Aggregate Implications of Corporate Lending by Nonfinancial Firms*

Miguel H. Ferreira
University of Cambridge

November 2021

[JOB MARKET PAPER]
Please click here for the latest version

Abstract

Beginning in the early 1990s, the share of risky securities held by U.S. nonfinancial firms increased from 28% of total financial assets to more than 40% by the end of 2017. I start by empirically showing that in the Great Recession, firms with a high share of risky financial assets suffered, on average, a larger investment drop. Making use of a business-cycle heterogeneous firms model amplified with a savings portfolio decision, where the risky asset are corporate bonds, I argue the decrease in the real interest rate since the 1980s generates a rise in the risk premium consistent with the data and can fully account for the observed increase in risky asset holdings. This portfolio reallocation causes capital to decrease by up to 30% more following a large shock that generates a decrease in investment similar to the Great Recession. The exposure of firms to corporate bonds ends up creating a financial linkage between firms and propagates the shock from defaulting borrowers to lenders.

Keywords: risky assets; corporate lending; firm heterogeneity; firm dynamics; business-cycle

JEL Classification: E22; E32; E44; G11; G23

*I am grateful to Pedro Brinca and Vasco M. Carvalho for all their invaluable advice and support. I greatly benefited from helpful comments from Tiago Berriel, Corina Boar, Ariel Burstein, Tiago Cavalcanti, Giancarlo Corsetti, Joel M. David, Burcu Eyigungor, Miguel Faria-e-Castro, Miguel A. Ferreira, Maren Froemel, Basile Grassi, Hans A. Holter, Aubhik Khan, Marc J. Melitz, Sara Moreira, Marco Del Negro, Adriano A. Rampini, Ricardo Reis, Pontus Rendahl, Cezar Santos, Felipe Schwartzmann, Tatsuro Senga, Jasmine Xiao and seminar participants at Lisbon Macro Club, Nova SBE, Cambridge, FRB St. Louis, PEJ 2019, Lubramacro 2019, CFM workshop. Email: migueltch-ferreira@gmail.com

1 Introduction

Financial asset holdings by nonfinancial firms almost doubled over the past 40 years. More than 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 business shows Apple is not a unique case. Total financial assets held by these corporations at 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 business 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.

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 their response to aggregate shocks. More concretely, I assess three different questions: (1) What explains the observed increase in the share of risky asset holdings by nonfinancial firms and how does it shape their investment de-

[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.

cisions? (2) How does the savings portfolio affect the propagation of aggregate shocks, more particularly productivity and financial ones? (3) Can policy influence firms' savings portfolio, and is implementing such policies optimal?

To answer these questions, I outline a model in which heterogeneous firms can invest in productive capital, rise debt, and save in a risk-free and/or risky asset. Corporate bonds are the risky asset in the outlined model. In the sample of firms considered in section 2, corporate bonds represented more than 60% of risky asset holdings by the end of 2017. Moreover, corporate bonds have a different risk profile than the second most held risky asset – government bonds other than treasuries. For example, corporate bonds are given a risk-weight of 100%, whereas government bonds besides treasuries are only 50% weighted. Considering this evidence, corporate bonds are the risky asset in the model.

First, I argue 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, which generates an endogenous increase in the excess return on corporate bonds in the model, consistent with that observed in the data. This increase in risky asset excess return causes firms to alter the composition of the savings portfolio, accumulating more risky assets.

Second, I show the riskiness of nonfinancial firms' savings portfolio, measured as the share of risky assets held, 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 Recession, the savings portfolio can amplify the investment decrease by up to 50% when compared with a standard heterogeneous firms model, with only cash savings. Firms holding corporate bonds creates 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.[2] For small shocks, which do not trigger a decrease in the return on risky assets, the opposite happens, with the riskier portfolio of savings allowing firms to better absorb the shock, due to the higher returns on this portfolio.

Third, I assess some policy implications. I illustrate that imposing on nonfinancial firms some of the regulation in place for the financial sector — such as capital requirements or countercyclical buffers — would have limited effects on aggregate outcomes, whereas a policy that limits the losses during recessions but keeps the benefits of the extra return during expansions, similar to the Secondary Market Corporate Credit Facility program announced by the FED during the COVID pandemic, would be the most effective.

Having laid out the overview of the paper, I next describe the steps undertaken for the empirical and quantitative analysis in detail. The paper starts by presenting some empirically stylized facts on the evolution of the nonfinancial firms' savings portfolio, on its composition across the distribution of firms, and how it may affect firms' investment. I highlight that since the beginning of the 1990s, the rise of risky asset holdings accounts for 70% of the observed increase

[2] 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.

in firms' financial assets. I then proceed by showing larger firms own the majority of these risky assets. Whereas small firms, on average, have larger savings-to-assets ratios, they accumulate mainly cash or near cash, risk-free securities. As firms grow, the share of savings to total assets starts decreasing but firms move toward a more risky savings portfolio. Corporate bonds, on average, represent more than 50% of the risky assets held by these firms. Analyzing the Great Recession period, I find that firms with a higher share of risky savings lowered investment, on average, twice as much than firms with a less risky portfolio. I also found that investment by firms holding more corporate bonds is more responsive to aggregate volatility, with the effects being persistent up to three years after.

I proceed by developing a business-cycle heterogeneous firms model that formally illustrates and quantifies the role of savings portfolio in explaining firms' responses to aggregate shocks. The model main features are as follows (1) Firms experience sequentially an idiosyncratic and an aggregate productivity shock and whereas they can reoptimize the asset portfolio before and after the idiosyncratic shock, they can only adjust the amount of outstanding debt before the idiosyncratic shock, following evidence by Xiao (2018) that firms adjust the asset side more frequently than the liability side of the balance sheet and (2) Firms can invest in risky productive capital, subject to convex adjustment costs with partial irreversibility, or save in a risk-free and/or risky asset (corporate bonds).

Corporate bonds are considered risky assets, due to the presence of unsecured default risk. After observing the aggregate productivity shock, firms that fail to pay back the outstanding debt and/or the fixed cost of production, default. Three other assumptions are crucial in generating the riskiness associated with the corporate lending process: (1) Lenders do not observe the idiosyncratic state of the borrower – consistent with the literature on theories of financial intermediation, firms are less efficient than banks in screening and monitoring borrowers;[3] (2)

[3] Several reasons have been given by the literature: banks have access to inside information while markets only have access to publicly available information; banks have economies of scale in the screening and monitoring process; 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 and Uhlig (2011) and Gande and Saunders (2012).

corporate bonds are not backed by collateral – as emphasized by Rauh and Sufi (2010), one of the major differences between corporate bonds and bank loans is that the latter is typically backed by collateral whereas the former is not; (3) bankruptcy costs in case of default – lenders can only recover a share of the defaulting firm's remaining value.

I then use the outlined model to rationalize the empirical savings distribution. Small firms save in risk-free assets mainly due to precautionary motives, to diminish the probability of default. As firms grow, the probability of default goes down and firms, looking to maximize return on savings, increase the share of risky asset holdings. Firms not yet at the optimal amount of capital save to finance future investment opportunities, whereas firms at the top of the distribution save to guarantee they will never become constrained again.

The savings portfolio affects firms' sensitivity to aggregate shocks. When the return on risky assets falls below the risk-free rate, firms more exposed to risky securities lower their investment by more compared with similar firms holding mainly risk-free securities. This effect is amplified in periods when the risky asset return becomes negative and firms lose part of their savings. In this scenario, more exposed firms may end up defaulting as well.

With the mechanisms that explain the distribution of savings and its micro implications in hand, I proceed to analyze the aggregate effects. I first explore the determinants of the increase in risky asset holdings over the past three decades. I find the decrease in the real interest rate fully explains the observed increase. This decrease in the interest rate causes a shift to the right of the firm size distribution, with firms becoming on average larger and growing faster as a consequence of the lower cost of debt. Because larger firms are, on average, more willing to hold high-risk high-yield securities, the shift of the size distribution directly accounts for 13% of the increase. The remaining 87% is explained by an increase in the risky asset excess return. As firms become larger, the percentage of defaulted debt decreases, which explains the increase in the excess return.

I proceed by assessing the quantitative importance of the identified mechanisms in response to a negative productivity and financial shock. When the shock happens, the default rate rises which causes the return on corporate bonds to decrease, causing more exposed firms to lower their investment by more than firms only holding risk-free securities. Some of the more exposed firms end up defaulting as well. Both margins contribute to a decrease in investment that is 50% larger compared with the results of a model with no risky asset holdings. When considering small shocks that do not trigger a decline in the return on corporate bonds lower than the risk-free rate, the opposite happens. In this case, firms have a higher return on their savings, which allows them to better absorb the negative shocks without defaulting or causing investment to drop.

To validate the model mechanism, I collect data on corporate bond holdings by publicly listed firms from their yearly financial reports. Using these data, I test some of the model mechanisms. I find empirically that, in accordance with the model mechanism, firms with more corporate bond holdings tend to grow faster and are more exposed to aggregate volatility than firms with more cash holdings. I equally find that following debt issuances firms save more in cash, which supports the precautionary channel mechanism, but save more in corporate bonds in response to increases in sales. Empirical evidence also suggests decreases in the real interest rate are associated with an increase in the riskiness of the savings portfolio.

I conclude the paper by analyzing some policy implications. I start by testing the implementation of a policy that limits losses during recessions but keeps the benefit of extra returns on risky assets during expansions, similar to the Secondary Market Corporate Credit Facility program introduced by the Fed during the COVID pandemic. This policy would be an efficient one for minimizing the costs of risky savings, while keeping the benefits extra returns during normal times in place. I also test the implications of applying some of the existing financial sector regulation to nonfinancial firms. I test the policies that more closely relate to the portfolio of assets' riskiness, such as capital requirements weighted by the asset's risk and counter-cyclical buffers. I illustrate that the impacts of adopting such measures would be limited. Because the majority of the regulation would only be binding for large firms that can sustain big losses without defaulting or lowering investment, the aggregate effects would be limited.

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 and Thomas (2008), Jermann and Quadrini (2012), Khan and Thomas (2013), Clementi and Palazzo (2016), and Carvalho and 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.

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 and Karmakar (2017) and Begenau and Salomao (2018a) 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 and Winberry (2018) also explore the importance of firms' financial position in shaping their response to shocks by illustrating how firms' propensity to hire in response to monetary shocks changes according to whether the firms are constrained. 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 and Whited (2009), Nikolov and Whited (2014), Bigio (2015), Lyandres and Palazzo (2016), Cunha and Pollet (2017), and Gao et al. (2021) argue some of the main determinants of corporate cash holdings are (1) precautionary motives, (2) inter-temporal 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 and Palazzo (2017) and Chen et al. (2017) for more details).

Other papers, such as Duchin et al. (2017), Cardella et al. (2015) or Darmouni and Mota (2020), 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: Section 2 introduces some stylized facts on the distribution of risky asset holdings and its potential effects on investment. In section 3, I describe the model. Section 4 presents the calibration strategy and the algorithm to solve the model. In section 5, I inspect the mechanisms and discuss the main results. Section 6 presents some policy implications, and section 7 concludes.

2 Stylized Facts

In this section, I start by exploring the aggregate evolution of the firms' savings portfolio composition over the past 40 years using data from the flow of funds. I then use two datasets to assess which firms hold the risky assets: Compustat, which has all the publicly listed firms; and the Quarterly Financial Report (QFR) data from the Census Bureau, which includes small, not publicly listed firms. I establish that, overall, risky asset holdings as a percentage of total firms' assets have been increasing since the early 1980s, and that as firms grow, they tend to adopt riskier portfolios. Moreover, using data collected from firms' financial reports on corporate bond holdings, I find corporate bonds represent more than 50% of risky assets held by these firms. I then proceed by empirically exploring some of the potential effects of holding risky securities. Using both Compustat and collected data on corporate bond holdings by nonfinancial firms, I find a positive correlation between the share of risky assets and the drop in investment during the Great Recession, as well as with firms' investment response to aggregate volatility.

Aggregates

Before assessing which firms hold risky assets and how the financial-assets portfolio shapes firms' responses to shocks, analyzing the evolution of the financial-assets portfolio composition is important. Using aggregate data from the flow of funds, Figure 1 establishes that the risky securities weight on firms' savings portfolio has been increasing over time. The question then becomes whether this increase translates into a growth in risky savings as a percentage of total assets. Additionally, is the increase explained by a drop in risk-free securities held or by faster growth of risky savings?

Figure 2 answers these questions by providing the evolution of risky, risk-free, and total financial assets as a percentage of firms' total assets.[4] As the figure shows, total financial asset holdings by firms almost doubled from 1980 to the end of 2018, going from close to 25% to just below 50%, a fact that is acknowledged in the literature (see, e.g., Begenau and Palazzo (2017) and Chen et al. (2017)). Contrary to what most the literature has been assuming, it is not cash or near-cash risk-free financial assets that account for the majority of this increase. Since the beginning of the 1990s, risky securities account for 70% of the increase in total financial assets held by nonfinancial firms.

The first question this paper proposes to answer is, what justifies the evolution of the share of risky asset holdings by nonfinancial firms? The model in section 3 rationalizes this increasing

[4] I consider risky assets to be government bonds excluding treasuries, corporate bonds, equity, mortgage-backed securities, and investment fund shares. Risk-free assets consist of cash and bank deposits, treasuries, and commercial paper.

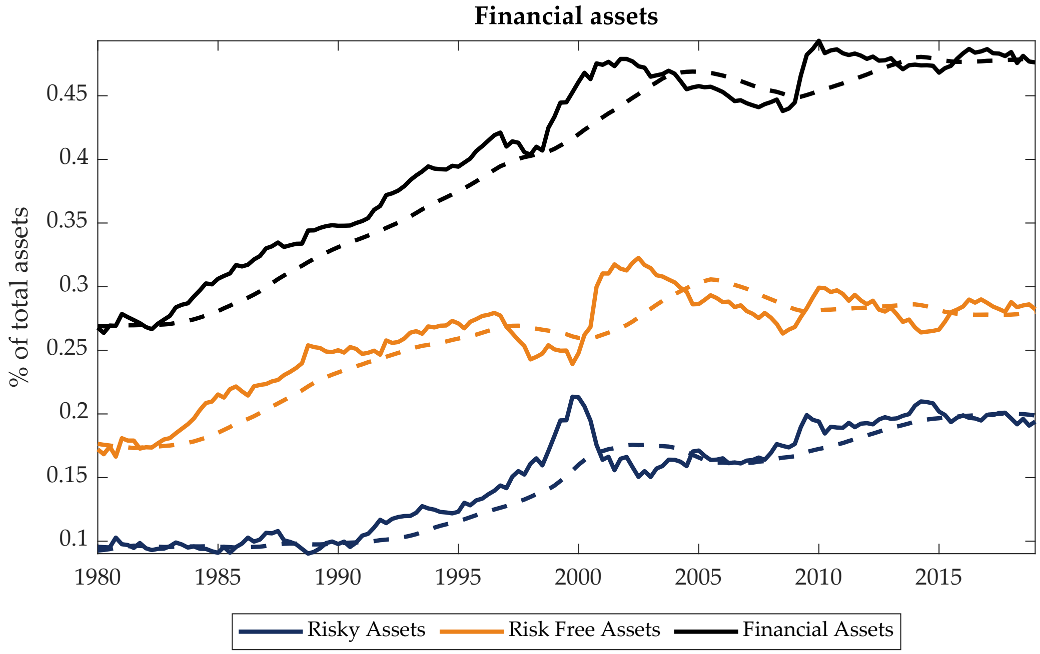

Figure 2: Data for all nonfinancial corporate business in the US. Black line represents all financial assets; orange line, the risk-free ones; and blue line, the risky held by these firms as a percentage of their total assets. Dashed lines represent the HP trend. From 1980 to 1990, 90% of the growth of financial asset holdings was explained by the increase in risk-free asset holdings. Since 1990, 70% of the increase in financial assets is explained by the growth in risky asset holdings. Source: Flow of Funds, Board of Governors of the Federal Reserve System.

trend with the decrease in the real interest rate. I initially calibrate the model to match the share of risky asset holdings in the 1980s, using the average real interest rate in the 1980s. Plugging into the model the average real interest rate over the last five years, the model generates a risk-premium increase consistent with the one observed in the data, which explains the increase in firms' risky asset holdings.

