096
Mean share risky $k \geq Q3_k$/mean share risky $k \leq Q1_k$	Compustat	4.3758	4.7373
Share of debt in firms age=1	Compustat	0.1097	0.0682
Entrants average leverage	Compustat	0.2160	0.2207

Table 1: Calibration fit

rate of firms older than five years of age from the Longitudinal Business Database (LBD) from the U.S. Census Bureau for the 2003-2014 period.

As the model is solved in partial equilibrium, the interest rate in the benchmark calibration is set to 6.126%, which corresponds to the five-year moving average of the real interest rate, measured as the lending rate minus GDP deflator, in 1989, the year when the share of risky asset holdings reached the minimum value since the beginning of the 1980s. The real interest-rate series is taken from the World Bank database.

Internaly calibrated parameters: The remaining parameters $\{C_f, f_e, \sigma_\epsilon, \sigma_z, \rho_z, \omega\}$ are calibrated using the simulated method of moments (SMM). I use these six parameters to match six data moments, which can be divided into two different groups. The first group is composed of three moments targeted to discipline the distribution of risky asset holdings. For the first two moments, the standard deviation of the share of risky savings; and the ratio between the average share of risky savings for firms in the top versus bottom quartile of asset distribution, I use Compustat data from from 2001 to 2018. Following Duchin et al. (2017) I consider Compustat item "long-term investments" to be risky savings and the item "cash and cash equivalents" to be the risk free savings. The third moment, average share of risky savings, is calculated using data from the U.S. flow of funds.

The remaining three moments are chosen to discipline the return on risky savings. These moments are the exit rate for all firms, for which I use data from LBD; entrants' average leverage; and share of total debt in new entrants, which I calculate using Compustat data. The return on risky assets depends on the share of defaulted debt, making matching the default rate in the data important. Also, because small/young firms are the ones defaulting in the model, disciplining the size and leverage of these firms is important. In table 1, I present the model fit to the selected data moments,

4 Results

In this section, I describe the model results. I start by illustrating the determinants of the savings decision. I then proceed to study the causes of the share of risky assets increase. I conclude the section by analyzing how the firms' portfolio of savings affects aggregate responses to a productivity and financial shock.

4.1 Savings Distribution

Below I detail the two mechanisms which explain the firm's assets portfolio composition: an intra-temporal effect, in the form of portfolio diversification, and an inter-temporal effect, in the form of saving to finance future investment opportunities.

Intra-temporal effect: Portfolio diversification To illustrate the intra-temporal mechanism at play in explaining firms' savings portfolios, I shut down the real frictions in the model, the capital convex adjustment costs and irreversibility, and I assume the firm's problem to be static.

The model generates a strong correlation between the size of the firm and savings. Small firms hold a larger share of savings, composed mainly of risk-free savings, whereas, as firms grow, savings decrease and the portfolio composition tends more toward high-yield high-risk assets.

Figure 3 illustrates this relationship between the firm's size, savings, and portfolio composition. It demonstrates how risky savings increase with the initial size of the firm, while risk-free savings decrease. When firms are small, the probability of default is high, firms do precautionary savings in the risk-free security. As firms grow, the probability of default tends toward zero, so firms expose themselves more to high-risk high-return assets - capital and risky savings. Once the

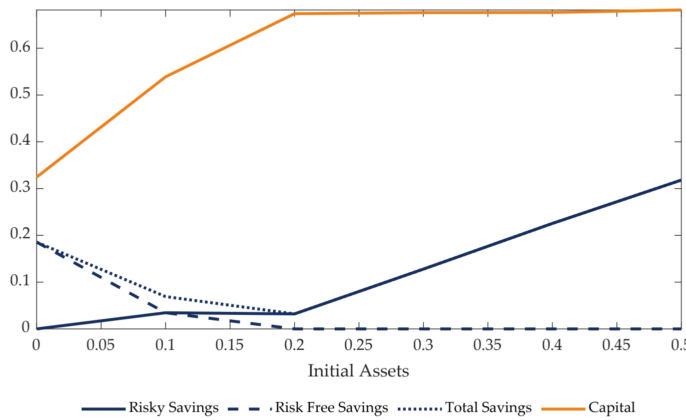

Figure 3: Capital (orange line), risky savings (blue solid line), risk-free savings (blue dashed line), and total savings (blue dotted line) for different initial endowments. As firms grow, they start savings less in risk-free assets and move into risky assets, while increasing capital.

optimal amount of capital is reached, the firm will focus on saving exclusively in the risky asset to maximize its savings' returns.

It's important to note that firms start investing in risky assets before attaining their optimal capital levels. This behavior results from a portfolio diversification effect that reduces the firms' default risk while maximizing their returns on savings. The two default threshold equations, (7) and (8), capture this effect: a firm more exposed to risky assets is able to absorb a negative productivity shock without defaulting. The same is true for firms more exposed to capital, which can sustain a negative shock to the return on risky assets without defaulting. This portfolio-diversification effect is why firms that have not yet reached their optimal amount of capital save in risky assets.

Inter-temporal effect: Saving to finance future investment In addition to the intra-temporal effect, the presence of partial irreversibility, will add an extra motive for firms to hold savings, by generating inaction regions. When a firm finds itself in one of these regions it will opt to save to finance future investments, with some firms saving in risky assets. In the stochastic steady state, more than 30% of the firms are inactive in any given period.

The left panel of figure 4 plots the distribution of savings by firms in the inac-

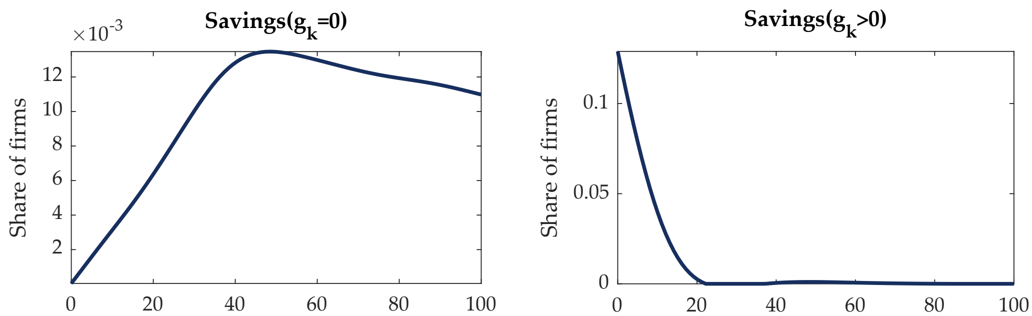

Figure 4: Savings distribution by firms in the inaction region in the left panel (growth rate of capital $g_k = 0$), and by growing firms in the right panel ($g_k > 0$). While the majority of growing firms have zero savings, firms in the inaction region accumulate savings to finance future investments.

tion region, whereas the right panel plots the savings distribution by firms with a growth rate of capital larger than zero. While a large fraction of growing firms have no savings, firms in inaction regions are accumulating savings to finance future investments.

A fraction of this savings will be allocated in risky assets. Table 2 reports the intensive margin, the average share of risky savings, and the extensive margin, % of firms with risky asset holdings, of the savings decisions by firms in inaction and growing regions. The differences are significant. Both intensive and extensive margin measures are almost twice as high for firms in the inaction region, with 47% of firms in the inaction region holding risky assets, and an average share of risky savings of 38%. These numbers are 24% and 16%, respectively, for growing firms.

Incorporating partial irreversibility of capital into the model is crucial for generating firms that have not yet reached their optimal capital levels but already

Moment	$g_k = 0$	$g_k > 0$
Average share risky savings	38.2%	16.3%
% firms with risky savings	47.3%	24.2%

Table 2: Average share of risky savings and fraction of firms with risky savings equal for firms in inaction regions ($g_k = 0$) and growing firms ($g_k > 0$).