Small vs. Large Firms

After establishing that risky assets held by nonfinancial firms have been increasing both as a share of firms' total assets and as a share of financial assets, I proceed by analyzing which firms hold the risky assets. To do so, I use the survey data Quarterly Financial Report (QFR) conducted every quarter by the Census Bureau, which, in comparison to Compustat, has the advantage of including small, non-publicly listed firms. The survey covers four sectors of the US economy: manufacturing, mining, wholesale, and retail trade. The survey excludes manufacturing firms with total assets below $250,000 and for the remaining sectors, firms with assets below $50 mil-

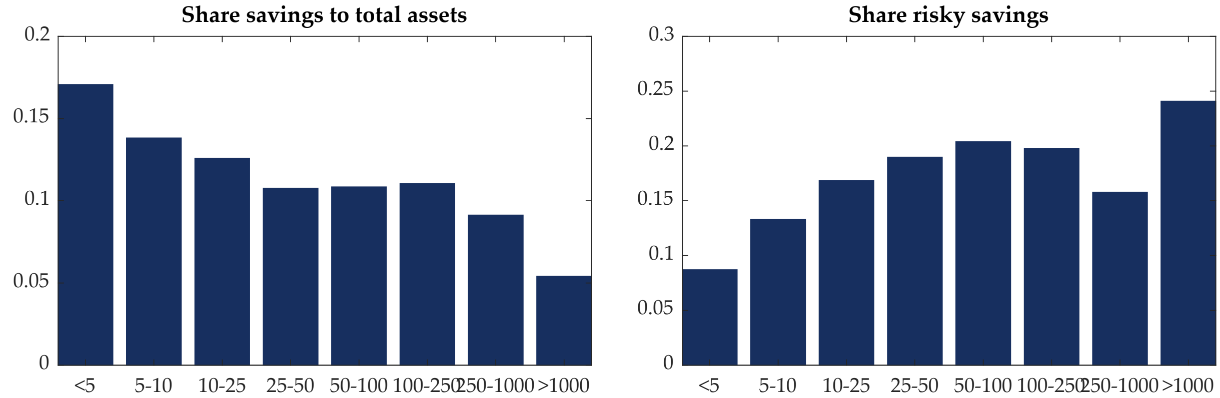

Figure 3: The left panel shows the average savings to total assets over the 2001-2018 period by bin size for manufacturing firms. The right panel shows the average share of risky financial assets over the 2001-2018 by bin size for manufacturing firms. The respective size bins are on the x-axis. Data from Quarterly Financial Report, Census Bureau.

lion. For this reason, I consider only the manufacturing sector.[5]

The QFR has two drawbacks: (1) It is not at the firm level, with data being aggregated into size bins, which limits my ability to order firms by risky asset holdings, size, or other financial variables; and (2) the size bins are in nominal terms, which with nominal and real growth will cause firms to drift from the lower to the highest bins. Because I am interested in the share of risky asset holdings within bins and not the total amount, this controls for the two potential problems as the share risky assets is not affected by the number of firms in each size bins.

Figure 3 shows the average shares of financial to total assets in the left panel and the percentage of risky to financial assets in the right panel. To cover the same sample period as with the Compustat data in the next section, I compute the averages over the 2001-2018 period for the different size bins.[6] Notice that despite firms in the lower size bins having more financial securities as a percentage of total assets, they are also the groups that hold mainly cash or risk-free, near-cash securities. For the larger size bins, firms tend to hold less financial securities as

[5]The dataset is a stratified random sample. This stratification is done by size. Since 1982, firms with a book value of assets above \$250 million are sampled with certainty. The remaining firms are randomly selected, and once they are selected, they stay in the survey for eight quarters. So, approximately one eight of the sample is rotating every quarter. A firm, after being surveyed for eight quarters, if it has assets below \$50 million is not eligible to be surveyed again for the next 10 years. If it has assets between \$50 and \$250 million, is not eligible for selection again over the following two years.

[6]The QFR has eight size bins in total: firms with total assets under \$5 million, between \$5 million and \$10 million, from \$10 million to less than \$25 million, from \$25 million to \$50 million, above \$50 million to less than \$100 million, between \$100 million and \$250 million, starting at \$250 million until \$1 billion and above \$1 billion. These are the size bins presented in Figure 3.

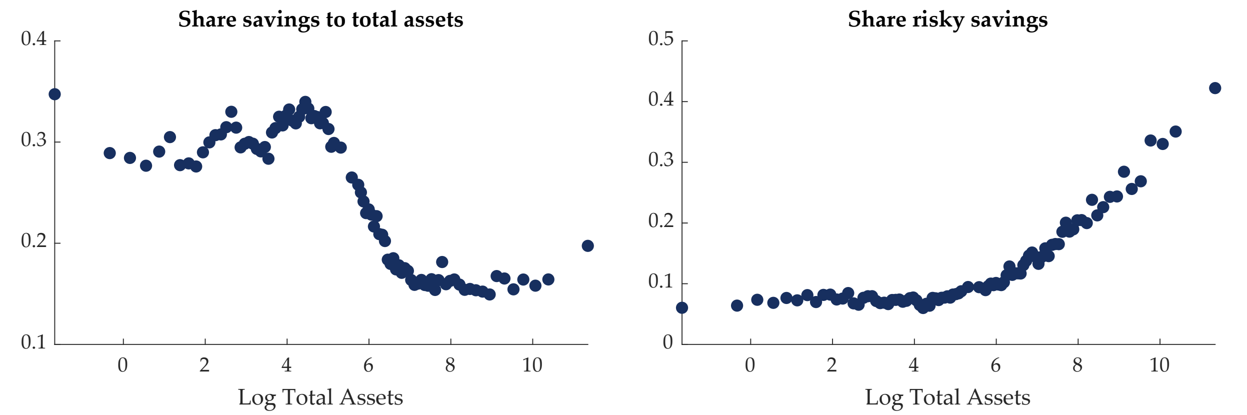

Figure 4: The left panel shows the share of savings to total assets on the y-axis and log(total assets) on the x-axis. As firms grow in size, they decrease their savings rate, but from a certain size onwards, they start accumulating more savings again. The right panel shows the share of risky savings on the y-axis and log(total assets) on the x-axis. As firms grow in size, they increase their holding of risky assets.

a percentage of total assets but have a larger share of risky securities.

Distribution among larger firms

The QFR data, despite the identified problems, illustrates that the majority of risky assets are held by the larger firms. Therefore, I proceed by using the data for publicly listed firms to illustrate the distribution of risky assets among the larger firms. For this purpose, I use Compustat data from 2001 to 2018. Because no microdata are available on the financial assets constituting the nonfinancial firms' portfolios, I consider as a proxy for risky assets 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.[7]

To establish the relation between overall savings and the size of the firm, I use the ratio between total savings ("cash and cash equivalents" plus "long-term investment") divided by Compustat item "total assets". 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.

Figure 4 illustrates that smaller firms have, on average, a larger share of their total assets as savings but hold less than 10% in risky securities. As firms grow, the share of savings shrinks, but the percentage of risky asset holdings increases. At a given point, firms start accumulating

[7] 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.

more savings again, continuing to increase the share of risky assets. Both of these facts are in accordance with the findings from the QFR data, with smaller firms having, on average, more financial assets, but holding mainly cash or risk-free, near-cash securities, with larger firms holding riskier portfolios.

Corporate bond holdings

In this section, I focus on one particular asset among the risky ones - corporate bonds - for two reasons: (1) By the end of 2017, corporate bonds represented more than 60% of risky assets held by nonfinancial firms; (2) corporate bonds have a different risk profile than government bonds other then treasuries, which, according to the Basel III agreement, have a risk weight of 50%, whereas corporate bonds are 100% weighted.

For these reasons, I collect data on corporate bond holdings by nonfinancial publicly listed firms in the US in the period spanning from 2009 to 2017.[8] 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 Analysis 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 B.1.[9]

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 18 to 21 in Appendix B.1). More importantly, the distribution of corporate bond holdings is similar to that of overall risky assets, as illustrated in Figure 22 in Appendix B.1, with the market value of corporate bond holdings

[8] 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 B.1 for further details on the data-collection procedure.

[9] 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.

increasing with the size of the firm.[10]

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 8 to 11 in Appendix B.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 23 to 26 in Appendix B.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.

Risky asset holding consequences

After establishing which firms hold the risky assets and that the holdings of this type of security have been increasing both in value and in the percentage of total assets since the early 1980s, I proceed to answer the second main question of this paper: What are the consequences of the increase in risky asset holdings by nonfinancial firms? Intuitively, one could think of several reasons why a firm response to a shock could be affected by the financial-assets portfolio. For example, during the Great Recession, firms with a higher fraction of risky securities could have sustained larger losses, due to the drop in the value of their financial assets. This decrease in financial assets' value may have several negative impacts: (1) reduces the internal financing available, (2) decreases the value of collateral due to the drop in the assets' value, and (3) raises leverage ratios as assets lose value.

I proceed in two steps: (1) I use Compustat data on risky and risk-free asset holdings to assess how firms' financial-assets portfolio composition affected the investment during the Great

[10] 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.

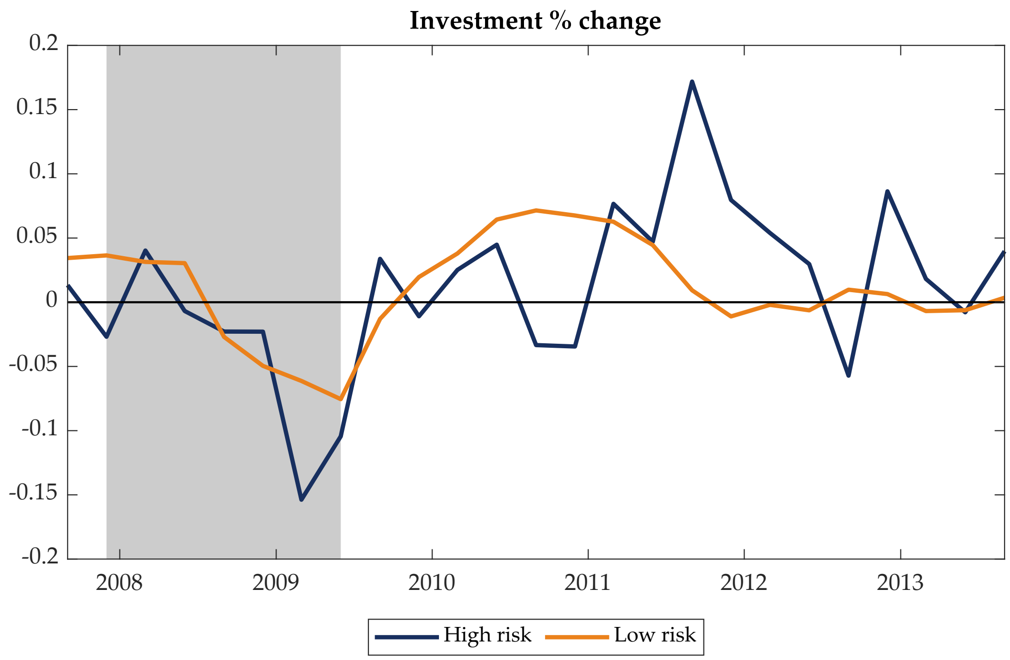

Figure 5: On the y-axis the average investment % change. Blue and orange line represent the firms with the share of risky assets above 70% and below 30%, respectively. Firms with a larger share of risky assets, on average, dropped investment by more during the crisis (15.8% and 7.2% investment drop during the Great Recession for firms with high and low share of risky savings, respectively.)

Recession, and (2) assess how firms' investment sensitivity to aggregate volatility depends on corporate bond holdings.

Compustat Data

To validate the intuition that firms' financial portfolio composition affects their response to shocks, starting with a non-parametric approach and looking for signs of different investment responses during the Great Recession depending on the share of risky asset holdings is instructive. In Figure 5, we can see the average percentage change in investment during the Great Recession by firms with a share of risky assets above 70% (blue line) and below 30% (orange line). The figure shows that firms with a riskier portfolio of financial assets lower their investment by more during this period. Firms with a high share of risky asset holdings lower their investment, on average, by 15.8%, twice as much as firms with a low-risk portfolio of financial assets.

In Figure 27 in Appendix B.2, I present smoothed deviations from investment HP trend during the financial crisis. I compare two different groups of firms: (1) firms with a share of risky assets above 70% and below 30%, similar to Figure 5 and (2) firms with a positive share against firms with zero risky assets. Conclusions are robust across both cases, with trend investment during the Great Recession reducing considerably more for firms with a higher share of risky assets.

To formally test how investment response during crises depends on firms' financial portfolio, I estimate the following difference-in-differences specification:

$$ln(Inv)_{ijt} = \gamma crisis_t + \alpha risky_{ij2008Q2} + \beta crisis_t * risky_{ij2008Q2} + \lambda_i + \theta_{jt} + \epsilon_{ijt}, \qquad (1)$$

where crisis is a dummy variable equal to 1 between 2008 and 2010, $risky_{ij2008Q2}$ 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 (1) is presented in column (1) of Table 1. I here consider the dummy $risky_{ij2007}$ equal to 1 if a firm holds more than 70% of risky financial securities, similar to Figure 5. As suggested by the non-parametric approach, 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), respectively, of Table 1 respectively, 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 28 to 30 in Appendix B.2 present some robustness tests for the threshold values to

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

Table 1: β coefficient from specification (1) 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.

split among the two groups of firms. Figure 28 presents the specification (1) β coefficient for threshold value spanning from 0 to 0.7. Figures 29 and 30 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.

Web-scraping data

I now proceed to assess if firms' investment response to shocks also depends on the share of corporate bonds. Because data are available only from 2009 onwards, I cannot replicate the same exercise as I did with the Compustat data, to assess 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 (1) 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 the yearly volatility of the S&P500 daily returns in year t-1 $S\&P\_vol_{t-1}$, the volatility

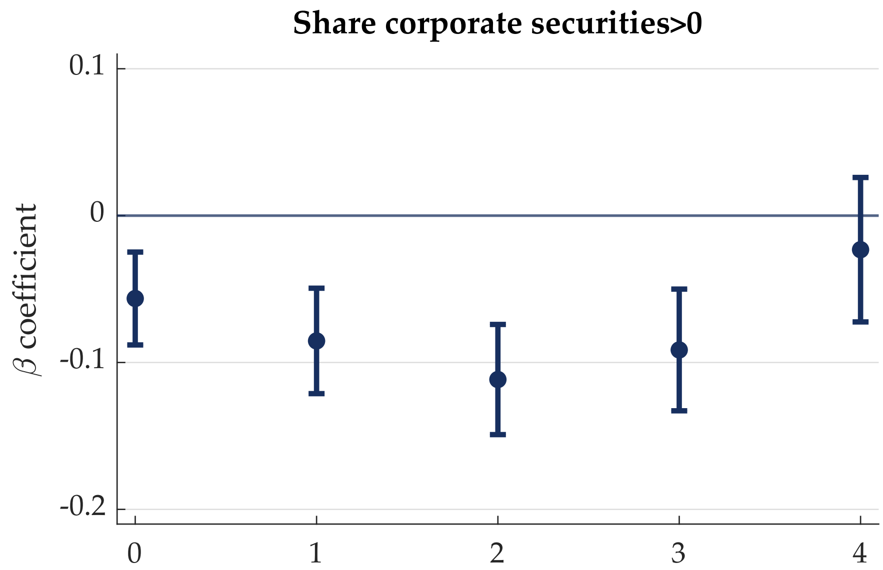

Figure 6: On the y-axis we have the β coefficient from equation (2), and on the x-axis, horizon h. Error bars represent the 95% confidence interval. Results indicate increases in volatility have a stronger negative effect on firms with a positive amount of corporate bond holdings, up to three years after.

measure used by Bloom et al. (2007), while controlling for firm fixed effects λ_i and sector fixed effects θ_j:

$$ln(Inv)_{ijt+h} = \gamma S\&P\_vol_{t-1} + \alpha risky_{ijt-1} + \beta S\&P\_vol_{t-1} * risky_{ijt-1} + \lambda_i + \theta_j + \epsilon_{ijt}. \quad (2)$$

I equally 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 6 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 31 to 33 in Appendix B.2.[11]

[11] 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 indeed have a different risk profile that more strongly

3 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 (lend to other firms). 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 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.[12]

Figure 7 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 ($\hat{a}_f^r$).[13] Firms reoptimize the asset side to maximize the expected discounted value given

affects firms' investment decisions.

[12]This assumption is motivated by the fact that the variation (measure 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).

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

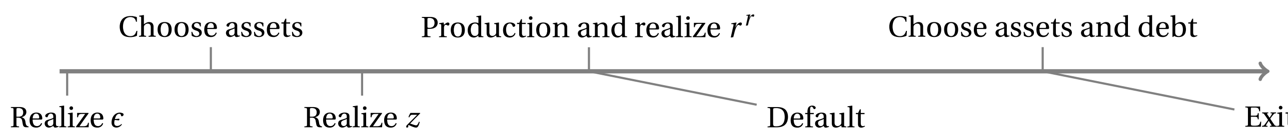

Figure 7: Firms timing in the model

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.[14] With probability η, a firm will leave the market and all its remaining assets will be distributed as dividends to households. This assumption guarantees not all firms will outgrow financial constraints in the model, and thus results in a firm distribution more in line with the data.[15]

Upon surviving the exogenous shock, firms enter in 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:

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

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

$$y = \epsilon z k^{\alpha}, \tag{3}$$

where I assume the idiosyncratic shock ϵ follows a Markov chains, $\epsilon \in E \equiv \left(\epsilon_1, ..., \epsilon_{N_\epsilon}\right)$, where $Pr(\epsilon' = \epsilon_i | \epsilon = \epsilon_j) \equiv \pi^{\epsilon}_{ij} \leq 0$ and $\sum_{j=1}^{N_\epsilon} \pi^{\epsilon}_{ij} = 1$, and aggregate productivity z also follows a Markov chain , $z \in Z \equiv \left(z, ..., z_{N_z}\right)$, where $Pr(z' = z_i | z = z_j) \equiv \pi^{z}_{ij} \leq 0$ and $\sum_{j=1}^{N_z} \pi^{z}_{ij} = 1$. 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. This assumption is important for two reasons: (1) Generates a firm distribution more in line with the data, and (2) helps discipline the firms' savings portfolio. As firms grow and their default probability declines, firms will not jump to the optimal amount of capital right away, due to the convex adjustment costs. During this growth stage, firms share of savings allocated towards corporate bonds grows in order to maximize expected returns on savings, which will be key to the mechanism, because these firms' exposure to the cycle increases with the share of risky savings.

The adjustment costs take on the following form:

$$g(k', \hat{k}) = \frac{F_{k_1,t}}{2} \left(\frac{k' - (1-\delta)\hat{k}}{\hat{k}} \right)^2 \hat{k}, \tag{4}$$

with

$$F_{k_1,t} \equiv p^+_k \times \mathbb{1}_{[(k'-(1-\delta)\hat{k})>0]} + p^-_k \times \left(1 - \mathbb{1}_{[(k'-(1-\delta)\hat{k})>0]}\right), \tag{5}$$

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 variable equal to 1 if the firm increases capital. Additionally, similar to other papers in the literature (see, e.g. Abel and Eberly (1996) , Begenau and Salomao (2018b)), I assume $0 \leq p^-_k < p^+_k$, which captures the costly reversibility of investment. This assumption amplifies the riskiness of capital because a firm cannot invest today without considering the cost of downsizing if a negative shock happens, generating inaction regions. This assumption, again, is key to mechanism. As firms postpone investment decisions, they accumulate savings, and the larger the firm is, the more likely it is to save in risky assets and the more it is affected by variations in the cycle.

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

$$g(\hat{k}, k) = \frac{F_{k_1,t}}{2}\left(\frac{\hat{k}-k}{k}\right)^2 k, \tag{6}$$

with

$$F_{k_1,t} \equiv p_k^+ \times \mathbb{1}_{[(\hat{k}-k)>0]} + p_k^- \times \left(1 - \mathbb{1}_{[(\hat{k}-k)>0]}\right). \tag{7}$$

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 savings, and credit to provide to other companies, as well as debt. 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

$$\hat{x} = y - C_f - b + (1 + r^{rf})\hat{a_f^{rf}} + (1 + r^r)\hat{a_f^r}, \tag{8}$$

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).[16]

Given this default rule, the default thresholds for aggregate productivity and return on risky

[16]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 and Quadrini (2001), Hennessy and 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.

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

$$\underline{z} = \frac{C_f + b - (1 + r^{rf})\hat{a}_f^{rf} - (1 + r^r)\hat{a}_f^r - p_k^-(1-\delta)\hat{k}}{\epsilon \hat{k}^\alpha}, \tag{9}$$

$$\underline{r}^r = \frac{C_f + b - (1 + r^{rf})\hat{a}_f^{rf} - p_k^-(1-\delta)\hat{k} - y(z)}{\hat{a}_f^r} - 1. \tag{10}$$

Conditional on surviving the default and exogenous exit stages, firms continue to the next period and decide whether to distribute dividends among its shareholders. Firms still growing value liquidity more than dividends and will adopt a zero-dividend policy. If the firm decides to distribute dividends, following Chen et al. (2017), I assume the firm's dividend policy targets a value dependent on capital and revenues and is given by

$$d = \kappa y^{\kappa_y} \hat{k}^{\kappa_k}, \tag{11}$$

where κ, κ_k and κ_y are parameters that will be directly calibrated from the data and will determine how the dividend depends on firms' profits and capital. This dividend policy will capture the dividend rigidity observed in the data.

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 after the exit shock $V^1(\epsilon, \hat{k}, \hat{x}, S)$. 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 is given by

$$
\begin{aligned}
V^1(\epsilon, \hat{k}, \hat{x}, S) = & \max_{k', b', a_f^{rf'}, a_f^{r'}, d} \quad d + \beta E[\hat{V}^0(\epsilon', k', x', S)] \qquad (12) \\
s.t: \quad & x' = a_f^{rf'} + a_f^{r'} \\
& d = \begin{cases} 0 \\ \kappa y^{\kappa_y} \hat{k}^{\kappa_k} \end{cases} \\
& g(k', \hat{k}) = \frac{F_{k_1,t}}{2} \left(\frac{k' - (1-\delta)\hat{k}}{\hat{k}} \right)^2 \hat{k}.
\end{aligned}
$$

To simplify the problem computationally, I assume firms only distribute dividends when they face a zero probability of default. As Khan and Thomas (2013) show, firms do not distribute dividends unless they assign zero probability of being constrained in any future state. In their setup, because firms have the same discount factor as households, they prefer to save rather than distribute dividends for precautionary reasons, so they diminish the probability of being constrained in the future.

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

$$\hat{V^0}(\epsilon', k', x', b', S) = \max_{\hat{k}', \hat{a}_f^{rf'}, \hat{a}_f^{r'}} \left[\int_{\underline{r}^{r'}} \int_{\underline{z}'} V^0(\epsilon', \hat{k}', \hat{x}', S') dF(\epsilon') dF(S') \right] \tag{13}$$

$$s.t: \quad \hat{a}_f^{r'} + \hat{a}_f^{rf'} + g(\hat{k}', k') \leq a_f^{r'} + a_f^{rf'}$$

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

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

$$S' = \Gamma^{S'}(S)$$

$$E(r^{r'}) = \Lambda(S').$$

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 $E(r^{r'}) = \Lambda(S')$. V^0 is the value of the firm after the debt settlement and production stage but before the exit shock, defined as

$$V^0(\epsilon', \hat{k}', \hat{x}', S') = (1 - \eta) V^1(\epsilon', \hat{k}', \hat{x}', S') + \eta(\hat{x}' + p_k^-(1 - \delta)\hat{k}'), \tag{14}$$

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

Potential Entrants

A continuum of potential entrants is endowed with an initial amount of capital k_0, which is targeted to be a given percentage of incumbents' average capital. Potential entrants draw a signal for their productivity tomorrow ϵ_0, which will follow the same Markov chain as incumbents' productivity. At the end of the period, potential entrants decide whether to enter and pay the fixed cost f_e or stay out of the market. Entry is feasible if the amount of debt the potential entrant can raise is enough to pay for the fixed entry costs and if the value of entering is larger than continuing out. Once it enters, the firm chooses capital and risk-free and risky assets for next period to solve $V^1(\epsilon_0, k_0, 0, S)$

$$V_e(\epsilon_0, k_0, 0, S) = \max(0, V^1(\epsilon_0, k_0, 0, S) - f_e). \tag{15}$$

To simplify the problem computationally, I follow Arellano et al. (2016), and from the set of firms for whom entering is optimal, I randomly select a subset that guarantees the number of entering firms is equal to the number of exiting firms.

Financial Intermediary

The financial intermediary collects the risky savings from firms a_f^r and uses it 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 and 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 and Thomas (2013), Khan et al. (2017), Ottonello and Winberry (2018)), 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 and Uhlig (2011) and Gande and 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 a risk premium ω:

$$q^r = q^{rf} - \omega. \tag{16}$$

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

$$1 + r^r = \frac{\frac{1}{q^r}\int_{non-default} b_{non-default} d\mu + \int_{default} \min(b_{default}, \chi((\hat{x}_{default} + p_k^- \hat{k}_{default}))) d\mu}{\int b d\mu}. \tag{17}$$

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:

$$
\begin{aligned}
W^f(\phi,S) = \max_{\phi'} D^f + E[d_{S'}(S)W^f(\phi',S')] \quad (18)\\
s.t: \quad D^f = \int (1-\mathbb{1}_{[default]}(\epsilon,k,x,S))\phi d[\epsilon\times k\times x]\\
+\int \mathbb{1}_{[default]}(\epsilon,k,x,S)\min(\chi(x'+p_k^- k),\phi)d[\epsilon\times k\times x]\\
\int a_f^{r'} d\mu = \int q^r(\epsilon,k,x,S)\phi' d\mu.
\end{aligned}
$$

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 (12), (13), and (14).

ii. Financier value and policy functions solve the financier problem (18).

iii. Debt price satisfies equation (16) and return on debt satisfies equation (17).

iv. The measure of firms evolves according to

$$
\mu' = \eta\int (1-\mathbb{1}_{[default]}(z,k,x,S))\phi d[z\times k\times x] + \mu_e. \quad (19)
$$

4 Calibration and Model Fit

In this section, I first elaborate on the calibration strategy and the numerical algorithm to solve the model. Then, I analyze the steady-state firm distribution and how it compares to the data.

4.1 Calibration

The length of each period is one year, in line with the data I use in section C to validate some of the 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 2.

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 and Thomas (2013) and set to 0.6. Lastly, the discount factor is set to 0.96.

Parameters with a direct counterpart in the data: 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.

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 and Thomas (2013)
Dividend Policy			
κ	0.727	Constant	Compustat
κ_k	0.070	Dividend sensitivity to capital	Compustat
κ_y	0.479	Dividend sensitivity to sales	Compustat
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 2: Parameters

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

The elasticities κ_k and κ_y as well as κ are estimated empirically using the following regression, in the spirit of Chen et al. (2017):

$$\ln(Dividends)_{ijt} = \kappa + \kappa_y \ln(Revenues)_{ijt} + \kappa_k \ln(TotalAssets)_{ijt} + \lambda_i + \theta_{jt} + \epsilon_{ijt}, \qquad (20)$$

where i stands for firm, j for sector, and t for year. λ_i and θ_{jt} are firm and sector-year fixed effects, respectively. Values obtained are $\kappa = 0.727$, $\kappa_k = 0.070$, and $\kappa_y = 0.479$. The elasticity with respect to revenues being less than one indicates the dividend is relatively rigid and does

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 3: Calibration fit

not fluctuate as much as revenues. The dividend's smoothness will induce savings by large firms to guarantee they can maintain a constant dividend even when profits decrease.

Because 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.

Endogenous parameters: The endogenous parameters are $\{C_f, f_e, \sigma_\epsilon, \sigma_z, \rho_z, \omega\}$. I use these six parameters to match six data moments: the exit rate of all firms, entrants' average leverage, share of total debt in new entrants, average and standard deviation of share of risky savings across the firm distribution, and the ratio between the average share of risky savings for firms in the top versus bottom quartile of total asset distribution. The first three moments are chosen to discipline the return on risky savings. In section 3, I establish that 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 my model, disciplining the size and leverage of these firms is important. The last three moments are important to discipline the distribution of risky asset holdings in the economy.

In Table 3, I present the model fit to the selected data moments. Although all parameters affect all model moments, identifying a more pronounced impact of some parameters on some moments is possible.

First, I target the default rate of all firms to be 8.24%, which is the average default rate over the 2003-2014 period from the LBD from the U.S. Census Bureau. Despite the risk premium affecting this moment through changing the cost of debt, the parameter that most directly affects this moment is the fixed cost of production, which is set to 8.006. The risk-premium ω delivered by the calibration is 0.01 and helps to match the average share of risk-free savings in the economy. Because I want to explain the observed increase in risky savings since late 1980s, here I target this moment at the end of the 1980s.[17]

The entrants' average leverage is from the Compustat sample of firms that went public in a given year over 2007-2017. This moment is mainly pinned down by the fixed cost of entry, set to 2.414. The other three moments are all matched using the volatility of both aggregate and idiosyncratic productivity, $\sigma_z = 0.074$ and $\sigma_\epsilon = 0.15$, as well as the persistence of the aggregate shock $\rho_z = 0.949$. Although the volatility of the idiosyncratic process has a stronger impact on the share of debt in one-year-old firms, the moments governing the aggregate productivity process help discipline the overall riskiness of corporate bonds and consequently match the standard deviation of the share of risky savings and the ratio between the average share of risky assets of firms in the third quartile versus the first quartile of the capital distribution.

4.2 Algorithm

The numerical algorithm I use employs the inner-and-outer loop proposed by Krusell and Smith (1998). I iterate between an inner loop that solves the firms' problem and an outer loop that simulates the economy for the equilibrium prices and updates the forecast rules until convergence in the equilibrium outcomes. I here provide a brief overview of the algorithm. For more details, check Appendix E.1.

In my 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 and 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

[17] Unfortunately, for the micro moments of the distribution of risky asset holdings, I do not have data going back to the 1980s. Therefore I use the Compustat data spanning from 2007 to 2017 and assume the distribution does not change across time, only the average holdings.

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}:

$$\begin{bmatrix} \log B^{f'} \\ \log K' \\ r_r \end{bmatrix} = A + B \begin{bmatrix} \log B^{f} \\ \log K \end{bmatrix} + C \log(z). \tag{21}$$

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.

5 Quantitative Analysis

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

5.1 Savings Distribution

I am interested in understanding the mechanisms that explain firms' portfolio of savings. To do so, I proceed incrementally and start with a simplified version of the model, that enables the understanding of the baseline mechanisms. I then go back to the full-scale model and identify the remaining mechanisms.

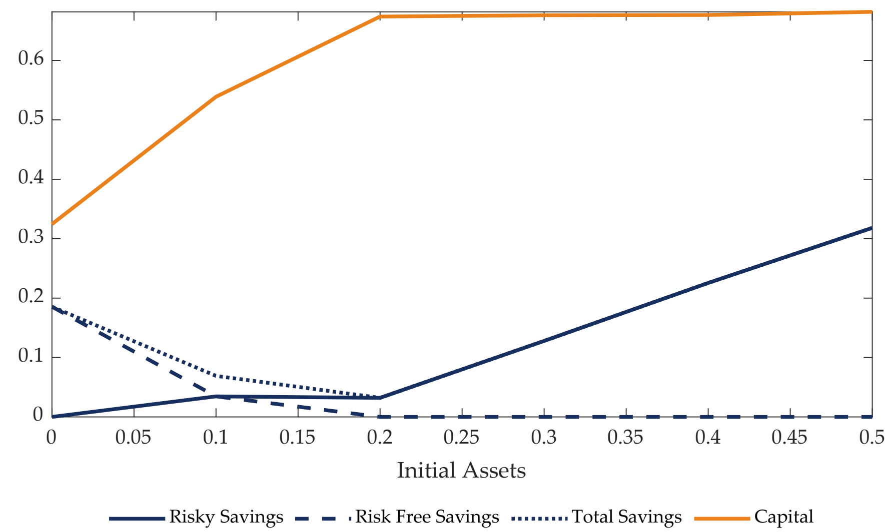

Figure 8: Capital (orange line), risky savings (blue solid line), risk-free savings (blue dashed line), and total savings (blue dotted line) for different initial endowments. As firms grow, they start savings less in risk-free assets and move into risky assets, while increasing capital.

Intratemporal effect: Precautionary savings

To illustrate the mechanisms at play in explaining firms' savings portfolios, I shut down some of the benchmark model features and keep only the necessary assumptions to explain the observed savings-portfolio composition across firms. Namely, I assume this model is static, with firms starting with a given endowment. Similar to the benchmark model, firms sequentially observe two productivity shocks, the idiosyncratic one ϵ followed by aggregate productivity z. At the beginning of the period, before observing ϵ, firms choose debt and, after observing ϵ but before observing z, they choose how to allocate their resources (debt + endowment) in capital or savings in a risk-free (with constant and known return) or/and risky asset (with uncertain return). Additionally, firms suffer no capital adjustment costs, and no other agents are in the economy. For more details on the model, see Appendix A.

This model generates a pattern between the size of the firm (initial endowment) and savings similar to the one illustrated in Figure 4. 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 8 illustrates this relation between the firm's size, savings, and portfolio composition. It shows how risky savings are increasing in the initial size of the firm, while risk-free savings are decreasing, just as observed empirically. Although firms are small, the probability of default is high, so firms save in risk-free assets to eliminate the default risk. 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. After implementing the optimal amount of capital, the firm will exclusively save in the risky asset to maximize the return on its savings.

Notice the firms are not only saving in risky assets after reaching the optimal amount of capital, which stems from a portfolio-diversification effect that will decrease the firms' probability of default while maximizing the returns on savings. Equations (26) and (27) in Appendix A 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.

To empirically test the mechanisms here identified, I use the collected data on corporate bond holdings by nonfinancial firms, used in section 2 and described in more detail in Appendix B.1. To test the precautionary-savings motive, I regress cash and corporate bond holdings on sales and debt. 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, sales should decrease the company's risk, leading to an increase in corporate securities held by the firm. Results in Table 12 in Appendix C.1 validate the mechanism illustrated in this section, with an increase in debt associated with larger increments in cash holdings, whereas an increase in revenue results in a larger accumulation of the risky asset corporate bonds. For more details, see Appendix C.1.

Intertemporal effect: Saving to finance future investment

From the static model, we learned that small firms tend to hold more risk-free savings for precautionary reasons, whereas large firms looking to maximize the returns on savings invest exclusively in the risky asset. In the benchmark model, the presence of partial irreversibility, with the cost of buying capital larger than the selling price, will add an extra motive for firms to hold

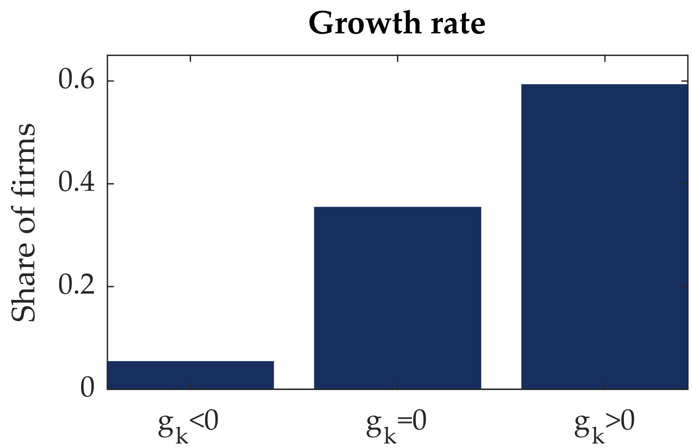

Figure 9: Share of firms with negative capital-growth ($g_k < 0$), positive growth ($g_k > 0$) and in inaction region ($g_k = 0$). Only firms not at the optimal amount of capital were considered. More than 30% of firms find themselves in inaction regions.

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.