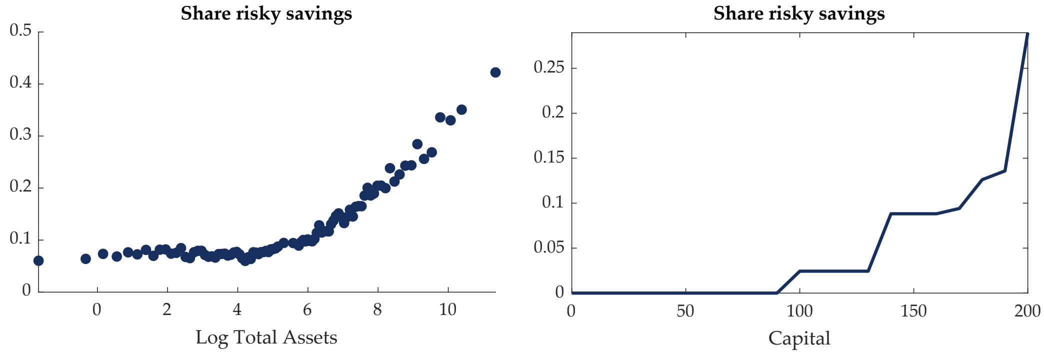

Figure 5: On the left panel, the empirical relation, from Compustat, between the share of risk-free savings — on the y-axis — and log(total assets) — on the x-axis. On the right panel, the same relation in the model, with the share of risk-free savings on the y-axis and capital on the x-axis. As firms grow in size, they increase their holding of risky assets both empirically and in the model.

hold significant portions of risky savings. Figure 5 compares the distribution of risky savings across different size groups in the Compustat data and in the model. The model presents a good fit with the empirical distribution: smaller firms holding mainly risk-free securities to minimize the probability of default; firms at the very top holding mainly risky securities; firms in the middle of the distribution saving to finance future investments, holding some fraction of risky assets. [10]

4.2 Aggregate Implications

I next use the model to answer two questions: (1) What explains the increase in risky asset holdings since the beginning of the 1990s? (2) What are the macroeconomic consequences of this increase?

Increase in risky asset holdings To explain the increase in risky asset holdings since the beginning of the 1990s, I input the observed real interest-rate path over the last three decades into the model. The benchmark calibration, discussed in

[10] Figure 8 in Appendix B shows the model does a good job in matching the standard deviations of risky savings across the size distribution as well. The dispersion at the bottom of the distribution is low because firms hold mainly precautionary savings, whereas at the top, volatility of both idiosyncratic and productivity shocks explain the higher standard deviation of risky savings.

Share risky savings	1989	2017	Variation
Data	29.18%	41.89%	12.71 p.p.
Model	29.25%	42.36%	13.11 p.p.

Table 3: Share of risky savings observed variation and implied variation by the model when changing the real interest rate.

section 3, targets the five year average of the share of risky savings at the end of 1989 and uses as input the same five year average of the real interest rate. In this section, I compare the benchmark calibration with a model using the five-year average of the real interest rate in 2017 and analyze how much of the observed increase in the share of risky asset holdings can be attributed to the change in the real interest rate.[11]

To do so, I feed into the model the 2017 real interest rate and recalibrate the fixed cost of production to keep the default rate unchanged. The default rate is the main driver of the risky asset excess return. With the decrease in the real interest rate, the costs of debt would drop and fewer firms would default. The sharp decrease in the default rate would overshoot the risky asset excess return when compared with its observed trend and over account for the increase in the share of risky asset holdings.

Results are presented in table 3. The observed variation in the data from 1989 to 2017 is a 12.71 percentage-point increase in the share of risky assets. The model, by changing the real interest rate while keeping the default rate constant, generates a similar increase of 13.11 percentage points. This finding suggests the decrease of the real interest rate alone fully accounts for the observed increase in risky asset holdings.

The mechanism has two different components. The first concerns the change in the distribution of firms. As the risk-free interest rate drops, debt becomes cheaper. As a consequence, firms will grow faster and accumulate more capital. This effect is depicted in figure 6, which plots the distributions of firms for both the 1989 and 2017 calibrations. The figure shows the increase in the share of

[11] I use five year averages to abstract from yearly changes and focus on the trend.

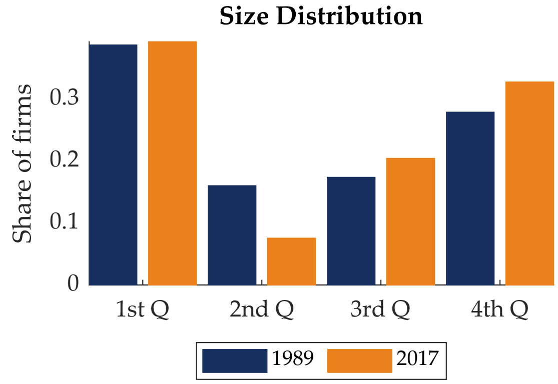

Figure 6: Firm size distribution for the 1989 calibration (blue bars) and 2017 calibration (orange bars). The figure plots the share of firms (y-axis) in each quartile of the distribution (x-axis). With the decrease in the interest rate there is a shift of the distribution to the right, with a larger fraction of firms at the top of the distribution.

firms at the top of the distribution. This movement in the distribution will have a direct impact on the share of risky savings, given that, as illustrated in figure 5, large firms have a riskier savings portfolio.

The second component is an indirect effect of the changes in the distribution of firms. As firms become larger, the share of defaulted debt goes down, which generates a 0.33 percentage point increase in the risky asset excess return in the model, which represents 75% of the observed increase between the 1989-2017 period.[12] Overall, the shift of the distribution to the right explains 13% of the increase in risky asset holdings, while the increase in the excess return explains the remaining 87%.

Aggregate outcomes Lastly, I assess the macroeconomic implications of firms' savings portfolio. I start by comparing the aggregate responses to unanticipated small and large negative productivity and financial shocks in a model with no risky assets and in the benchmark model. A small shock is characterized by a 1% drop in both aggregate productivity and the recovery rate, while a large shock represents a 10% decrease in aggregate productivity and a 33% drop in the re-

[12] The spread between Moody's Baa corporate bond yields and 10-year treasury from 1989 to 2017 increased 0.44 percentage points (from 2.141% to 2.581%).

Moment	Large negative		Small negative	
	Non-risky	Risky	Non-risky	Risky
Investment	-8.58%	-13.01%	-0.22%	-0.14%
Capital	-2.71%	-3.53%	-0.07%	-0.06%
Default rate	9.12%	10.19%	6.21%	6.21%
r^r-r^{rf}	-	-3.85p.p.	-	0.92p.p.

Table 4: Investment, capital, default rate, and excess return on risky assets' response to small and large negative productivity and financial shocks in a model with no risky assets and a model with only risky assets. Investment and capital are presented as percentage deviations from steady-state level, whereas the default rate and the difference between r^r and r^{rf} are in absolute values. A small shock is a 1% drop in TFP and in the recovery-rate parameter, whereas a large shock is a 10% TFP drop and a 33% decrease in the recovery rate.

covery rate.[13] In table 4, I present the investment and capital percentage change from the steady-state value in response to the two shocks across both models, whereas I present default rate and $r^r - r^{rf}$ in absolute values. The table shows that for relatively small shocks, the differences across the two models are minor. In fact, the model that accounts for risky savings even presents a smaller investment drop and consequently capital decreases by less. This finding is explained by the fact that, given the small shock, the default rate is not largely affected, which does not lead to a decrease in r^r. Given that in the risky asset model, firms are still making a larger return on their savings, they can better absorb the shocks, which causes investment to fall by less.

For a large shock, the opposite situation occurs, with a larger drop in investment and capital in the risky asset model. This result is explained by r^r falling below the risk-free return, which causes firms to lose part of their savings, inducing higher default rates and a larger drop in investment. Overall, the investment drop ends up being 50% larger in the risky asset model, which causes capital to decrease 30% more.

The identified mechanism is only triggered in relatively large recessions when the return on risky assets falls below the risk-free rate. In that scenario, firms lose

[13] I calibrate the shock so that it yields an investment drop of 13%, similar to the decrease of gross fixed capital formation in the U.S. during the Great Recession.

part of their savings, which leads to larger drops in investment and increases in the default rate. If the shock is small and the return on risky assets is still above the risk-free rate, the portfolio of savings allows firms to better absorb shocks without causing investment to drop or more firms to default. Figure 9 in Appendix B presents the impulse response functions to both shocks in the two models.

5 Mechanism validation

Nonfinancial firms holding risky financial assets (or corporate bonds) does not necessarily warrant a reassessment of the cyclical properties of firm dynamics model. At the core of the mechanism highlighted in the previous section is the fact that firms which hold these financial assets present higher investment elasticity to large shocks. This section aims to validate this mechanism with Compustat and webscrapped data. In particular, I show that firms that held a higher share of risky financial assets, or more specifically corporate bonds, just before the Great Financial Crisis drop their investment by significantly more during the Crisis.

Compustat Data I use Compustat data from 2001 to 2018. Following Duchin et al. (2017), I consider as a proxy for risky assets the Compustat item "long-term investments" — assets firms intend to hold for more than one year — and for risk-free assets, the item "cash and cash equivalents" — cash plus assets firms intend to sell within a year.[14] To illustrate the riskiness of the savings portfolio, I compute the share of risk-free savings, measured as "cash and cash equivalents" divided by total savings.

To validate the model mechanism that firms' financial portfolio composition affects their response to shocks, I estimate the following difference-in-differences specification:

[14] Although these two items are more closely related to the liquidity of the assets, Duchin et al. (2017) establish that the vast majority of risky assets are equally illiquid.

$$ln(Inv)_{ijt} = \gamma crisis_t + \alpha risky_{ij08Q2} + \beta crisis_t * risky_{ij08Q2} + \lambda_i + \theta_{jt} + \epsilon_{ijt}, \quad (17)$$

where crisis is a dummy variable equal to 1 between 2008 and 2010, $risky_{ij08Q2}$ is a dummy variable equal to 1 if the share of risky assets for firm i in sector j at the end of 2008 Q2, the quarter before the stock market crash, is higher than a given threshold, and 0 otherwise, and λ_i and θ_{jt} are firm and sector-quarter fixed effects. Note the coefficient of interest here is β, which captures the different response of investment during the Great Recession across the two groups.

The β coefficient for specification (17) is presented in column (1) of table 5. Here, I consider the dummy $risky_{ij08Q2}$ equal to 1 if a firm holds more than 70% of risky financial securities. As suggested by the model mechanism, β is negative. Firms with a high share of risky assets lowered investment by more 7.1 percentage points during the Great Recession. This result is robust to the inclusion of both sector-crisis dummy fixed effects or the inclusion of firm control variables, such as log of total assets, log of revenues, log of cash and cash equivalents and leverage. Both results are presented in columns (2) and (3) in table 5 together with the coefficient's sign of each covariate. Larger firms, with more cash and revenues experience a smaller decrease in investment during the great recession, while more leverage firms experienced a larger decrease.

Figures 10 to 12 in Appendix B present some robustness tests for the threshold values to split among the two groups of firms. Figure 10 presents the specification (17) β coefficient for threshold value spanning from 0 to 0.7. Figures 11 and 12 present the β coefficients for threshold values spanning from 0 to 0.7 for the specification in columns (2) and (3), respectively. Results are robust across all specifications and threshold values, with firms with a higher share of risky assets sustaining larger investment drops during the Great Recession. Lastly, I do a placebo test, in which I consider the dummy variable $risky_{ijt}$ to be equal to 1 if firm i in period t has a share of risky assets to total financial assets above 70%. In table 8 results for t spanning from 2005 to 2014 are presented. Results are only significant when considering t to be equal to 2008 or 2009, the years of the Great

	(1)	(2)	(3)
β	-0.071	-0.055	-0.089
	(0.023)	(0.023)	(0.027)
Firm FE	Yes	Yes	Yes
Sector-Time FE	Yes	No	Yes
Sector-Crisis dummy	No	Yes	No
Time FE	No	Yes	No
$ln(asset)_{ijt-1}$	-	-	(+)
$ln(revenues)_{ijt-1}$	-	-	(+)
$ln(cash)_{ijt-1}$	-	-	(+)
$leverage_{ijt-1}$	-	-	(-)

Robust standard errors in parentheses

Table 5: β coefficient from specification (17) in the first column. In the second column, I add sector-crisis dummy fixed effects, and in column (3) I include firm controls as well. Results across all specifications indicate firms with a higher share of risky asset holdings lowered investment more severely.

Financial Crisis, providing support to the main results.

Web-scraping data Having demonstrated the impact of risky financial asset holdings using the Compustat data, I now turn to one specific asset class. The model focus particularly on corporate bonds, which by the end of 2017 represented more than 60% of risky assets held by nonfinancial firms. For this reason, I collect data on corporate bond holdings by nonfinancial publicly listed firms in the US in the period spanning from 2009 to 2017.[15] These assets are included in the Compustat item “long-term investments" but are not reported separately.

To collect the data, I wrote a web-scraping code to go through the firms' yearly financial reports, publicly available in the Electronic Data Gathering Anal-

[15]I only have few observations before 2009. Only after 2009, with the implementation of the Statement of Financial Accounting Standards (SFAS) No. 157, were firms mandated to report the value of the major asset classes in their balance sheet. Therefore, I abstract from evaluating if the portfolio of assets played a role in the propagation of the financial crisis. See Appendix D.1 for further details on the data-collection procedure.

ysis and Retrieval website, and extract the market value of corporate bonds held by each firm. I then manually confirm the extracted values. More details on the code and data can be found in Appendix D.1.[16]

After confirming the extracted values by the code, I end up with 9,151 observations spanning from 2009 to 2017, around 12% of total Compustat observations over the same period. Overall, the firm distribution over total assets, investment, cash holdings, and leverage in my sample is comparable to that in the Compustat data (see figures 16 to 19 in Appendix D.1). More importantly, the distribution of corporate bond holdings is similar to that of overall risky assets, as illustrated in figure 20 in Appendix D.1, with the market value of corporate bond holdings increasing with the size of the firm.[17]

Overall, on average, through the 2009-2017 period, this group of firms held corporate bonds securities that amounted to more than $254 billion at the end of the year, which represents 5% of their total assets, 63.7% of cash, 31.9% of cash and cash equivalents, or 49.12% of total risky assets. These holdings have been mainly concentrated in the high-tech and health-care industries, which highlights the importance of controlling for sector fixed effects. More details on the data on corporate bond holdings can be seen in tables 10 to 13 in Appendix D.1.

In line with figure 1, I find that in the 2009-2017 period, corporate bond holdings by nonfinancial publicly listed firms were also increasing. Figures 21 to 24 in Appendix D.1 show that during this period, corporate bond holdings went from representing 3.6% of total assets in 2009 to 5.3% in 2017, from 40% of cash in 2009 and to 63.5% by 2017 and from 40% of risky assets in 2009 to more than 65% by 2017.

I now proceed to assess if firms' investment response to shocks also depends on the share of corporate bonds. As data is available only from 2009 onward, I cannot replicate the same exercise as I did with the Compustat data, to assess

[16]Some of the firms' corporate bonds holdings are included in pension benefit plans. In this analysis, I exclude these holdings because they are not part of the firms' savings to finance the main activity.

[17]Firms do not report details on which corporate bonds they are holding specifically, only total amounts. However, the majority of firms state they hold a well-diversified portfolio to avoid being exposed to the idiosyncratic risk of any specific firm.

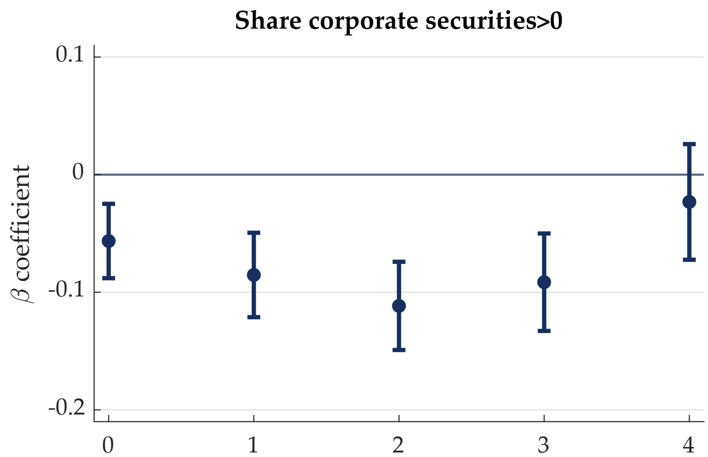

Figure 7: On the y-axis we have the β coefficient from equation (18), and on the x-axis, horizon h. Error bars represent the 95% confidence interval. Results indicate increases in volatility have a stronger negative effect on firms with a positive amount of corporate bond holdings, up to three years after.

how the investment response during the crisis period depended on the share of corporate bond holdings. Instead, I test how a firm's investment response to changes in aggregate volatility depends on the financial-assets portfolio composition. I adopt a similar strategy to equation (17) and interact dummy variable $risky_{ijt-1}$ - equal to 1 if the share of risky assets for firm i, in sector j, in year t-1 is above a given threshold - with $S\&P\_vol_{t-1}$, the yearly volatility of the S&P500 daily returns in year t-1 the volatility measure proposed by Bloom et al. (2007), while controlling for firm fixed effects λ_i and sector fixed effects θ_j:

$$ln(Inv)_{ijt+h} = \gamma S\&P\_vol_{t-1} + \alpha risky_{ijt-1} + \beta S\&P\_vol_{t-1} * risky_{ijt-1} + \lambda_i + \theta_j + \epsilon_{ijt}. \tag{18}$$

Additionally, I test for the presence of persistent effects of volatility on firms' investment depending on the riskiness of the savings portfolio by running Jordà (2005) local projections up to horizon $h \in [0,4]$. Results for the zero share of corporate bond holdings threshold are presented in figure 7 and indicate the existence of a persistent, stronger negative impact of volatility on investment by firms' with a positive holding of corporate securities when compared with the control group. Up to three years after the increase in volatility, the effect is still 10% stronger on the treatment group than on the control. Results are robust to different thresholds for splitting the firms into the two groups, as shown in figures 13 to 15 in Appendix B.[18]

Lastly, I test the model predictions of precautionary savings being in the form of cash while non-precautionary savings being in a higher risk higher yield asset in the form of corporate bonds. To test the determinants of portfolio composition, I regress cash and corporate bond holdings on sales and debt

$$Y_{ijt} = \beta_1 Revt_{ijt-1} + \beta_2 Debt_{ijt-1} + X_{ijt-1} + \alpha_i + \lambda_{jt} + \epsilon, \tag{19}$$

where Y is either cash or corporate bond holdings by firm i in sector j in year t, $Revt$ is revenues and $debt$ long term debt. X_{ijt-1} is a vector of control variables while α_i and λ_{jt} are firm and sector year fixed effects respectively. The variables are in levels, in this particular regression, so that the coefficients can be interpreted as $1 increase in debt/revenues contributes to $x change in cash or corporate bond holdings. The hypothesis is that, on the one hand, increases in debt should have a stronger impact on firms' default probability and be associated with stronger increases in cash holdings. On the other hand, cash-flow increases should decrease the company's risk, leading to an increase in corporate securities held by the firm.