Figure 9 shows the capital growth-rate distribution by non-defaulting firms, excluding firms at the optimal amount of capital. More than 30% of these firms find themselves in inaction regions, where they make no investment in capital. These firms will instead save to finance future investments. The left panel of Figure 10 plots the distribution of savings by firms in the inaction reaction, whereas the right panel plots the savings distribution by firms with a capital growth rate larger than zero. Although 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 4 reports the average risky savings and the fraction of firms with a share of risky savings equal to 0 for firms in inaction regions and growing regions. The differences are significant. Although more than 75% of growing firms do not hold any risky savings, this number is close to 50% for firms in inaction regions. Also, the average share of risky savings more than doubles, going from 16% to more than 38%.

Moment	$g_k = 0$	$g_k > 0$
Average share risky savings	38.2%	16.3%
Share risky=0	52.7%	75.8%

Table 4: Average share of risky savings and fraction of firms with risky savings equal to 0 for firms in inaction regions ($g_k = 0$) and growing firms ($g_k > 0$).

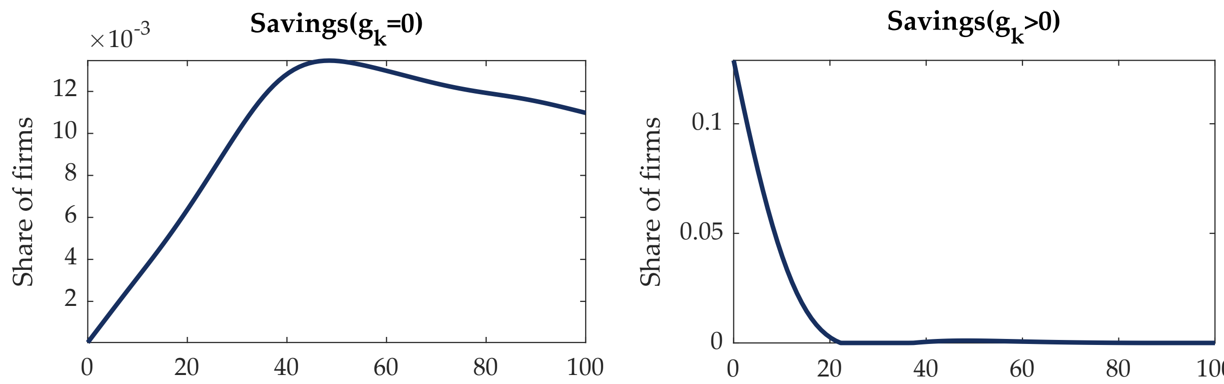

Figure 10: Savings distribution by firms in the inaction region (growth rate of capital g_k equal to 0) in the left panel, and by growing firms in the right panel. Although the majority of growing firms have zero savings, firms in the inaction region accumulate savings to finance future investments.

The inclusion of partial irreversibility of capital in the model is then crucial in generating firms that are not yet at the optimal amount of capital but that already hold large fractions of risky savings. Figure 11 compares the distribution of risky savings across the different size bins in the 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 saving to avoid becoming constrained again and to guarantee they can pay the smooth dividend, holding mainly risky securities; firms in the middle of the distribution saving to finance future investments, holding some fraction of risky assets. [18]

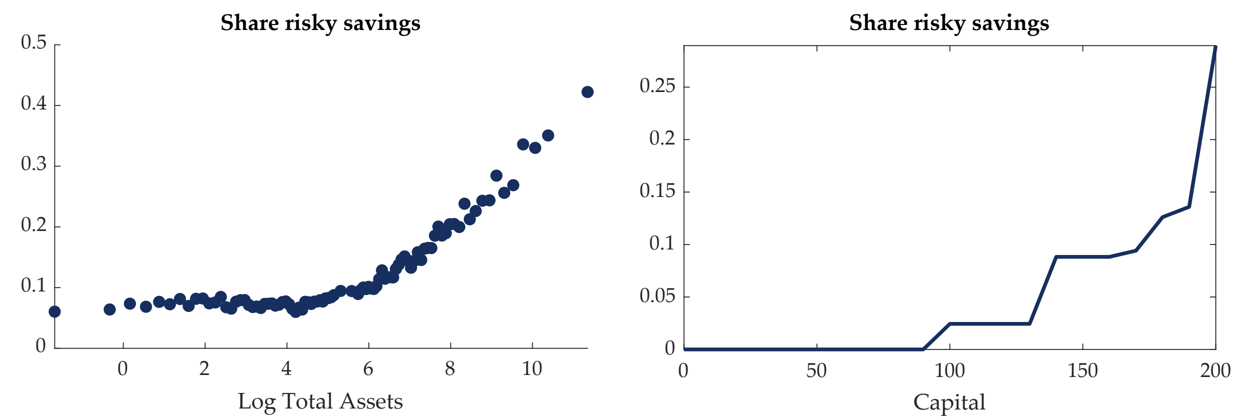

Figure 11: On the left panel, the empirical relation between the share of risk-free savings — on the y-axis — and log(total assets) — on the x-axis. On the right panel, the same relation in the model, with the share of risk-free savings on the y-axis and capital on the x-axis. As firms grow in size, they increase their holding of risky assets both empirically and in the model.

[18] Figure 35 in Appendix F.2 shows the model does a good job in matching the standard deviations of risky savings across the size distribution. 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.

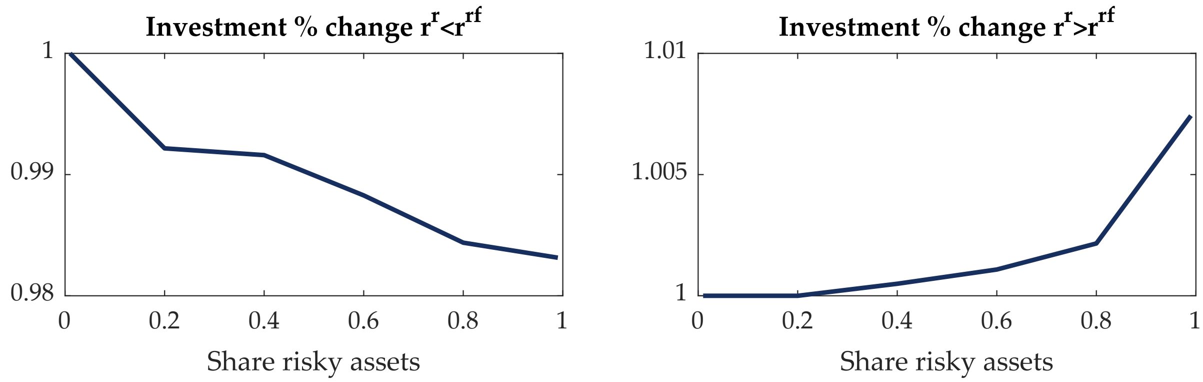

Figure 12: Investment change relative to risk-free-only scenario, for different levels of risky savings. In the left panel, investment % change when r^r falls below r^{rf}, and in the right panel, when r^r is above r^{rf}. Investment is sensitive to the share of risky assets. In periods when r^r falls below r^{rf} investment can be up to 2% lower, whereas in periods when r^r is above r^{rf} investment can be up to 1% higher.

5.2 *Micro Implications of Savings Portfolio*

I next study how the savings portfolio affects firms' investment decisions and probability of default. To isolate this effect, I use the benchmark calibration parameters while changing the share of risky asset holdings from 0% to 100%. Instead of allowing firms to optimally choose this share, I impose it to compare investment decisions across the same firms with just a different share of risky savings.

Figure 12 reports the investment % change relative to the risk-free only scenario, for different levels of risky savings. The left panel illustrates the case when the return on the risky asset r^r falls below the risk-free interest rate r^{rf}, while the right panel reports the opposite situation, when r^r is above r^{rf}. Results indicate investment is sensitive to the composition of the savings portfolio. In the scenario in which r^r falls bellow the risk-free rate, investment drops by almost 2% when increasing the share of risky assets from 0 to 1. The sensitivity is amplified if we would consider only periods when r^r falls below 0 and firms lose part of their savings. In this situation, the investment drop is above 4%, as illustrated in Figure 36 in Appendix F.2. In the opposite scenario, when r^r is above r^{rf}, investment can increase by almost 1%, as depicted in the right panel of Figure 12.

Figure 13 illustrates that the portfolio of savings not only affects investment, but also causes some firms to default in periods when r^r drops below r^{rf}. Again, this effect is amplified when considering periods when r^r falls below 0, as reported in Figure 37 in Appendix F.2.

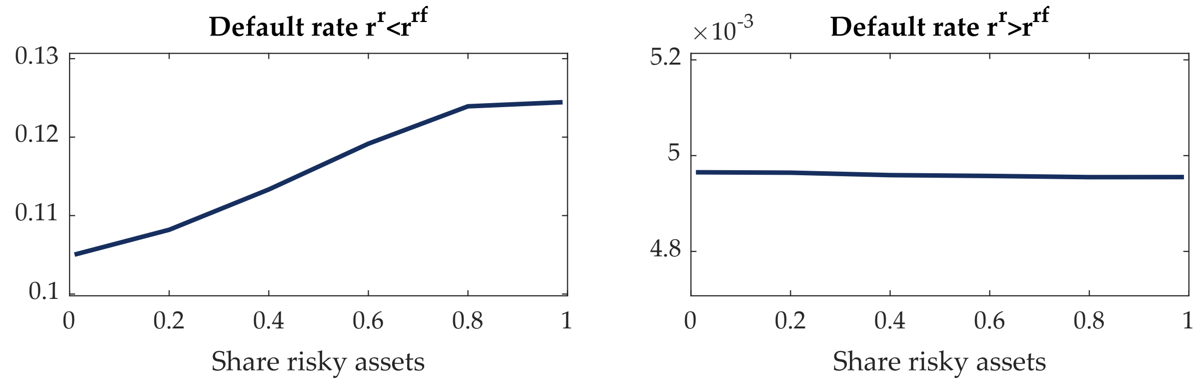

Figure 13: Investment change relative to risk-free only scenario, for different levels of risky savings. In the left panel investment % changes when r^r falls below r^{rf}, and in the right panel, when r^r is above r^{rf}.

5.3 Aggregate Consequences

With the distribution of risky asset holdings and the micro consequences of the savings portfolio, 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 rationalize the increase in risky asset holdings since the beginning of the 1990s, I feed into the model the observed real interest-rate path over the last several decades. The benchmark calibration, discussed in section 4.1, 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 the same year. In this section, I compare the benchmark calibration with a model with 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 explained by the change in the real interest rate.[19]

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

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

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

in the share of risky asset holdings.

Results are presented in Table 5. The observed variation in the data from 1989 to 2017 is a 12.71 percentage-point increase in the share of risky savings. My 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 14, which plots the distributions of firms for both the 1989 and 2017 calibrations. The Figure shows the increase in the share of 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 11, large firms have a riskier savings portfolio.

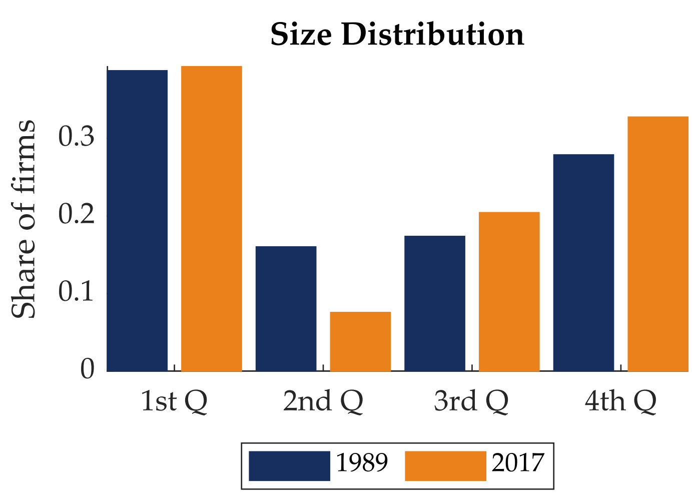

Figure 14: Firm size distribution for the 1989 calibration (blue bars) and 2017 calibration (orange bars). The Figure plots the share of firms (y-axis) in each quartile of the distribution (x-axis). With the decrease in the interest rate there is a shift of the distribution to the right, with a larger fraction of firms at the top of the distribution.

Moment	Variation	Contribution
Excess return	0.32p.p.	86.8%
Distribution		13.2%

Table 6: Components of the increase in risky asset holdings. The shift to the right of the distribution explains 13% of the increase, whereas the increase in the excess return explains 87%.

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.[20] Overall, the shift of the distribution to the right explains 13% of the increase in risky asset holdings, whereas the increase in the excess return explains the remaining 87%, as reported in Table 6.

In Appendix C.1, I test empirically if the real interest rate and risk premium are determinants of risky asset holdings. Again, I use the collected data on corporate bond holdings. Table 13 in Appendix C.1 shows that increases in the real interest rate are associated with decreases in the share of risky asset holdings, whereas increases in the risk premium have the opposite effect. For more details, see Appendix C.1.[21]

In appendix F.1, I illustrate that the interest-rate passthrough to capital is more limited when accounting for different types of financial assets. The inclusion of a risky asset limits the capital increase in response to a decrease in the interest rate, because an endogenous increase occurs in the excess return on risky assets.

[20] 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%).

[21] Another potential aggregate determinant of risky asset holdings is the volatility of the aggregate productivity shock. This variable has a strong impact on the risky asset expected return and consequently on firms' willingness to have a riskier savings portfolio. An increase in volatility generates a spike in corporate bonds' riskiness because it may translate into larger recessions and, therefore, sharper increases in default rates and decreases in the risky savings return. This increase in volatility would then cause firms to reallocate their portfolio of savings into the risk-free asset. See Figure 40 in Appendix F.2 for an illustration of the impact of this variable on risky asset holdings. Although, empirically, since the 1980s, no apparent sustained change occurs in the aggregate volatility – measured either by the VIX index or by the volatility of the daily returns on the S&P 500 – that can help justify the risky asset increasing trend. Figure 34 in Appendix F.2 presents the evolution of both variables since the 1980s.

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 7: 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.

Aggregate Outcomes

Lastly, I assess the macroeconomic implications of firms' savings portfolio. I start by comparing the aggregate responses to small and large negative productivity and financial shocks in a model with no risky assets and in my benchmark model. A small shock is characterized by a 1% drop in both aggregate productivity and the recovery rate, whereas a large shock represents a 10% decrease in aggregate productivity and a 33% drop in the recovery rate. In Table 7, 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, just as the mechanism identified in section 5.2 predicts.

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

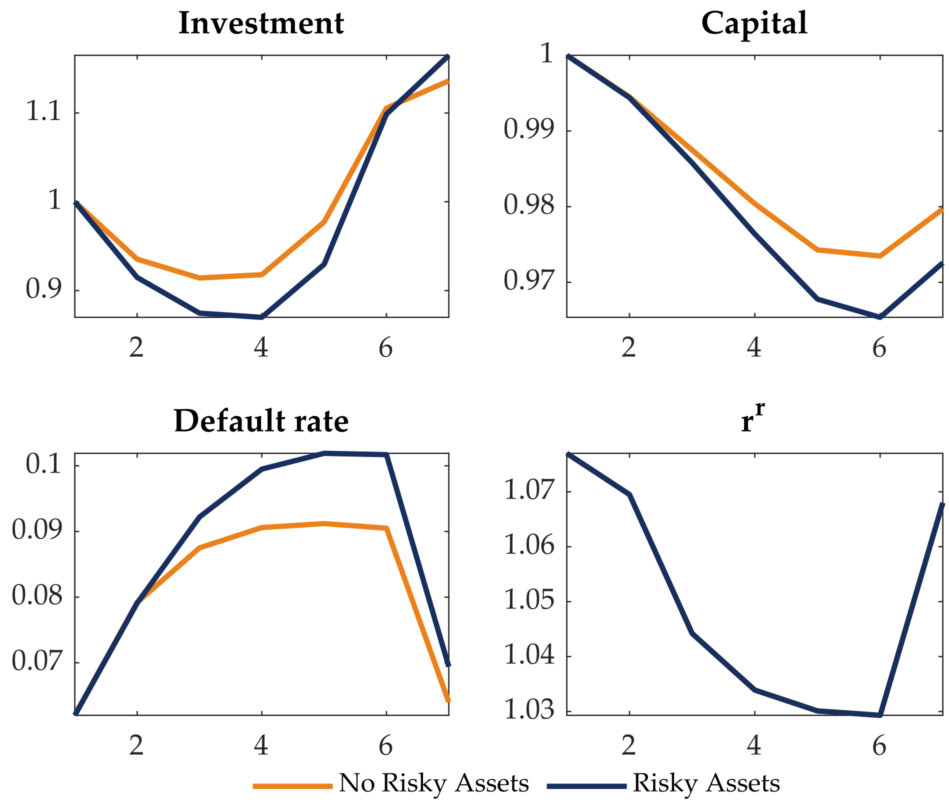

Figure 15: Impulse response functions to a negative financial and productivity shock. The top panels show the investment (left) and capital (right) responses to the shock. The bottom panel shows the default rate (left) and return on risky assets (right). The orange line represents the model with no risky asset, and the blue line represents the economy with only risky assets. The capital drop is up to 30% larger in the risky savings model, and the investment drop is up to 50% larger.

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.

I now proceed by comparing the impulse response functions to both negative productivity and financial shocks in the model with no risky savings with a model with only risky savings. 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.

Figure 15 presents the impulse response functions to both shocks in the two models. When the negative productivity shock takes place, some firms close to the default threshold end up leaving the market, causing the share of defaulted debt to increase. This effect, together with the drop in the recovery rate, causes the return on risky assets to decrease. As Figure 13 shows, the more exposed firms are to risky assets, the higher the sensitivity of the default rate to r^r.