Results, presented in table 6, show that a $1 increase in revenues is associated with a $0.14 raise in corporate bonds holdings and a $0.03 decrease in cash, while a $1 raise in long term debt is associated with a stronger increase in cash — $0.07 — than in corporate bonds — $0.05.[19] This result is consistent with the model

[18] The control group here differs from the one in the previous exercise. Whereas the control group previously had no risky savings, here I control for firms that have no corporate bond holdings, which does not mean they cannot have other forms of risky savings. The fact that results still go through is either a reflex that corporate bonds represent, on average, 50% of risky assets, or that they have a different risk profile that more strongly affects firms' investment decisions.

[19] Usually, in the corporate finance literature, an increase in the firm's leverage is associated with a decrease of the cash to assets ratio (see for example Bates et al. (2009)). This results is not opposite to mine. What I am showing is that $1 increase in debt is associated with a raise of $0.07 in cash. The remaining $0.93 dollars may be allocated in some other assets, which would explain the decrease of the cash to assets ratio.

VARIABLES	(1) Corporate Bond Holdings	(2) Cash
β_1	0.141	-0.029
	(0.020)	(0.012)
β_2	0.054	0.072
	(0.011)	(0.007)
Observations	4,769	4,730
R-squared	0.955	0.910

Standard errors in parentheses

Table 6: Cash and corporate bond holdings regressed on revenues and long term debt.

predictions that precautionary savings are in the form of cash while savings from revenues are allocated in higher risk higher yield assets such as corporate bonds.

6 Conclusion

In this paper, I study the aggregate implications of nonfinancial firms' allocation of savings between risk-free and risky assets. I develop a heterogeneous firms model that rationalizes why firms save in risky assets. Two reasons explain the savings-portfolio composition: (1) portfolio diversification effect, to minimize the default risk, and (2) maximize the return on savings to finance future investment opportunities. These two mechanisms generate a pattern of savings portfolio similar to the data, with smaller firms having more risk-free savings, and as firms grow, the share of risky assets grows as well.

I proceed by showing how the decrease in the real interest rate since the 1980s has caused a shift to the right of the firm size distribution, which explains the raise in risky asset holdings. I then evaluate the consequences of this increase. In response to an aggregate shock that generates an investment drop similar to the Great Recession, the portfolio of savings can cause an investment drop up to 50% larger.

I finish the paper by providing empirical evidence in support of the model's results. During the Great Financial Crisis, firms with a high share of risky assets significantly dropped their investment by more than firms with a low share of risky assets.

Overall, I show that firms' savings-portfolio composition has important aggregate consequences and that firms savings should not be treated as only cash.

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A Additional tables

Parameter	Value	Description	Source
Preferences			
β	0.96	Firm discount factor	Literature
Production			
α	0.66	Return on capital	Literature
p_k^-	0.57	Price of sold capital	Bloom (2009)
δ	0.06	Depreciation rate	Literature
k_0	0.171	Entrants share of average incumbents capital	Compustat
η	0.065	Exogenous probability of exit	LBD
Financial intermediary			
χ	0.64	Recovery rate of defaulted debt	Xiao (2018)
Idiosyncratic productivity			
ρ_ϵ	0.6	Persistence of the idiosyncratic shock	Khan & Thomas (2013)
Endogenous parameters			
C_f	8.006	Fixed cost of production	Calibration
f_e	2.414	Entry cost	Calibration
ω	0.01	Risk premium	Calibration
σ_ϵ	0.15	Volatility of idiosyncratic shock	Calibration
σ_z	0.074	Volatility of aggregate shock	Calibration
ρ_z	0.949	Persistence of aggregate shock	Calibration

Table 7: Parameters

	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014
Treatment	-0.017	0.029	0.015	-0.071	-0.047	0.017	0.005	0.018	0.003	-0.023
	(0.023)	(0.022)	(0.022)	(0.023)	(0.024)	(0.025)	(0.025)	(0.026)	(0.028)	(0.026)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Sector-Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Robust standard errors in parentheses

Table 8: β coefficient from specification (17). Dummy variable risky takes the value of one if at the end of the respective year in each column the share of risky assets was above 70%.

B Additional Graphs

Figure 8: On the left panel, the empirical relation between the standard deviation of the share of risky savings — on the y-axis — and log(total assets) — on the x-axis. On the right panel, the same relation in the model, with the standard deviation of the share of risky savings on the y-axis and capital on the x-axis.

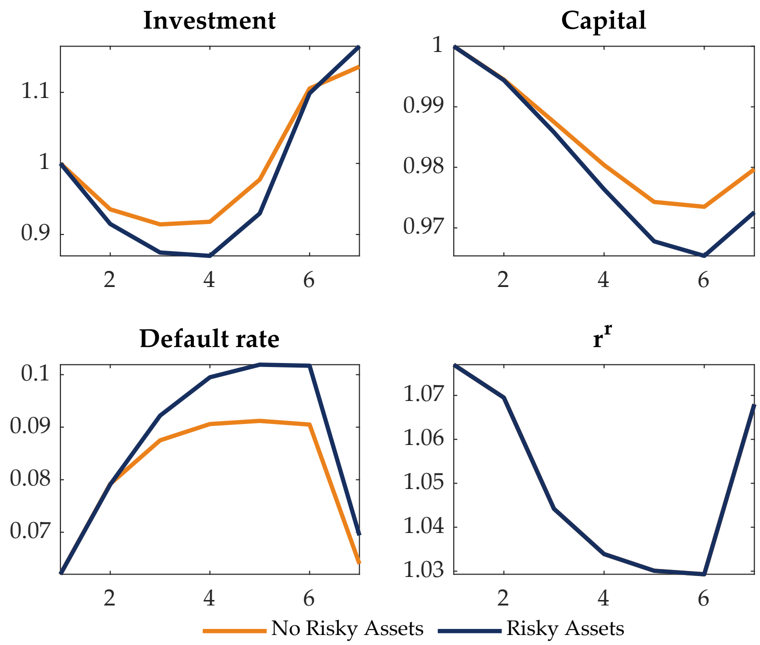

Figure 9: Impulse response functions to a negative financial and productivity shock. The top panels show the investment (left) and capital (right) responses to the shock. The bottom panel shows the default rate (left) and return on risky assets (right). The orange line represents the model with no risky asset, and the blue line represents the economy with only risky assets.

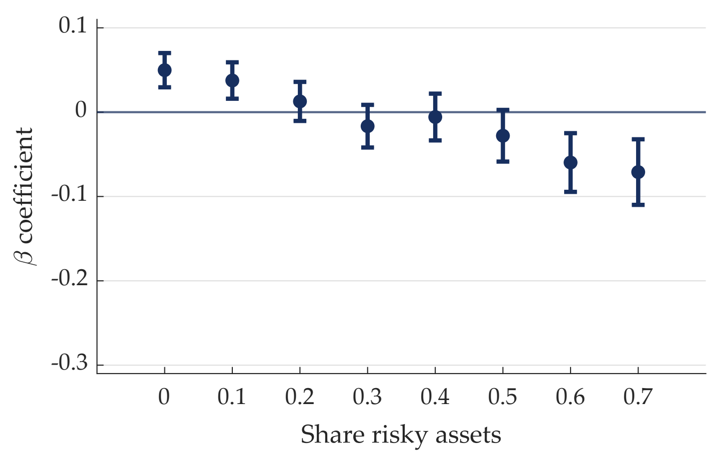

Figure 10: On the y-axis we have the β coefficient from equation (17) and on the x-axis we have the cutoff value of the share of risky asset holdings between the two groups. Error bars represent the 95% confidence interval.

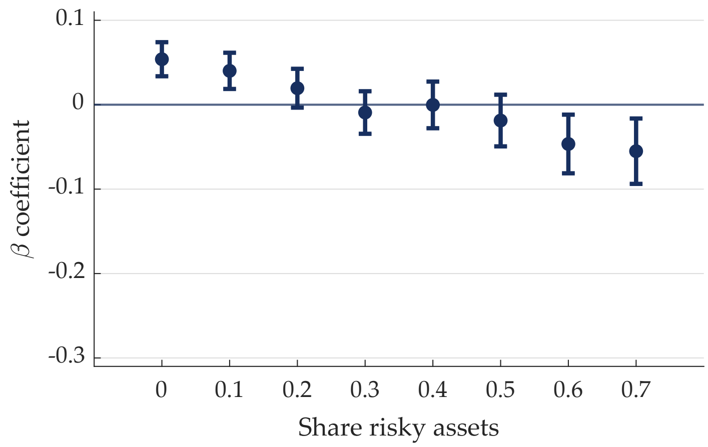

Figure 11: On the y-axis we have the β coefficient from equation $ln(Inv)_{ijt} = \gamma crisis_t + \alpha risky_{ijt} + \beta crisis_t * risky_{ijt} + crisis_t * \gamma_j + \lambda_i + \theta_j + \epsilon_{ijt}$ where crisis is a dummy variable equal to 1 between 2008 and 2010, risky is a dummy variable equal to 1 if the share of risky assets is higher than the x-axis value and γ_j, λ_i and θ_t are sector, firm and quarter fixed effects. Error bars represent the 95% confidence interval.

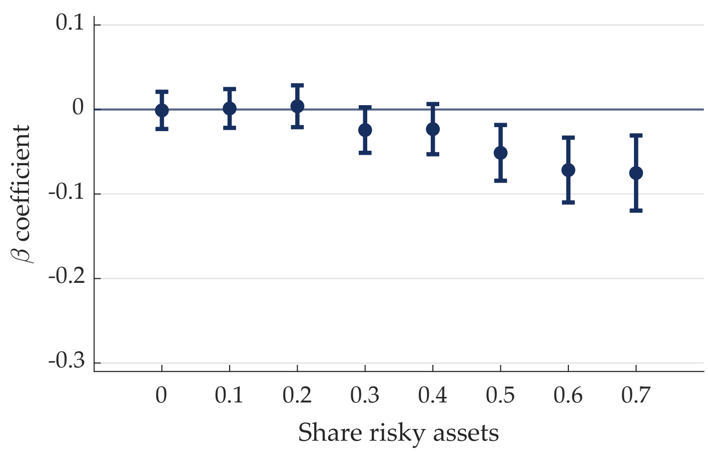

Figure 12: On the y-axis we have the β coefficient from equation $ln(Inv)_{ijt} = \gamma crisis_t + \alpha risky_{ijt} + \beta crisis_t * risky_{ijt} + X_{ijt} + \lambda_i + \theta_{jt} + \epsilon_{ijt}$ where crisis is a dummy variable equal to 1 between 2008 and 2010, risky is a dummy variable equal to 1 if the share of risky assets is higher than the x-axis value, X_{ijt} is a vector of firm control variables ($ln(assets)_{ijt}$, $ln(revenues)_{ijt}$ and $ln(cash)_{ijt}$), λ_i and θ_{jt} are firm and crossed quarter sector fixed effects. Error bars represent the 95% confidence interval.

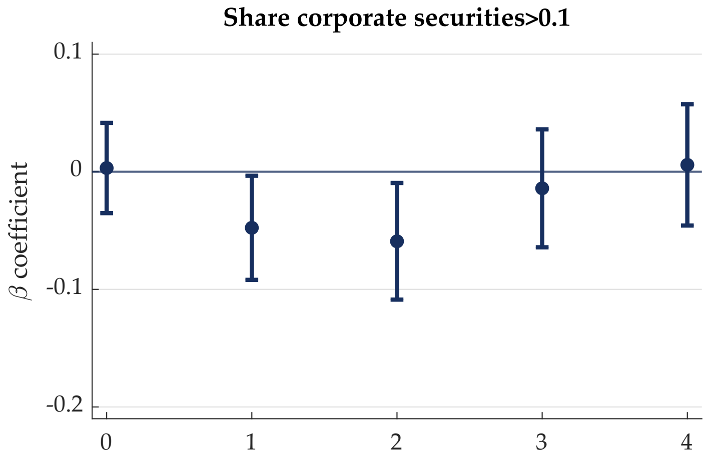

Figure 13: On the y-axis we have the β coefficient from equation (18) with the $risky_{ijt-1}$ dummy variable equal to 1 if the share of corporate bond holdings to total assets is higher than 0.1 and on the x-axis the horizon h. Error bars represent the 95% confidence interval.

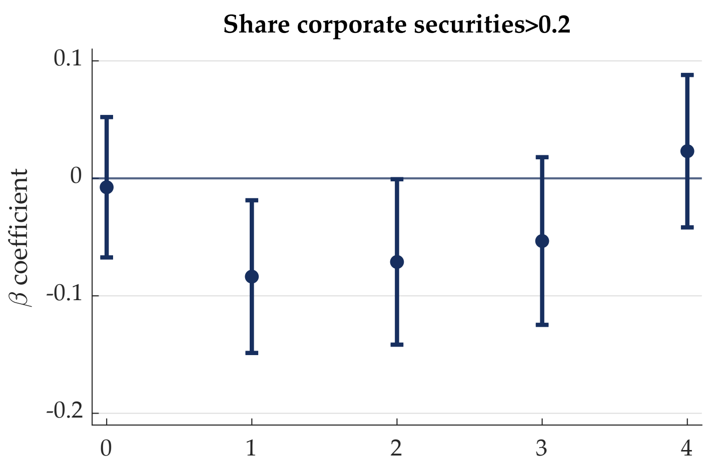

Figure 14: On the y-axis we have the β coefficient from equation (18) with the $risky_{ijt-1}$ dummy variable equal to 1 if the share of corporate bond holdings to total assets is higher than 0.2 and on the x-axis the horizon h. Error bars represent the 95% confidence interval.

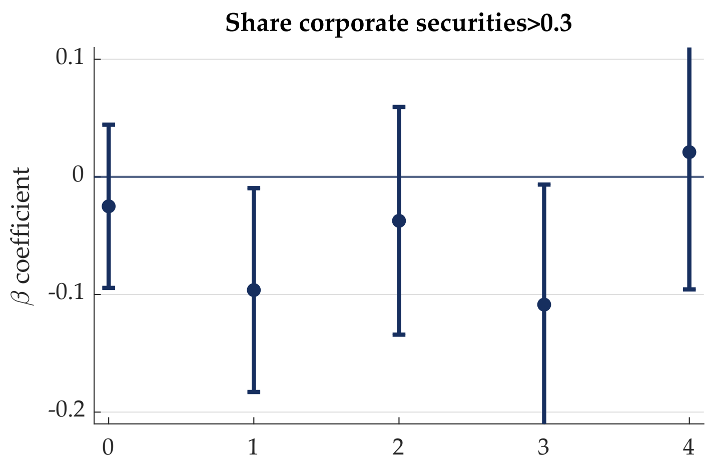

Figure 15: On the y-axis we have the β coefficient from equation (18) with the $risky_{ijt-1}$ dummy variable equal to 1 if the share of corporate bond holdings to total assets is higher than 0.3 and on the x-axis the horizon h. Error bars represent the 95% confidence interval.

C Algorithm

The model is solved using Krusell & Smith (1998) inner-and-outer loop procedure, where I iterate between and inner loop that solves the firms' problem, and an outer loop that simulates the economy, and uses the simulated data to iterate on the forecasting rules. More precisely, the algorithm consists of the following steps

1. Initiate the outer loop by guessing forecast rules implied by the following system of equations, used by agents to forecast future prices

$$\begin{bmatrix} \log B^{f'} \\ \log K' \\ r_r \end{bmatrix} = A + B \begin{bmatrix} \log B^{f} \\ \log K \end{bmatrix} + C \log(z). \tag{20}$$

   The explicit form chosen for the forecast rules are assumptions and verified that are good approximations.

2. Taking as given the current forecast rules, solve the incumbent's problems (equations 9). I start by defining the grid for the firm state variables $\{\epsilon, k, x, S\}$, with S being the aggregate state of the economy comprised by aggregate productivity z and the distribution of firms μ. As previously noted in the main text, the intractable object μ is approximated by the aggregate capital K, debt B and productivity z. The firm perceived state is then captured by $\{\epsilon, k, x, K, B, z\}$.

   From the firm's budget constraint, I find its savings. Then, I just need to find the share of risky savings $\gamma = \frac{a^r}{a^r + a^{rf}}$ that maximizes the firm's value instead of solving for both the amounts of risk-free a^{rf} and risky savings a^r. The firm's decision variables become $\{k, b, \gamma\}$.