In this scenario, the economy with a larger fraction of risky savings, experiences a sharper increase in the default rates, which causes r^r to decrease even more. As illustrated in Figure 12, the larger the share of risky savings, the more investment becomes sensitive to r^r. This mechanism, together with the stronger drop in r^r, explain the sharper decrease in investment, and consequently capital, in the risky asset economy. Overall, the investment drop ends up being 50% larger in the risky asset model, which causes capital to decrease 30% more.

I conclude this section by using my model to obtain estimates of the impact of the portfolio of savings on the macroeconomy on average over the business-cycle. Table 17 in Appendix F.2 presents the values for different aggregate variables in an economy with only risky savings relative to a risk-free savings only. On average, given that the identified mechanism only triggers in large recessions that are rare over the business-cycle, effects are, on average, small. Nonetheless, the amplification of large recessions causes average default rates to be higher, which leads to lower capital and consequently output.

On the opposite side, the increase in risky holdings leads to a decline in capital misallocation. The higher default rates are a consequence of less productive firms leaving the market. At the same time, the firms that survive are the more productive ones that can take advantage of faster growth during periods when r^r is above r^{rf}. Both effects will cause a larger share of capital to be allocated in smaller more productive firms, decreasing the capital misallocation. Overall, the increase in risky savings diminishes capital misallocation but at the cost of lower output and more volatility.

6 Policy Implications

In this section I assess two different types of policies and their effects both on the firms' incentives to hold risky assets and on how they may limit the propagation of aggregate shocks. First, I study the impact of a market liquidity provision policy, which would limit risky asset losses during large negative shocks. Second, I evaluate the impact of implementing some of the financial

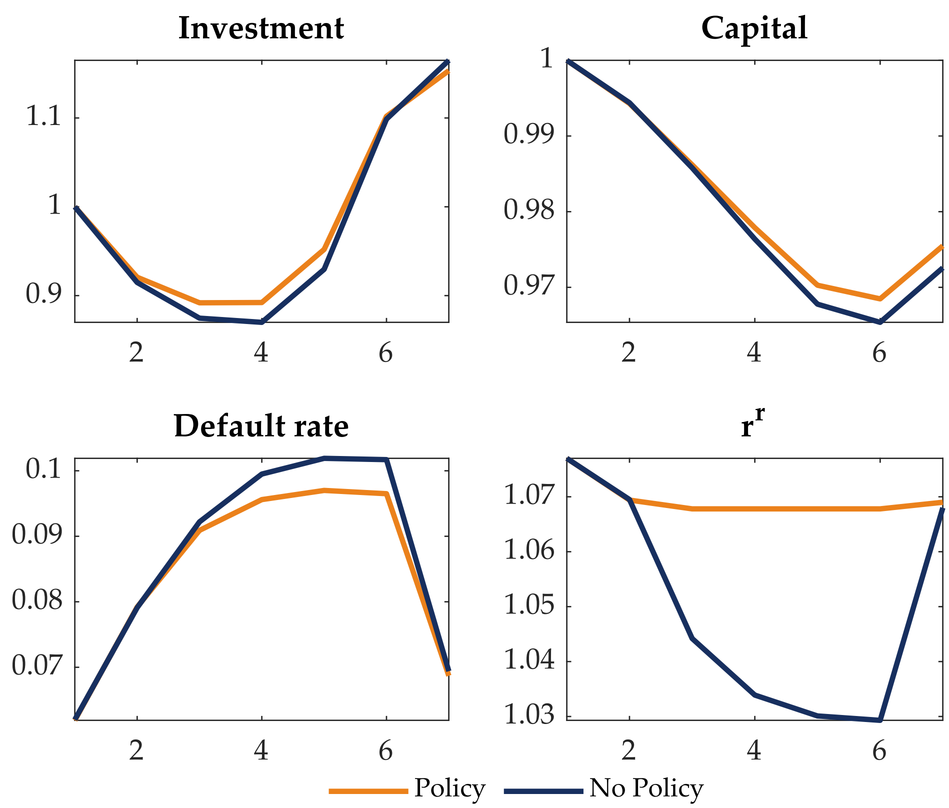

Figure 16: Impulse response functions to a negative financial and productivity shock. The top panels show the investment (left) and capital (right) responses to the shock. The bottom panels show the default rate (left) and return on risky assets (right). The orange line represents the model with policy intervention, and the blue line represents the economy with no policy intervention. The capital drop is 10% smaller with policy intervention, and the investment drop is 18% smaller.

sector regulations in the nonfinancial sector.

I start by assessing the effects of a market liquidity provision policy during large negative shocks, similar to the Federal Reserve Secondary Market Corporate Credit Facility (SMCCF) program. The objective of this program was to support market liquidity during the COVID pandemic by buying corporate bonds in the secondary market, preventing bond prices from decreasing, which is equivalent to preventing the value of these assets from deteriorating and investors from accumulating losses. I assume this policy to be equivalent to imposing, in the model, a lower bound on the risky asset excess return during large recessions, with the assumption being that the return on the risky asset does not fall below the risk-free rate.

Figure 16 shows the Impulse Response Functions to the same large shock as in section 5.3 for the risky asset model with and without the policy implementation. Contrary to the no policy scenario, the decrease in risky asset's return is limited as it never falls below the risk-free rate.

The presence of this lower bound for the return on corporate bonds limits the losses on risky savings and consequently the propagation of the negative shock from defaulting borrowers to lending firms. This limited propagation then guarantees the default rate does not increase as much, and, consequently, the decrease in investment and capital is smaller when compared to the response in the absence of any policy implementation. However, notice the investment and capital decrease are still larger than in the model with only risk-free assets plotted in Figure 15, which derives from the fact that, relative to the initial level, there is still a drop in expected returns on savings, which does not happen in the risk-free only model.

Depending on the announcement timing, the aforementioned policy may additionally have an impact on the share of risky asset holdings. If the policy is announced before the shock occurs, firms learn that the downside risk of corporate bonds becomes limited, triggering an increase in the share of risky asset holdings. This share would increase from the calibrated value of 29.25% to 78.3%. If the policy is only announced following the large shock, the impact on the portfolio of savings would be null.

This policy also has effects over the business-cycle. Table 18 in Appendix F.2 presents the results for this policy under the assumption that is only announced following large shocks. If this policy is implemented in all recessions during which the return on risky assets falls bellow the risk-free rate, the average recession would be smaller than in the absence of any policy, and closer to an average recession in the risk-free only model. The major distinction when compared with a risk-free only model is the positive effects that holding risky assets during expansions bring. During these periods, firms make larger returns on their savings, which will allow them to grow faster. This last effect dominates, resulting in larger output and capital.

Lastly, I assess the impact of implementing some of the financial sector regulations in the nonfinancial sector. Following the financial crisis and the revealed deficiencies in the financial sector, a new banking supervision accord was made — the Basel III agreement. Some new requirements were implemented and other already existing regulations were revised. The objective of some of the new regulation was to limit the exposure of financial institutions to risky assets in order to limit the propagation of negative shocks through the financial system. The purpose of implementing some of these policies in the nonfinancial sector would be similar: limiting the propagation of shocks from defaulting borrowers to nonfinancial lending firms.

I focus on the two measures from the Basel III agreement that more closely relate to the riskiness of the portfolio of assets: (1) Capital requirements - financial firms' Tier 1 capital must be at least 6% of the value of their risk-weighted assets.[22]; and (2) counter-cyclical buffers - the Tier 1 capital to risk-weighted assets ratio has to be 2.5 percentage points higher during periods of high credit growth.

The direct counterpart in my model to these two policies is imposing restrictions on the share of risky savings. To test the implications of the capital requirements measure I impose in the model that the share of risky savings has to be lower than 94%. The counter-cyclical buffers measure imposes one additional restriction that during downturns the maximum share of risky savings is 2.5 percentage points lower than during normal times. Both these policies have an impact on the average share of risky savings, with this figure decreasing from the calibrated value of 29.25% to 26.75% and 26.68% under the capital requirements and counter-cyclical measures, respectively. However, because the regulation would only be binding for the larger firms with zero probability of default and optimal capital adopted, no significant aggregate effects would be achieved, neither in response to a large shock nor on average over the business-cycle.

7 Conclusion

In this paper, I study the aggregate implications of nonfinancial firms' allocation of savings between risk-free and risky assets. I start by providing empirical evidence that risky asset holdings

[22] Because different assets have different risk profiles, the risk-weighted asset is a measure that takes into account the riskiness of each type of asset. For example, cash and government bonds have a zero weight because they are risk-free. Loans and other assets are usually given a weight of one due to the high-risk profile. Given that here I only have risk-free bonds, which are assigned a weight of zero, and corporate bonds, the risk-weighted assets are equal to the corporate bonds held by a firm.

have been increasing and explain about 70% of the increase in financial asset holdings since the early 1990s. Moreover, during the Great Recession, firms with a share of risky assets above 70% decreased investment by twice as much as firms with a share of risky assets lower than 30%.

I then proceed to develop a heterogeneous firms model that rationalizes why firms save in risky assets. Two reasons explain the savings-portfolio composition: (1) maximize expected returns on savings, and (2) diversify savings portfolio to decrease the probability of default. These two mechanisms generates 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 — in the form of corporate bonds in the model. 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. If the shock is instead small, not causing a drop in the return on risky assets, the portfolio of savings allows firms to better absorb the shock with investment and capital decreasing less.

I conclude by assessing the implications of two different sets of policies. The first one follows from the Fed Secondary Market Corporate Credit Facility program, and I assume losses from risky asset holdings would be limited during recessions. This type of policy diminishes the negative impacts of decreases in the return on risky assets during recessions while maintaining its benefits during expansions. Lastly, I test imposing the financial sector regulation on nonfinancial firms. Because the regulation would only be binding for larger firms that can sustain big losses without defaulting or decreasing investment, the aggregate effects would be limited.

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

References

Abel, A. B. and Eberly, J. C. (1996). Optimal investment with costly reversibility. *The Review of Economic Studies*, 63(4):581–593.

Almeida, H., Campello, M., and Weisbach, M. S. (2004). The cash flow sensitivity of cash. *The Journal of Finance*, 59(4):1777–1804.

Arellano, C., Bai, Y., and Kehoe, P. (2016). Financial frictions and fluctuations in volatility.

Bates, T. W., Kahle, K. M., and Stulz, R. M. (2009). Why do us firms hold so much more cash than they used to? *The journal of finance*, 64(5):1985–2021.

Begenau, J. and Palazzo, B. (2017). Firm selection and corporate cash holdings. Technical report, National Bureau of Economic Research.

Begenau, J. and Salomao, J. (2018a). Firm financing over the business cycle. *The Review of Financial Studies*, 32(4):1235–1274.

Begenau, J. and Salomao, J. (2018b). Firm financing over the business cycle. *The Review of Financial Studies*, 32(4):1235–1274.

Bigio, S. (2015). Endogenous liquidity and the business cycle. *American Economic Review*, 105(6):1883–1927.

Bloom, N. (2009). The impact of uncertainty shocks. *econometrica*, 77(3):623–685.

Bloom, N., Bond, S., and Van Reenen, J. (2007). Uncertainty and investment dynamics. *The review of economic studies*, 74(2):391–415.

Boot, A. W., Thakor, A. V., et al. (2010). The accelerating integration of banks and markets and its implications for regulation. *The Oxford handbook of banking*, pages 58–90.

Buera, F. and Karmakar, S. (2017). Real effects of financial distress: the role of heterogeneity.

Cardella, L., Fairhurst, D., and Klasa, S. (2015). What determines the composition of a firm's total cash reserves? *Texas Tech University unpublished working paper*.

Carvalho, V. M. and Grassi, B. (2019). Large firm dynamics and the business cycle. *American Economic Review*, 109(4):1375–1425.

Chen, P., Karabarbounis, L., and Neiman, B. (2017). The global rise of corporate saving. *Journal of Monetary Economics*, 89:1–19.

Clementi, G. L. and Palazzo, B. (2016). Entry, exit, firm dynamics, and aggregate fluctuations. *American Economic Journal: Macroeconomics*, 8(3):1–41.

Cooley, T. F. and Quadrini, V. (2001). Financial markets and firm dynamics. *American economic review*, 91(5):1286–1310.

Crouzet, N. (2017). Aggregate implications of corporate debt choices. *The Review of Economic Studies*, 85(3):1635–1682.

Cunha, I. and Pollet, J. M. (2017). Why do firms hold cash? evidence from demographic demand shifts. *Evidence from Demographic Demand Shifts (September 15, 2017)*.

Darmouni, O. and Mota, L. (2020). The financial assets of non-financial firms. *Available at SSRN 3543802*.

De Fiore, F. and Uhlig, H. (2011). Bank finance versus bond finance. *Journal of Money, Credit and Banking*, 43(7):1399–1421.

Diamond, D. W. (1984). Financial intermediation and delegated monitoring. *The review of economic studies*, 51(3):393–414.

Duchin, R., Gilbert, T., Harford, J., and Hrdlicka, C. (2017). Precautionary savings with risky assets: When cash is not cash. *The Journal of Finance*, 72(2):793–852.

Fama, E. F. (1985). What's different about banks? *Journal of monetary economics*, 15(1):29–39.

Gande, A. and Saunders, A. (2012). Are banks still special when there is a secondary market for loans? *The Journal of Finance*, 67(5):1649–1684.

Gao, X., Whited, T. M., and Zhang, N. (2021). Corporate money demand. *The Review of Financial Studies*, 34(4):1834–1866.

Gilchrist, S., Sim, J. W., and Zakrajšek, E. (2014). Uncertainty, financial frictions, and investment dynamics. Technical report, National Bureau of Economic Research.

Hennessy, C. A. and Whited, T. M. (2007). How costly is external financing? evidence from a structural estimation. *The Journal of Finance*, 62(4):1705–1745.

Hopenhayn, H. A. (1992). Entry, exit, and firm dynamics in long run equilibrium. *Econometrica: Journal of the Econometric Society*, pages 1127–1150.

Jeenas, P. (2018). Firm balance sheet liquidity, monetary policy shocks, and investment dynamics. *Unpublished Manuscript*.

Jermann, U. and Quadrini, V. (2012). Macroeconomic effects of financial shocks. *American Economic Review*, 102(1):238–71.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review*, pages 161–182.

Khan, A., Senga, T., and Thomas, J. (2017). Default risk and aggregate fluctuations in an economy with production heterogeneity. In *2017 Meeting Papers*, number 889. Society for Economic Dynamics.

Khan, A. and Thomas, J. K. (2008). Idiosyncratic shocks and the role of nonconvexities in plant and aggregate investment dynamics. *Econometrica*, 76(2):395–436.

Khan, A. and Thomas, J. K. (2013). Credit shocks and aggregate fluctuations in an economy with production heterogeneity. *Journal of Political Economy*, 121(6):1055–1107.

Krusell, P. and Smith, Jr, A. A. (1998). Income and wealth heterogeneity in the macroeconomy. *Journal of Political Economy*, 106(5):867–896.

Lanteri, A. (2018). The market for used capital: Endogenous irreversibility and reallocation over the business cycle. *American Economic Review*, 108(9):2383–2419.

Lyandres, E. and Palazzo, B. (2016). Cash holdings, competition, and innovation. *Journal of Financial and Quantitative Analysis*, 51(6):1823–1861.

Melcangi, D. (2018). The marginal propensity to hire. *FRB of New York Staff Report*, (875).

Nikolov, B. and Whited, T. M. (2014). Agency conflicts and cash: Estimates from a dynamic model. *The Journal of Finance*, 69(5):1883–1921.

Ottonello, P. and Winberry, T. (2018). Financial heterogeneity and the investment channel of monetary policy. Technical report, National Bureau of Economic Research.

Rauh, J. D. and Sufi, A. (2010). Capital structure and debt structure. *The Review of Financial Studies*, 23(12):4242–4280.

Riddick, L. A. and Whited, T. M. (2009). The corporate propensity to save. *The Journal of Finance*, 64(4):1729–1766.

Tauchen, G. (1986). Finite state markov-chain approximations to univariate and vector autoregressions. *Economics letters*, 20(2):177–181.

Xiao, J. (2018). Capital allocation and investment dynamics in credit crises. *Unpublished Manuscript*.

A Static Model

In this Section, I describe the one-period, partial equilibrium model of firm borrowing and asset allocation decision used in Section 5.1 to illustrate the mechanisms by which firms find it optimal to hold both risk-free and risky assets and some of the consequences of the savings portfolio composition.

The proposed model combines two productivity shocks and an uncertain return on the risky asset. Similar to the dynamic model, firms, before observing the first productivity shock and given the endowment level, decide on how much debt to hire. Following the first shock, firms decide how to allocate the resources (debt plus initial endowment) in productive capital or save in a risk-free or/and in a risky asset. Firms, after realizing the second productivity shock and the return on risky assets, default if fail to pay the debt.

The model generates a savings behavior across the firm size distribution similar to that observed empirically: savings rate is decreasing on the size of the firm, while the riskiness of the savings portfolio is increasing. The model proposes two mechanisms that rationalize the empirical pattern: 1) small firms have a higher savings rate for precautionary reasons and save mainly in risk-free assets to decrease the probability of default; 2) as firms grow, the default probability tends towards zero, and firms exposure to risky savings and capital raises as these two assets offer larger return rates.