   I discretize both idiosyncratic ϵ and aggregate z productivity into 5 and 3 grid points respectively, using Tauchen (1986). I discretize the idiosyncratic state x into 25 grid points, while endogenous state k has 31 grid points. For both these variables I define a convex grid that allows the model to have more precision when firms are small. The decision variable γ is linearly discretized into 11 grid points. The firm's problem is then solved using value function iteration combined with Howard's improvement step for a grid of prices ω.

3. Simulate the economy for T=2000 periods and N=10000 firms. In each period, the firms policy functions must be consistent with the price ω^*.

4. Once the simulation is finished, I use its data, disregarding the first 100 periods to remove the influence of initial conditions, to update the forecast rules. I run OLS regressions to estimate the coefficients of the system of equations (20). If the guesses for specification (20) coefficients converged the algorithm stops. If not, I update the forecast rules and go back to point 2.

In this framework, it is important to verify how well the forecast rules approximate the model true equilibrium. Table 9 shows the estimates of the forecast rule regressions as well as the R^2. As the high R^2 illustrate, the perceived laws of motions are accurate and thus, according to this common used metric, are good approximations to the model equilibrium. Moreover, the estimated coefficients are also in line with what would be expected from the model. For example, the stock of debt depends negatively on the stock of capital and on aggregate productivity. The more productive and the more capital firms have, the higher the internal funds which lowers the need for debt. Also the stock of capital depends positively on all variables considered. If firms hire more debt or are more productive they will use these resources to increase their stock of capital. Also, higher stock of capital and the aggregate productivity today will imply lower default rates that translate into higher returns on the risky asset.

With the model equilibrium found, I then proceed to estimate the impulse response functions. I simulate the economy for T=150 periods and N=10000 firms. To remove any sampling variations, I repeat the procedure 500 times. I assume the aggregates evolve normally until period 100, when an unanticipated negative productivity shock occurs. The shock lasts for 5 periods, and then goes back to its average level.

VARIABLES	Log(Debt)	Log(Capital)	Risky Return
B	-0.743***	1.053***	0.623***
C	0.627***	0.049***	0.099***
D	-0.379***	0.058***	0.130***
R-squared	0.980	0.978	0.853

*** p<0.01, ** p<0.05, * p<0.1

Table 9: Regression fit

D Data

D.1 Corporate bond holdings data collection

Data on corporate bond holdings is not available in Compustat. To collect this data, I have to go through the firms financial reports and extract the value on corporate bond holdings reported by the firms. To avoid doing this procedure manually, I wrote a web scrapping code in matlab to extract this values. The idea of the code is to enter in each firm financial report, identify the variable corporate bond holdings and extract the associated value.

To do this, I initially extract from Compustat the CIK codes for all the publicly listed firms over the 2009-2017 period.[20] In the EDGAR website, I can then use the CIK code to search for the financial reports of the associated firm. The http address for all the company yearly financial reports is always in the following format

"https://www.sec.gov/cgi-bin/browse-edgar?action=getcompany&*CIK=xxxxxxxxxx*
&*type=10-K*
&*dateb=*&*owner=exclude*&*count=40"*

The code is then programed to replace the x's in front of *CIK*= by the firm specific CIK code and enter the firm specific http address. From this address, it

[20]Before 2007 the firms' financial report appear in a different format that makes it harder to extract the values. Moreover, before 2009 firms were not obliged to report the financial assets hold and only a few would report the values of corporate bond holdings.

is extracted a financial report specific identifier, needed for the financial report http address, which always follows the following format

“https://www.sec.gov/Archives/edgar/data/xxxxxx/zzzzzzzzzzyyzzzzzz/zzzzzzzzzz-yy-zzzzzz
yy.txt"

where xxxxxx is the firm specific CIK and zzzzzzzzzzyyzzzzzz the financial report specific identifier in year yy. Once it has the addresses for all the firms financial reports, the web scrapping code enters each one, searches for the words “Corporate Debt Securities" and extracts the associated values. The code then repeats this process for the entire list of CIK codes initially extracted from Compustat.

Then, to test the accuracy of the code, I manually confirm 50% of the extracted values by comparing them to the reported values in the firms financial reports. The others 50% I check if the values make sense comparing to the overall financial assets holdings reported in Compustat. The code looks to extract the accurate values of corporate bond holdings as more than 95% of the values compared to the financial reports were correct and the remaining values had a reasonable size when compared to the firms overall financial asset holdings.

Overall, I end up with 9,151 observations, representing close to 12% of all Compustat observations over the same period of time. The firms that were not capture by the code either did not report corporate bond holdings or the financial reports were structure in a way that the web scrapping code was not able to identify the value.

To analyze if my sample is representative of the entire Compustat dataset, I compare the distribution of the firms in terms of investment, total assets, cash holdings and leverage ratios. Overall, the average firm in my sample is larger, holds more cash and invests more but has the same leverage ratio than the average firm in Compustat. Despite firms being on average larger, the distributions of these variables across both datasets are similar, as it is possible to observe in figures 16 to 19. While the distributions of log of total assets, log of investment and log of cash are slightly shifted to the right in my sample, the shapes of the distributions in both samples are similar and closely resemble a normal distribution. The leverage distribution presents both a similar average and pattern across both datasets.

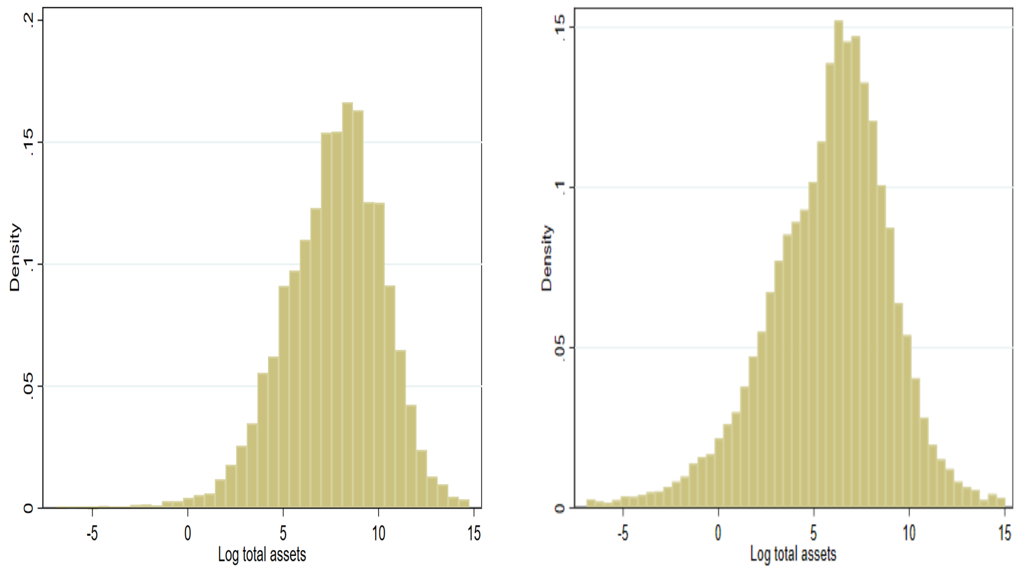

Figure 16: Histogram of log of total assets. On the left panel, the sample of firms for whom my web scrapping code was able to extract corporate bond holdings. On the right panel, the entire Compustat sample over the same period. The distributions have a similar behavior with the only difference of the distribution on the left panel being shifted to the right.

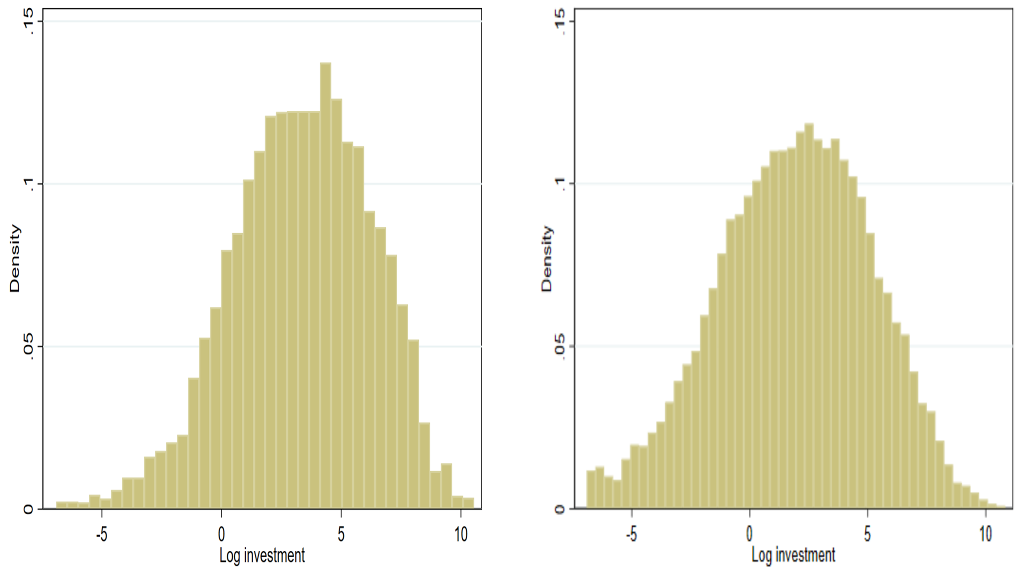

Figure 17: Histogram of log of investment. On the left panel, the sample of firms for whom my web scrapping code was able to extract corporate bond holdings. On the right panel, the entire Compustat sample over the same period. The distributions have a similar behavior with the only difference of the distribution on the left panel being shifted to the right.

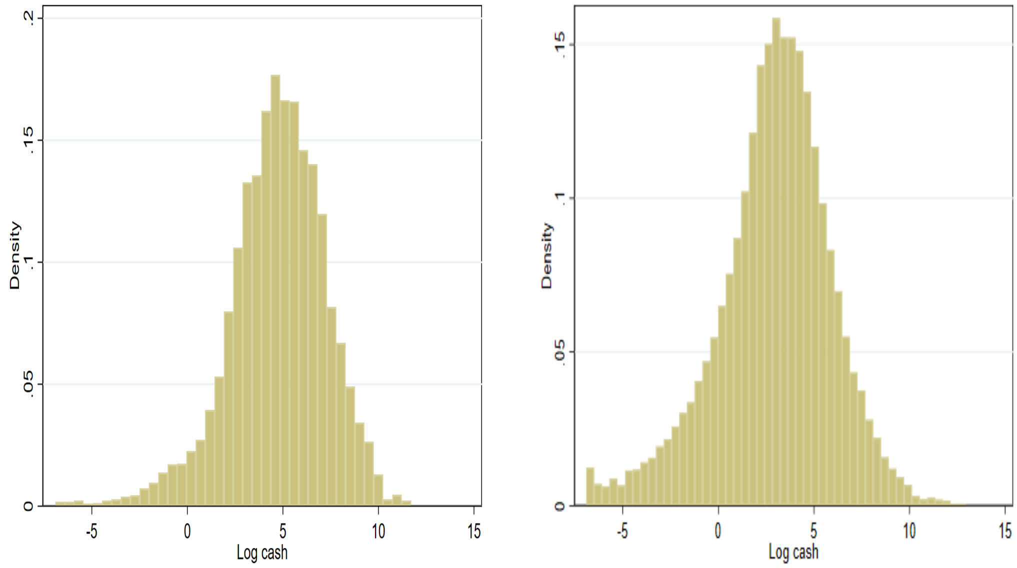

Figure 18: Histogram of log of cash holdings. On the left panel, the sample of firms for whom my web scrapping code was able to extract corporate bond holdings. On the right panel, the entire Compustat sample over the same period. The distributions have a similar behavior with the only difference of the distribution on the left panel being shifted to the right.

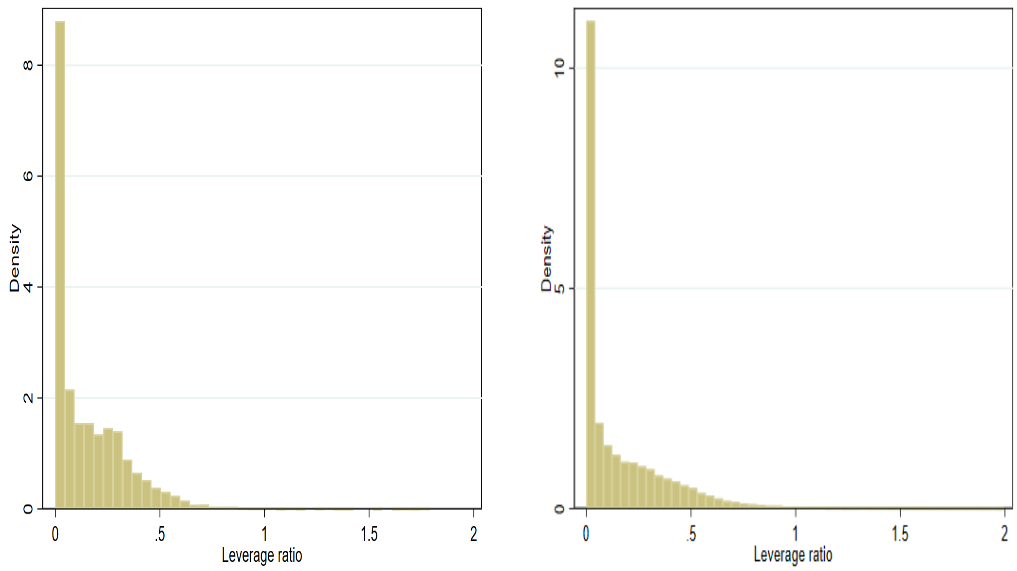

Figure 19: Histogram of leverage ratios. On the left panel, the sample of firms for whom my web scrapping code was able to extract corporate bond holdings. On the right panel, the entire Compustat sample over the same period. The distributions have a similar behavior and a similar average.

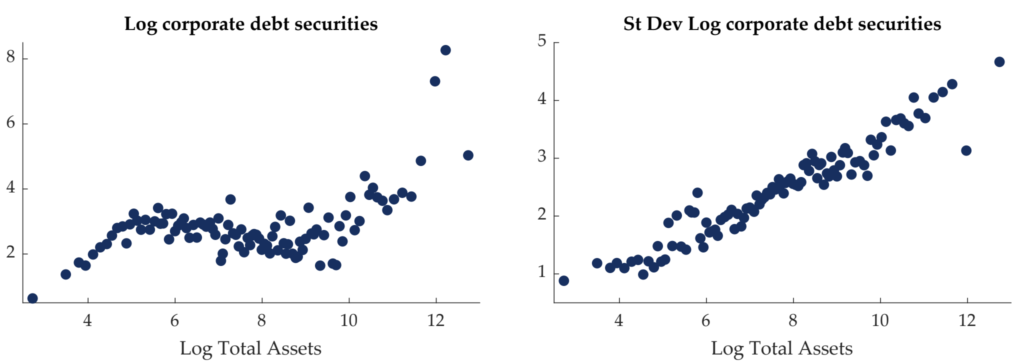

Figure 20: On the left panel, the empirical relation between corporate bond holdings — on the y-axis — and total assets — on the x-axis. On the right panel, the relation between the standard deviation of corporate bond holdings — on the y-axis — and total assets — on the x-axis. Consistent with the model, both the average and the standard deviation are increasing with the size of the firm.

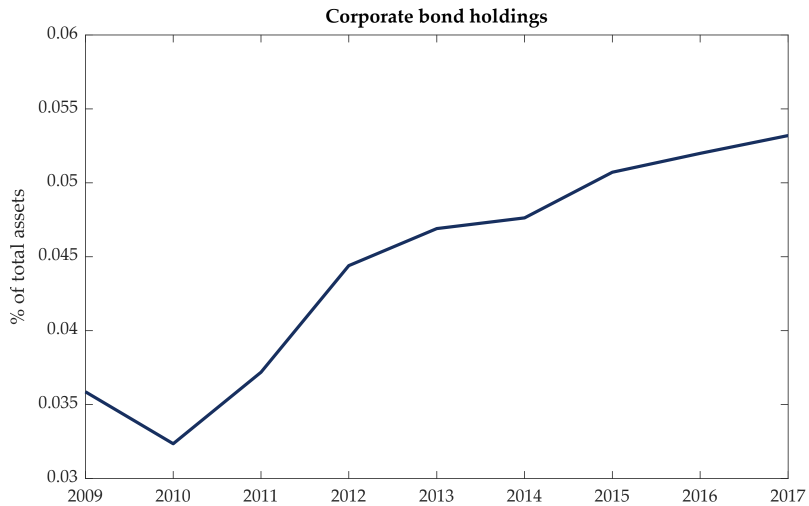

Figure 21: Aggregate corporate bonds to total assets ratio by publicly list firms.