A.1 Environment

Production

Firms hire capital k to produce output y using the following decreasing returns to scale production technology

$$y = \epsilon z k^{\alpha} \tag{22}$$

where ϵ and z are two independent productivity shocks, with $0 < \alpha < 1$ guarantying decreasing

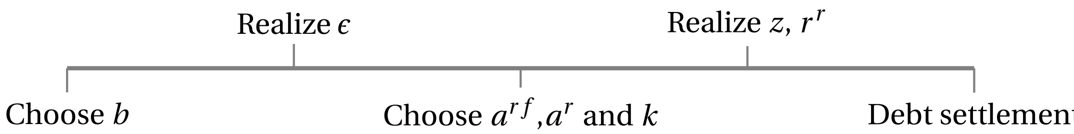

Figure 17: Timing in the static model

returns to scale and the existence of an optimal scale of production.[23]

Firms are endowed with an initial amount of assets a_0 that can use to finance investment in productive capital or save in either risk-free a^{rf} or risky a^r assets. Besides initial endowment, firms can borrow b to invest or save. Therefore, the budget constraint is given by

$$a_0 + b = k + a^{rf} + a^r \tag{23}$$

The return on risk-free assets r^{rf} is exogenous and known in advance while the return on risky assets r^{rf} is only realized at the end of the period. Firms know the probability distribution of the risky asset return and form rational expectations.[24]

Timing

To guarantee the right relation between firm size, amount of savings and portfolio composition, I adopt Xiao (2018) timing. Figure 17 summarizes it. At the beginning of the period firms choose the amount of borrowing subject to the interest rate on debt r^b. Following this decision, firms observe the first productivity shock ϵ. Before observing the second shock and the return on risky assets, firms decide on how to allocate their initial endowment a_0 plus the amount borrowed. Firms can invest in capital used for producing output, risk-free assets yielding a constant return r^{rf}, or risky assets that will yield a yet uncertain return r^r. Following this stage, firms observe z

[23] The two productivity shocks can be though as an idiosyncratic and an aggregate productivity shocks, similar to the ones in the dynamic model.

[24] Here I am assuming complete independence between productivity shocks and return on risky assets. In the dynamic model, risky assets take the form of corporate debt with firms not being able to design contracts that eliminate the risk from corporate borrowing. Firms will then charge a risk premium for saving in risky assets and the return on those savings will be affected by the percentage of firms defaulting, which is connected to the aggregate productivity, the second productivity shock. So, there will be a positive correlation between the productivity shock and return on risky savings, which is not present in this static model. Although, as I show in Section 5, the savings behavior across firm size distribution is not altered by this assumption.

and r_r, produce and repay their debt, if they have enough liquidity.

Debt settlement stage

At the end of the period, given the firm's choice of capital, risky and risk-free asset holding, its cash flow is

$$\pi(\epsilon, z, r_r) = \epsilon z k^{\alpha} + (1 + r^s) a^s + (1 + r^r) a^r \tag{24}$$

After realizing its cash flow, the firm decides whether to repay its lender $(1 + r^b)b$ or to default, in which case the lender takes full control of the firm's remaining resources. The default decision is based on net worth default rule, similar to the dynamic model. This means that the firm will default due to illiquidity — if it does not have enough resources to pay back the debt — even if it may have a positive continuation value. Therefore, the firm defaults if

$$\pi(\epsilon, z, r_r) < (1 + r^b) b \tag{25}$$

Given this, it is possible, for every combination of ϵ and r_r to find the minimum z required in order for the firm not to default

$$\underline{z} = \frac{(1 + r^b)b - (1 + r^{rf})a^{rf} - (1 + r^r)a^r}{\epsilon k^{\alpha}} \tag{26}$$

and for each combination of ϵ and z to find the minimum return on risky assets required for the firm not to default

$$\underline{r}^r = \frac{(1 + r^b)b - (1 + r^{rf})a^{rf} - \epsilon z k^{\alpha}}{a^r} - 1 \tag{27}$$

In this static model there is no continuation value, independently of default occurring or not. To approximate the static model as much as possible to the dynamic model I assume firms, in case of default, incur in a cost D that equates to the loss of the continuation value in the dynamic model.[25]

Firm's problem

Before observing the aggregate productivity shock z and the return on risky assets r_r, the firm, taking debt as given, maximize their expected profits by choosing capital k, risk-free assets a^{rf} and risky assets a^r

$$
\begin{aligned}
\max_{k,a_r,a_{rf}} E_{z,r_r}\left[\Pi|(e,b,\epsilon)\right] = & \int_{\underline{z}}\int_{\underline{r}_r}\left[\epsilon z k^{\alpha} + (1+r^{rf})a^{rf} + (1+r^{r})a^{r} - (1+r^{b})b\right] dF(z)dF(r^r) \\
& + \int^{\underline{z}}\int^{\underline{r}^r} -D\,dF(z)dF(r^r) \\
\text{s.t.: } & k + a^r + a^{rf} = e + b
\end{aligned}
$$

Before observing both ϵ, z and r^r, firms must decide on the amount of debt given the initial endowment e. Firms will take as given its optimal capital k^*, risk free a^{rf^*} and risky assets a^{r^*} policy functions for each possible ϵ and b when deciding on b

$$
\begin{aligned}
\max_{b} E_{\epsilon,z,r^r}\left[\Pi|e\right] = & \int_{\epsilon}\int_{\underline{z}}\int_{\underline{r}_r}\left[\epsilon z k^{\alpha} + (1+r^{rf})a^{rf} + (1+r^{r})a^{r} - (1+r^{b})b\right] dF(\epsilon)dF(z)dF(r^r) \\
& + \int^{\epsilon}\int^{\underline{z}}\int^{\underline{r}^r} -D\,dF(\epsilon)dF(z)dF(r^r)
\end{aligned}
$$

[25] In this static model, the assumption of a net worth default rule is equivalent to default by having equity value falling below zero. Although in the dynamic model, under persistent idiosyncratic productivity and aggregate shocks, the two hypothesis would differ. The decision for a net worth default rule is motivated by the less intensive computational task of not having to invert the firms value function to find the default threshold. Besides, as Gilchrist et al. (2014) mention, it is not clear empirically which of the two hypothesis is more plausible.

B Data

B.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.[26] 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 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.

[26] 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.

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. Although, the distributions of these variables across both datasets are similar, as it is possible to observe in Figures 18 to 21. 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.

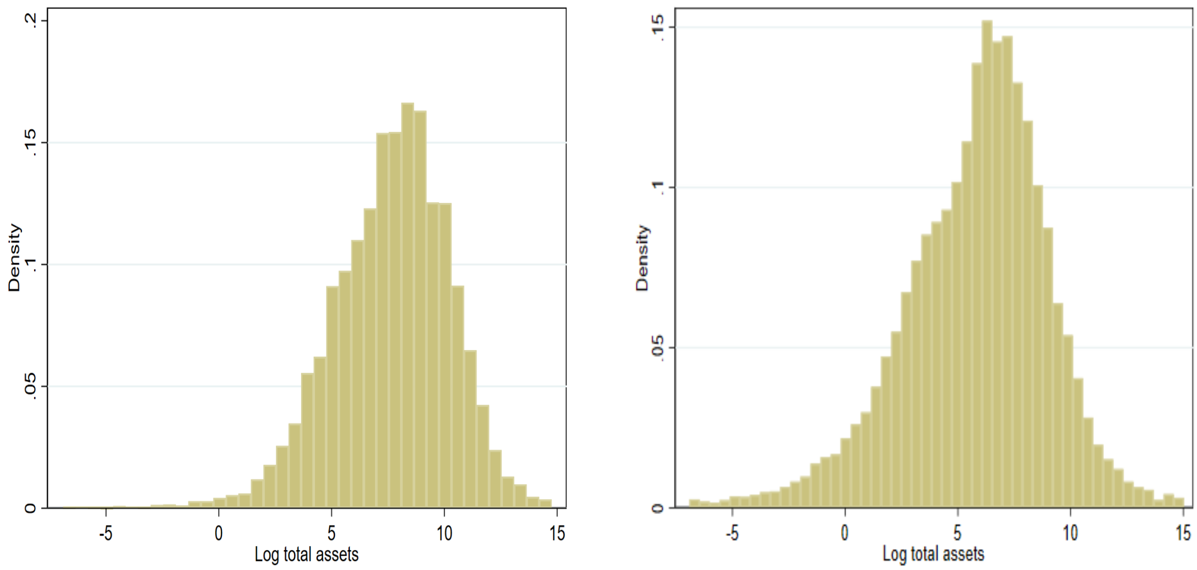

Figure 18: Histogram of log of total assets. On the left panel, the sample of firms for whom my web scrapping code was able to extract corporate bond holdings. On the right panel, the entire Compustat sample over the same period. The distributions have a similar behavior with the only difference of the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

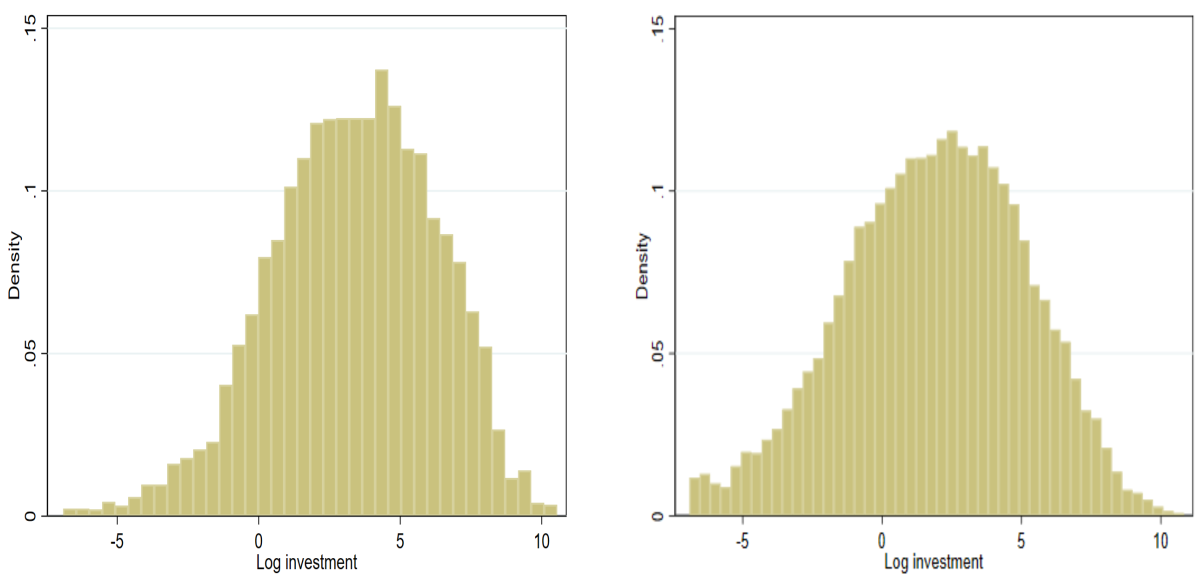

Figure 19: Histogram of log of investment. On the left panel, the sample of firms for whom my web scrapping code was able to extract corporate bond holdings. On the right panel, the entire Compustat sample over the same period. The distributions have a similar behavior with the only difference of the distribution on the left panel being shifted to the right.

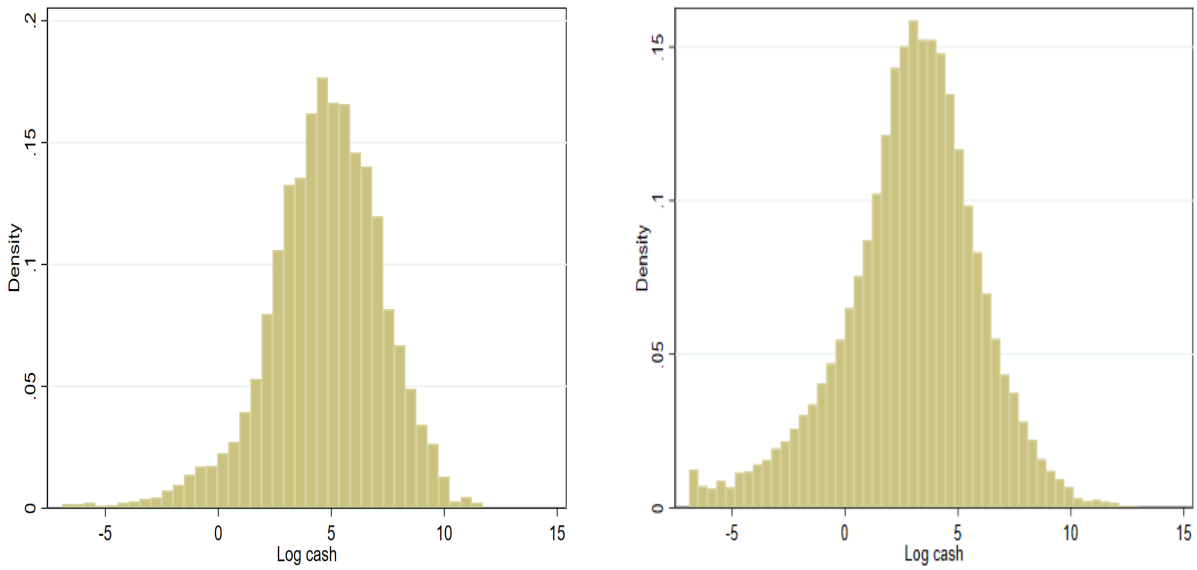

Figure 20: Histogram of log of cash holdings. On the left panel, the sample of firms for whom my web scrapping code was able to extract corporate bond holdings. On the right panel, the entire Compustat sample over the same period. The distributions have a similar behavior with the only difference of the distribution on the left panel being shifted to the right.

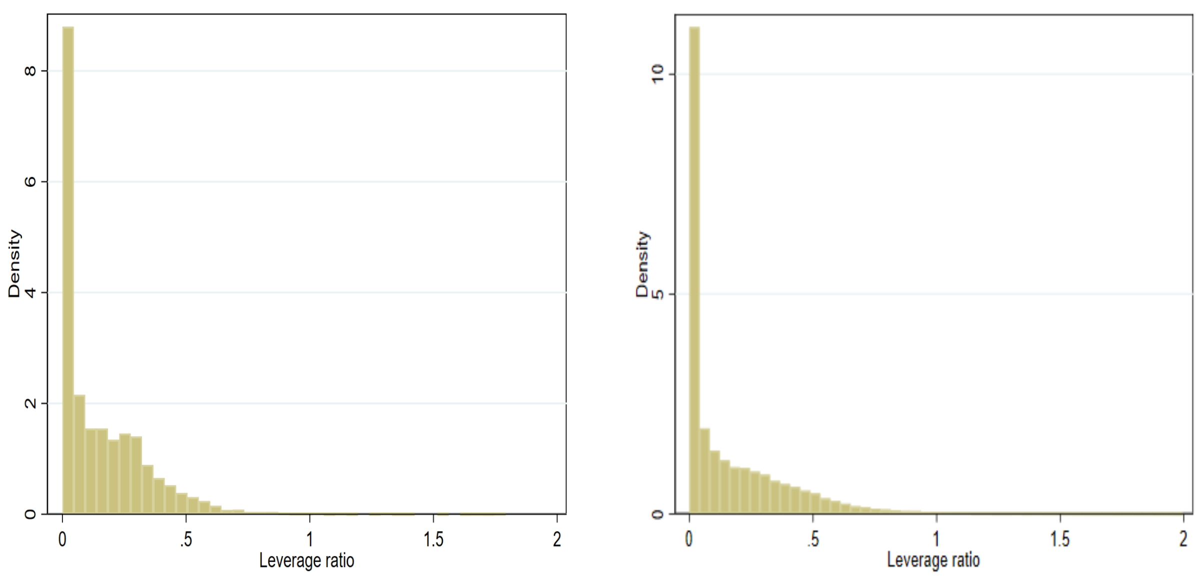

Figure 21: Histogram of leverage ratios. On the left panel, the sample of firms for whom my web scrapping code was able to extract corporate bond holdings. On the right panel, the entire Compustat sample over the same period. The distributions have a similar behavior and a similar average.

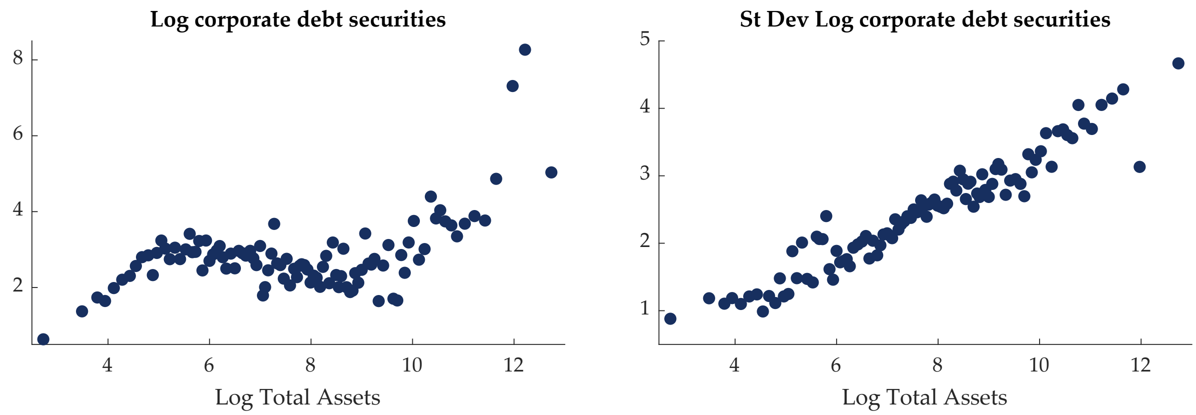

Figure 22: On the left panel, the empirical relation between corporate bond holdings — on the y-axis — and total assets — on the x-axis. On the right panel, the relation between the standard deviation of corporate bond holdings — on the y-axis — and total assets — on the x-axis. Consistent with the model, both the average and the standard deviation are increasing with the size of the firm.