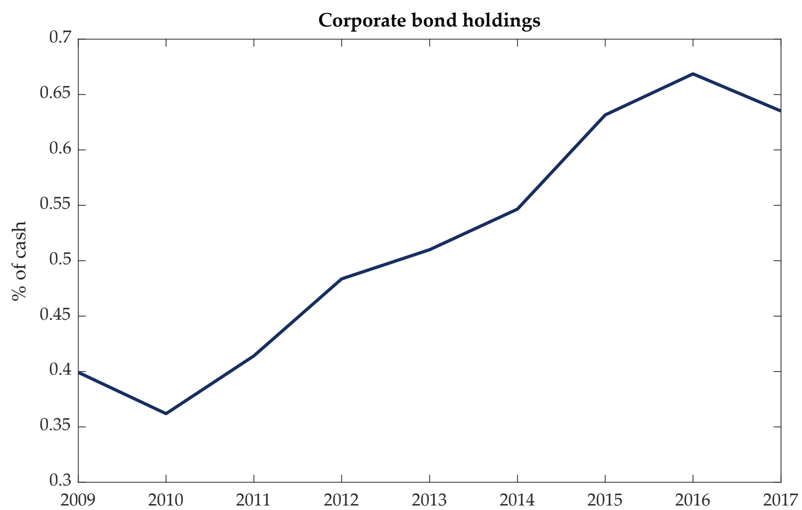

Figure 22: Aggregate corporate bonds to cash ratio by publicly list firms.

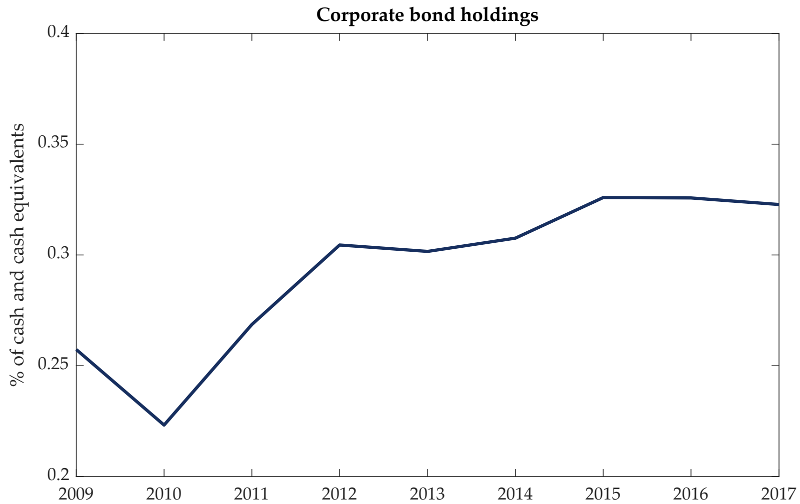

Figure 23: Aggregate corporate bonds to cash and cash equivalents ratio by publicly list firms.

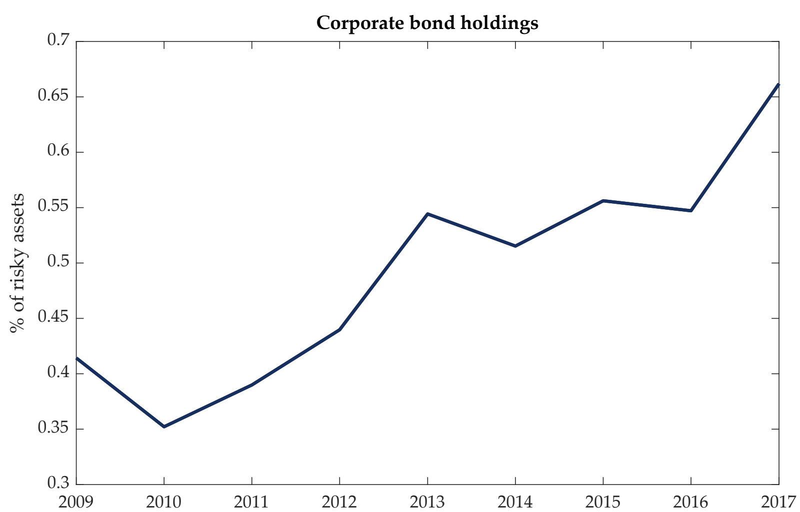

Figure 24: Aggregate corporate bonds to risky assets ratio by publicly list firms.

Name	Amount (M$)	Name	% Total Assets
APPLE INC	60998	INTERCEPT PHARMA INC	69.8
AMERICAN SCIENCE ENGINEERING	42229	TONIX PHARMACEUTICALS HLDG	66.2
GENERAL ELECTRIC CO	27686	ALPINE IMMUNE SCIENCES INC	62.6
ALPHABET INC	15555	XENOPORT INC	60.1
CISCO SYSTEMS INC	14318	ACHAOGEN INC	57.6
SPECTRUM BRND HLDG INC	10933	PTC THERAPEUTICS INC	55.6
AMGEN INC	9390	ENANTA PHARMACEUTICALS INC	53.4
QUALCOMM INC	9108	OVASCIENCE INC	51.0
AUTOMATIC DATA PROCESSING	7558	REGULUS THERAPEUTICS INC	48.8
PFIZER INC	6775	KYTHERA BIOPHARMA INC	48.5
GENERAL MOTORS CO	6699	CHIASMA INC	47.7
MICROSOFT CORP	6643	ZAFGEN INC	47.4
MERCK & CO	6249	SYNDAX PHARMACEUTICALS INC	45.8
BOEING CO	5344	PULSE BIOSCIENCES INC	44.8
MEDTRONIC PLC	5150	ADAPTIMMUNE THERAPEUTICS	44.8
FACEBOOK INC	5141	MITEK SYSTEMS INC	44.2
EBAY INC	4514	DYNAVAX TECHNOLOGIES CORP	43.7
GILEAD SCIENCES INC	4504	CERES INC	43.5
PAYPAL HOLDINGS INC	4168	XENCOR INC	43.2
INTEL CORP	3834	NEKTAR THERAPEUTICS	43.0

Table 10: Top 20 firms on corporate bond holdings - yearly averages 2009-2017

Name	% Cash and Cash Equivalents	Name	% Cash
AMERICAN SCIENCE ENGINEERING	27720.0	AMERICAN SCIENCE ENGINEERING	88460.0
CARRIAGE SERVICES INC	7225.0	CARRIAGE SERVICES INC	7225.0
LIBERTY EXPEDIA HOLDINGS INC	6564.0	LIBERTY EXPEDIA HOLDINGS INC	6564.0
SPECTRUM BRND HLDG INC	603.6	PHI INC	4384.0
KNIGHT-SWIFT TRPTN HLDGS INC	552.8	NEKTAR THERAPEUTICS	1220.0
HC2 HOLDINGS INC	544.6	XENCOR INC	969.1
ARMSTRONG WORLD INDUSTRIES	428.5	INTREPID POTASH INC	938.3
AUTOMATIC DATA PROCESSING	367.3	INTERCEPT PHARMA INC	888.4
JEFFERIES FINANCIAL GRP INC	308.7	SPECTRUM BRND HLDG INC	861.2
CENTURYLINK INC	299.8	JEFFERIES FINANCIAL GRP INC	743.0
UNIFIED GROCERS INC	289.1	ALPINE IMMUNE SCIENCES INC	666.9
PUBLIX SUPER MARKETS INC	187.9	HC2 HOLDINGS INC	629.3
HUMAN GENOME SCIENCES INC	176.5	PULSE BIOSCIENCES INC	605.9
APPLE INC	151.8	ENTROPIC COMMUNICATIONS INC	577.9
DSP GROUP INC	151.7	KNIGHT-SWIFT TRPTN HLDGS INC	554.8
SOLAREDGE TECHNOLOGIES INC	113.8	ALASKA AIR GROUP INC	550.7
APPFOLIO INC	112.0	ENANTA PHARMACEUTICALS INC	528.5
AKAMAI TECHNOLOGIES INC	110.1	PENUMBRA INC	492.7
CLEARONE INC	109.9	CHEMOCENTRYX INC	463.5
DESIGNER BRANDS INC	109.1	CAL-MAINE FOODS INC	462.8

Table 11: Top 20 firms on corporate bond holdings - yearly averages 2009-2017

Fama-French Industry	Amount (M$)	% Total Assets	% Cash and Cash Equivalents	% Cash
Total	704.20	7.9	94.0	259.7
Consumer	253.32	2.2	123.3	148.1
Manufacturing	221.06	2.0	18.0	26.7
High Tech	1,059.12	9.1	72.7	28.9
Health	847.30	17.6	269.8	885.8
Others	772.18	2.7	48.6	167.5

Table 12: Firm level analysis of risky investment by industry - yearly averages 2009-2017

Fama-French Industry	Amount (M$)	% Total Assets	% Cash and Cash Equivalents	% Cash
Total	254,273.8	5.0	31.9	63.7
Consumer	17,669.82	1.5	12.6	19.2
Manufacturing	15,423.42	0.9	13.4	16.5
High Tech	172,265.10	9.8	37.5	95.4
Health	83,491.78	9.5	46.5	94.1
Others	32,903.31	2.7	24.0	31.0

Table 13: Aggregate analysis of risky investment by industry - yearly averages 2009-2017

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