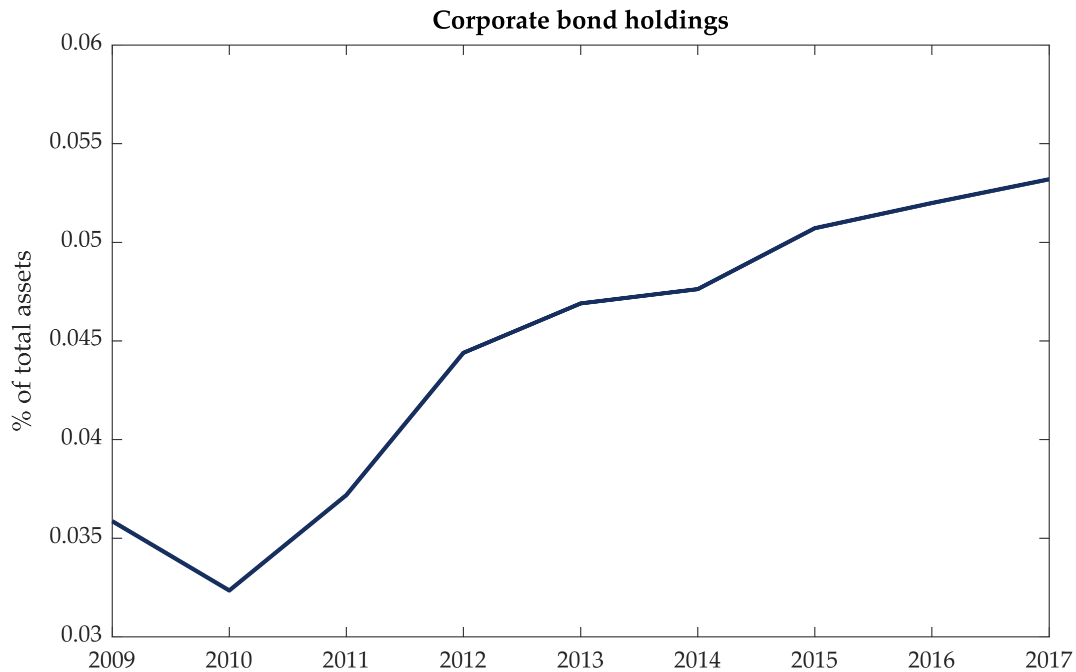

Figure 23: Aggregate corporate bonds to total assets ratio by publicly list firms.

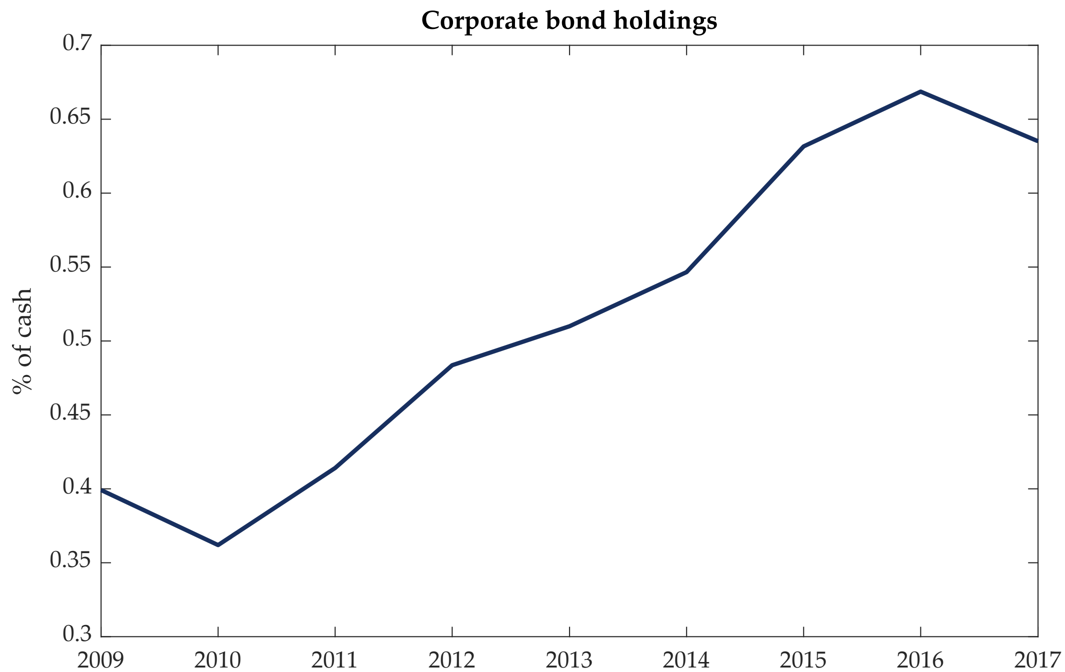

Figure 24: Aggregate corporate bonds to cash ratio by publicly list firms.

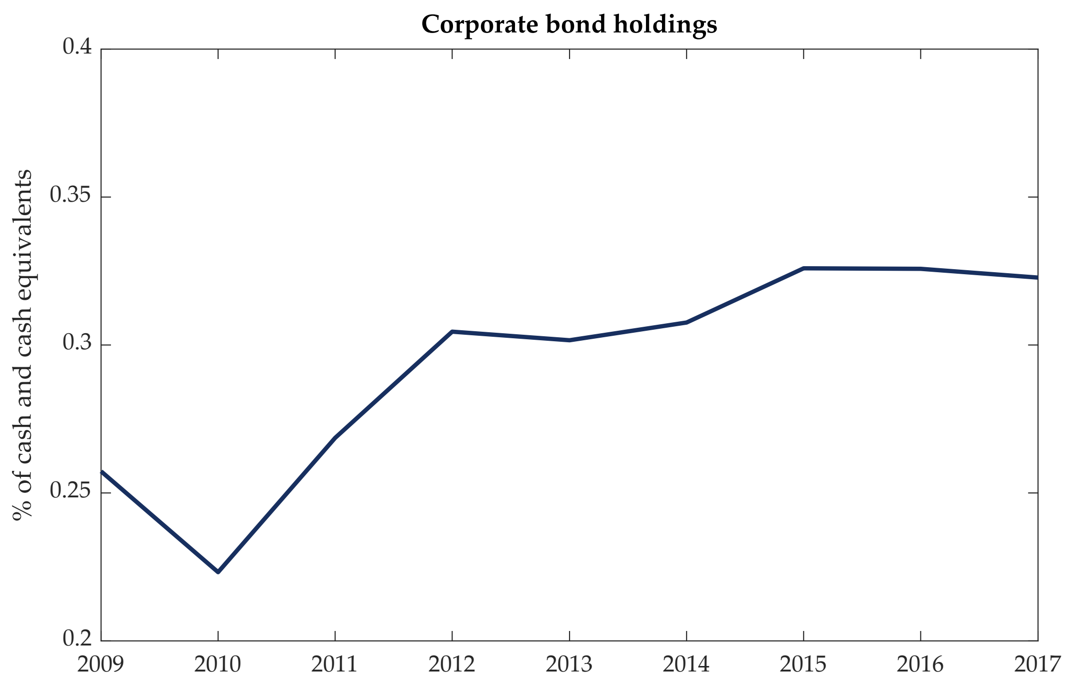

Figure 25: Aggregate corporate bonds to cash and cash equivalents ratio by publicly list firms.

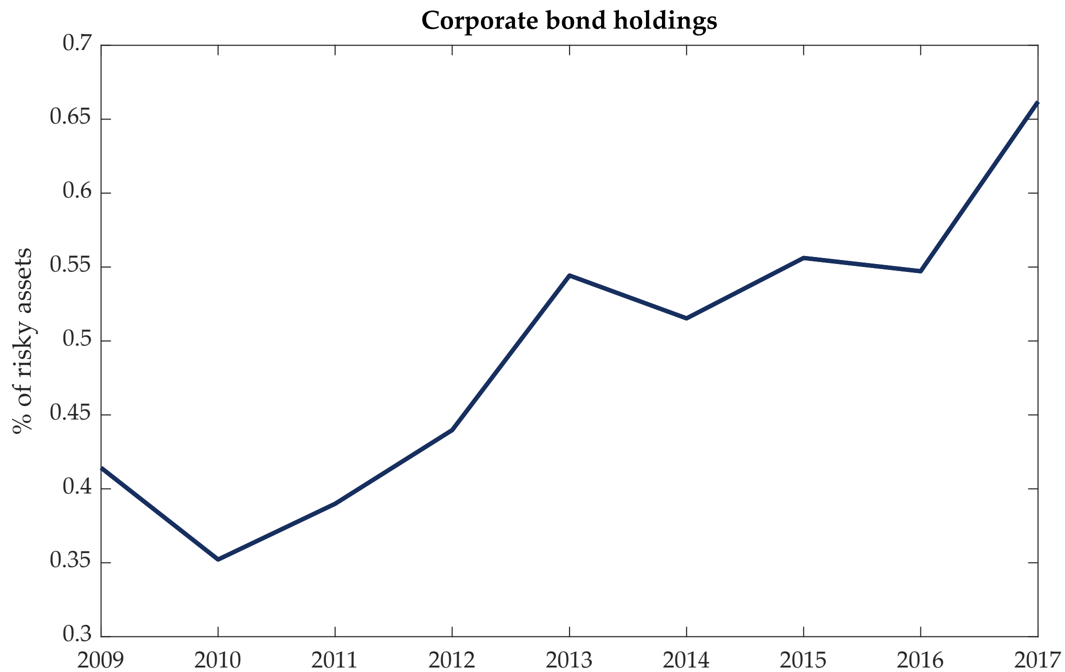

Figure 26: Aggregate corporate bonds to risky assets ratio by publicly list firms.

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 8: 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 9: 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 10: 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 11: Aggregate analysis of risky investment by industry - yearly averages 2009-2017

B.2 *Additional graphs*

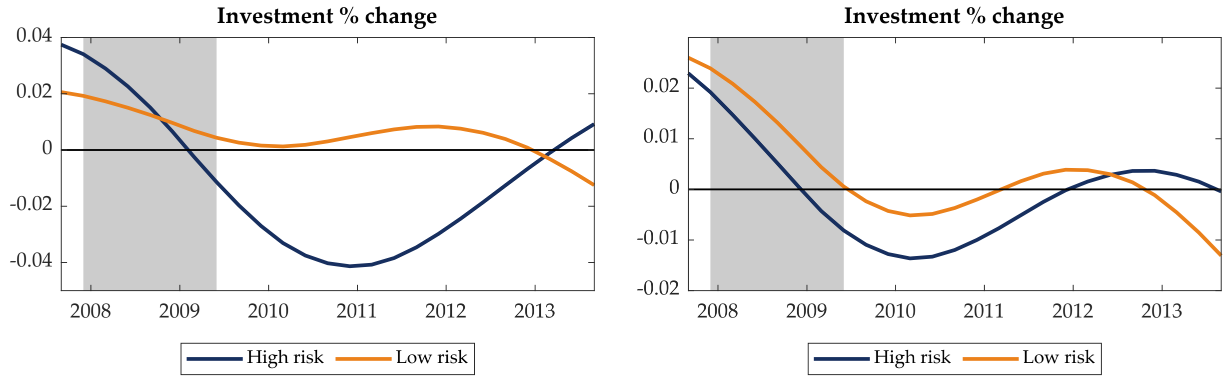

Figure 27: Both panels illustrate smoothed deviations from trend investment over the 2008-2013 period. The trend investment is obtain from an HP filter. On the left panel the blue line represents firms with share of risky savings above 70% and the orange line firms with a share below 30%. On the right panel the blue line represents firms that hold risky assets, and the orange line firms that do not hold risky assets. In both cases investment drops by more during the crisis for firms that have more risky assets.

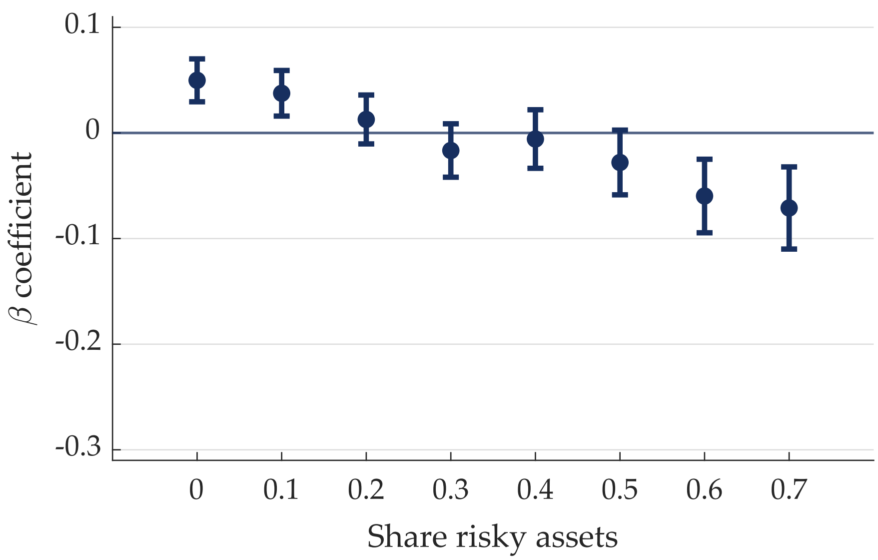

Figure 28: On the y-axis we have the β coefficient from equation (1) and on the x-axis we have the cutoff value of the share of risky asset holdings between the two groups. Error bars represent the 95% confidence interval. Results indicate that across the different thresholds, firms with more risky assets dropped there investment more during the Great Recession.

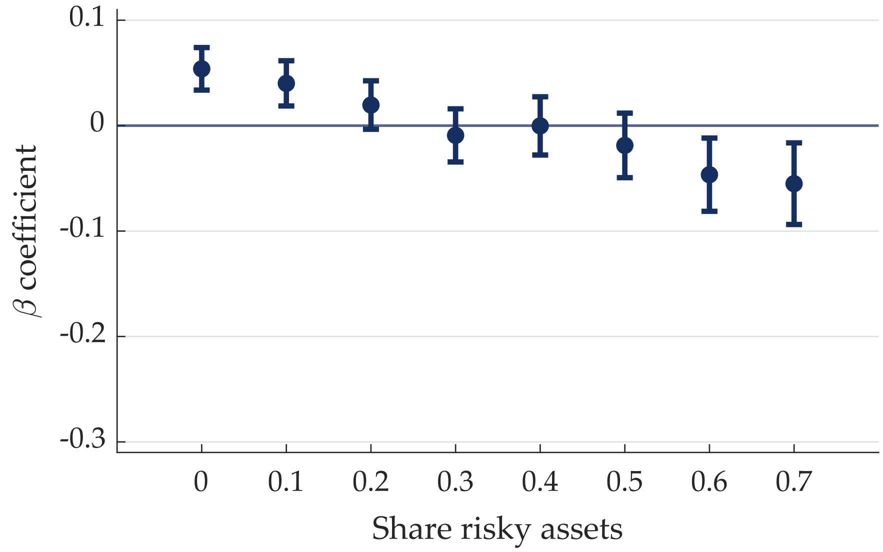

Figure 29: On the y-axis we have the β coefficient from equation $ln(Inv)_{ijt} = \gamma crisis_t + \alpha risky_{ijt} + \beta crisis_t * risky_{ijt} + crisis_t * \gamma_j + \lambda_i + \theta_j + \epsilon_{ijt}$ where crisis is a dummy variable equal to 1 between 2008 and 2010, risky is a dummy variable 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. Results indicate that across the different thresholds, firms with more risky assets dropped there investment more during the Great Recession.

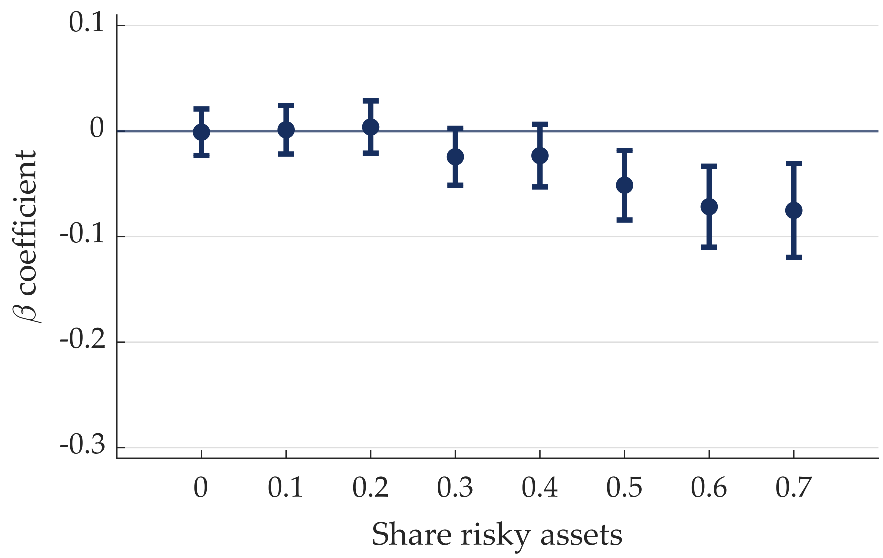

Figure 30: On the y-axis we have the β coefficient from equation $ln(Inv)_{ijt} = \gamma crisis_t + \alpha risky_{ijt} + \beta crisis_t * risky_{ijt} + X_{ijt} + \lambda_i + \theta_{jt} + \epsilon_{ijt}$ where crisis is a dummy variable equal to 1 between 2008 and 2010, risky is a dummy variable equal 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. Results indicate that across the different thresholds, firms with more risky assets dropped there investment more during the Great Recession.

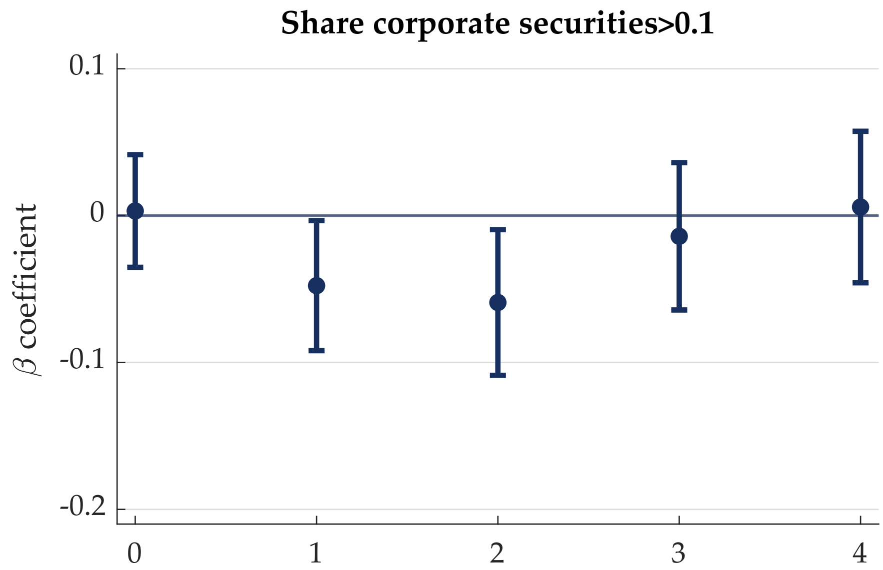

Figure 31: On the y-axis we have the β coefficient from equation (2) with the $risky_{ijt-1}$ dummy variable equal to 1 if the share of corporate bond holdings to total assets is higher than 0.1 and on the x-axis the horizon h. Error bars represent the 95% confidence interval. Results indicate that increases in volatility have a stronger negative effect on firms with a positive amount of corporate bond holdings, up to three years after.

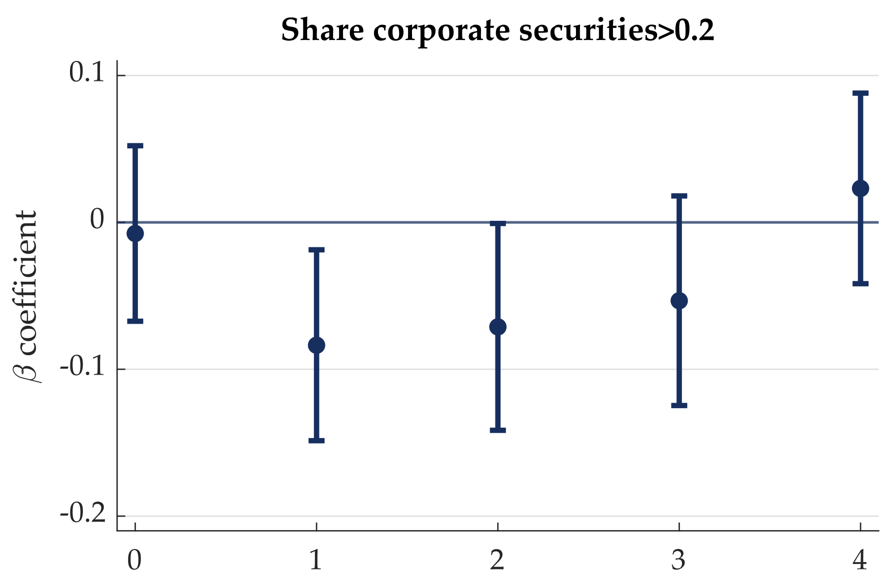

Figure 32: On the y-axis we have the β coefficient from equation (2) with the $risky_{ijt-1}$ dummy variable equal to 1 if the share of corporate bond holdings to total assets is higher than 0.2 and on the x-axis the horizon h. Error bars represent the 95% confidence interval. Results indicate that increases in volatility have a stronger negative effect on firms with a positive amount of corporate bond holdings, up to three years after.

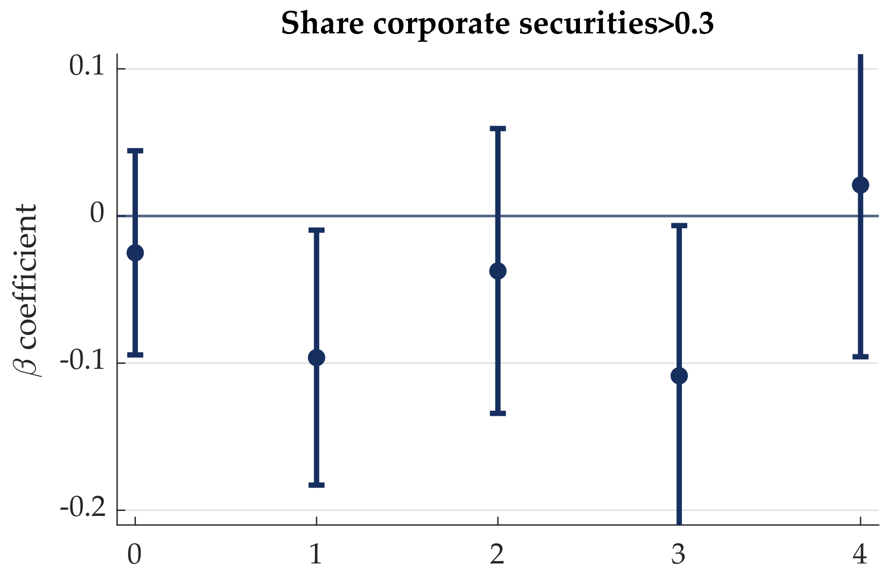

Figure 33: On the y-axis we have the β coefficient from equation (2) with the $risky_{ijt-1}$ dummy variable equal to 1 if the share of corporate bond holdings to total assets is higher than 0.3 and on the x-axis the horizon h. Error bars represent the 95% confidence interval. Results indicate that increases in volatility have a stronger negative effect on firms with a positive amount of corporate bond holdings, up to three years after.

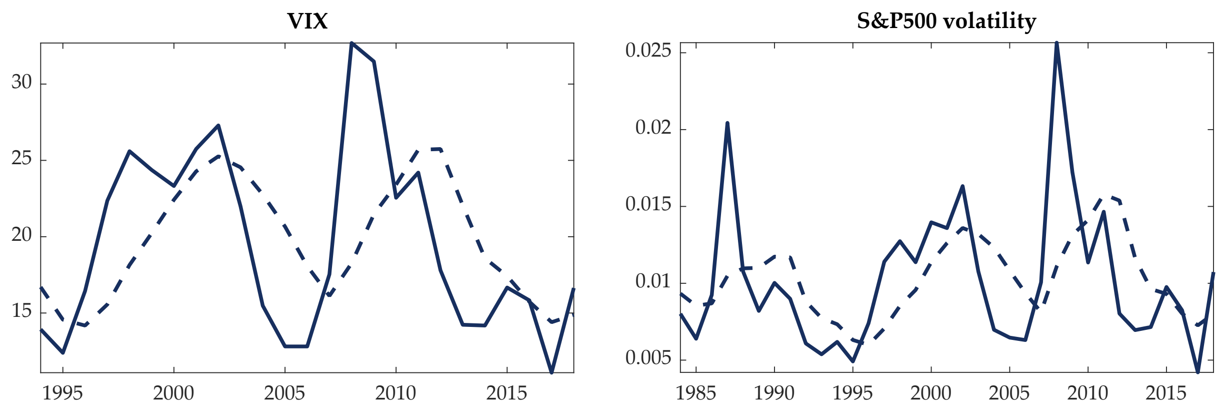

Figure 34: On the left panel, the black solid line represents the annual average of the VIX index. On the right panel, the annual S&P500 volatility, measured as the standard deviation of the daily returns over the year. The dashed lines represent the 5 year moving averages of the respective time series.

C Empirical Evidence

In this section I empirically test some of the model mechanisms. To ensure a better mapping between the model and the empirical analysis I use my new dataset that comprises corporate bonds holdings by publicly listed firms in the U.S. in the period spanning from 2009 to 2017.[27] I assess if the determinants of corporate bonds holdings and its impact on firms are in accordance with the model predictions.

C.1 Determinant of corporate bond holdings

In this section I test if the predictions of the model in terms of determinants of corporate bond holdings are in accordance with the data. I proceed in two steps: first, I test the static 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 do this, I regress cash and corporate securities held on debt and revenues. I find that increases in debt are associated with raises in cash, consistent with precautionary savings, while rises in revenues are allocated in the higher risk security; second, I test the quantitative model prediction that the real interest rate explains the increase in risky asset holdings through time, and that uncertainty and risk premium are also important determinants of corporate bond holdings. I find the empirical results to be in accordance with the model.

Precautionary savings: To test the static model predictions that precautionary savings are allocated in cash, while non-precautionary are in riskier assets with higher potential yield, I regress cash and corporate bond holdings on long term debt and revenues

$$Y_{ijt} = \beta_1 Revt_{ijt-1} + \beta_2 Debt_{ijt-1} + X_{ijt-1} + \alpha_i + \lambda_{jt} + \epsilon \tag{28}$$

where Y is either cash or corporate bond holdings by firm i in sector j in year t, $Revt$ is revenues

[27] I only have few observations before 2009. Only after 2009, with the implementation of the Statement of Financial Accounting Standards (SFAS) No. 157, it became mandatory for firms to report the value of the major asset classes in their balance sheet. Due to this fact, I abstract from evaluating if the portfolio of assets played a role in the propagation of the financial crisis.

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

Table 12: Cash and corporate bond holdings regressed on revenues and long term debt.

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. Results, presented in Table 12, 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 rise in long term debt has a stronger impact on cash — increase of \$0.07 — than on corporate bonds — increment of \$0.05.[28] This result is consistent with the model 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.

Aggregate determinants of corporate bond holdings: The quantitative model suggests the decrease in real interest rate can fully account for the increase in the share of risky savings, with other potential determinants being risk premium and aggregate volatility. To test this, I regress the share of corporate bond holdings $\frac{Corp\_bonds_{ijt}}{Assets_{ijt}}$ on the standardize real interest rate i_{t-1}, standardize aggregate volatility vol_{t-1} — measured as the yearly standard deviation of the daily returns on S&P500, similar to Bloom et al. (2007) — and standardize risk premium $risk\_premium_{t-1}$ — spread between Moody's Baa securities and 10-year treasury — while controlling for firms observables X_{ijt-1} and firm and sector fixed effects, α_i and λ_j respectively

[28]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) Share corporate debt	(2) Share corporate debt	(3) Share corporate debt	(4) Share corporate debt
β_1	-0.006***			-0.006***
	(0.001)			(0.001)
β_2		-0.004***		-0.005***
		(0.001)		(0.001)
β_3			0.001	0.005***
			(0.001)	(0.002)
Observations	5,631	5,036	5,631	5,034
R-squared	0.834	0.824	0.831	0.827

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Share of corporate debt holdings regressed on real interest rate, aggregate volatility and risk premium.

$$\frac{Corp\_bonds_{ijt}}{Assets_{ijt}} = \beta_1 i_{t-1} + \beta_2 vol_{t-1} + \beta_3 risk\_premium_{t-1} + X_{ijt-1} + \alpha_i + \lambda_j + \epsilon \tag{29}$$

Results, in Table 13, validate the model predictions with both increases in the real interest rate and aggregate volatility being associated with a decrease of the share of corporate debt holdings, while an increase in risk premium has the opposite effect.

C.2 Consequences of corporate bond holdings

In this section I test the model predictions that corporate debt holdings imply faster firms' growth. To test the firm growth hypothesis, I regress my proxy for firm growth — the first difference of the logarithm of total assets — on the share of cash and the share of corporate bond holdings. Results are in line with model predictions, with the share of corporate debt holdings being associated with faster growth for firms of the same size.

Firm's growth: I here test how firms' growth — measured as the first difference of the logarithm of total assets — is affected by both the share of cash and corporate bond holdings, while controlling for the firm's size and firm and sector year fixed effects[29]

[29] I include both the share of cash and share of corporate bond holdings as they don't sum to 1 as firms have other assets.

$$\Delta \ln(Assets) = \beta_1 \frac{Corp\_bonds_{ijt-1}}{Assets_{ijt-1}} + \beta_2 \frac{Cash_{ijt-1}}{Assets_{ijt-1}} + X_{ijt-1} + \alpha_i + \lambda_{jt} + \epsilon \tag{30}$$

Results, in Table 14, are in line with the model predictions with cash having no impact on growth while the share of corporate bond holdings is associated with larger firm growth for firms of the same size.

VARIABLES	(1) Growth	(2) Growth	(3) Growth
β_1		0.081*	0.064
		(0.046)	(0.050)
β_2	-0.060		-0.040
	(0.039)		(0.042)
Observations	4,761	4,798	4,759
R-squared	0.537	0.539	0.537

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Firm growth regressed on the share of cash and share of corporate bond holdings.

D Parameters

E Algorithm

E.1 Algorithm

The model is solved using Krusell and 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

$$\begin{bmatrix} \log B^{f'} \\ \log K' \\ (r^r - r^{rf}) \end{bmatrix} = A + B \log K + C \log B^f + D \log(z) \tag{31}$$

   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 both the incumbent and potential entrant problems (equations 12 and 15 respectively). 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 $\{\epsilon, k, x, K, B, z\}$.

   With the firm dividend policy given by $D = \kappa y^{\kappa_y} k^{\kappa_k}$, or zero if a firm is still constrained, this allows me to find firms total savings from equation (11). 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 (31). If the guesses for specification (31) 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 15 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.

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 15: Regression fit

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 a negative productivity shock occurs. The shock lasts for 5 periods, and then goes back to its average level.

Capital to total assets ratio	1989	2017	Variation
No risky asset model	8.42%	30.69%	22.27 p.p.
Risky asset model	8.16%	29.49%	21.33 p.p.

Table 16: Capital to total assets ratio and implied variation by the model when changing the real interest rate.

F Model: Additional results

F.1 Savings' portfolio and interest rate passthrough

Table 16 illustrates the impact of the interest rate decrease on the capital to total assets (capital plus total savings) ratio in the benchmark model and in the model with no risky asset. As expected, the capital to total assets ratio increases with the decrease of the real interest rate. Two mechanisms explain this: 1) debt becomes less costly and so firms have less need to accumulate assets to finance future investments; 2) the optimal amount of capital is higher given the lower outside option.

When comparing the variation from 1989 to 2017 in the no risky asset model to the benchmark case, it is possible to observe that the increase in the capital to total assets ratio is 4.41% larger in the model where firms can only save in the risk-free asset. This is in line with the predictions from Section 5.1: an increase in the share of risky assets holdings, when all else is equal, results in less capital and more savings. Here, as the real interest rate fall generates an increase in the risky asset excess return and, consequently, a portfolio reallocation by the firms, the interest rate impact on the amount of capital held by firms is diminished. The portfolio reallocation into high-risk high yield assets guarantees that the value of the capital outside option does not fall as much as in the no risky asset world. Consequently, the increase in capital is dampened by the endogenous increase in the risky asset excess return and the portfolio reallocation effect.

F.2 Additional graphs and tables

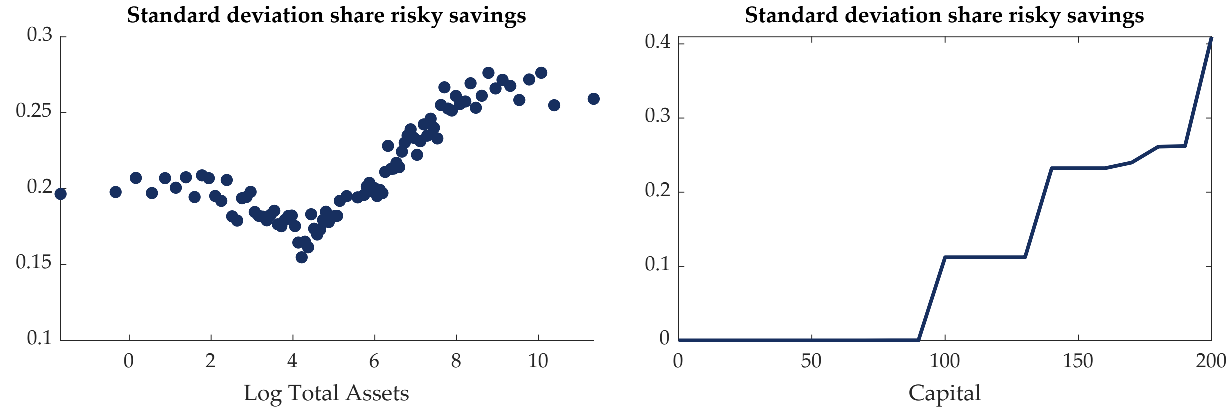

Figure 35: On the left panel, the empirical relation between the standard deviation of the share of risky savings — on the y-axis — and log(total assets) — on the x-axis. On the right panel, the same relation in the model, with the standard deviation of the share of risky savings on the y-axis and capital on the x-axis. As firms grow in size, the standard deviation of risky asset holdings for firms with that given size increases.

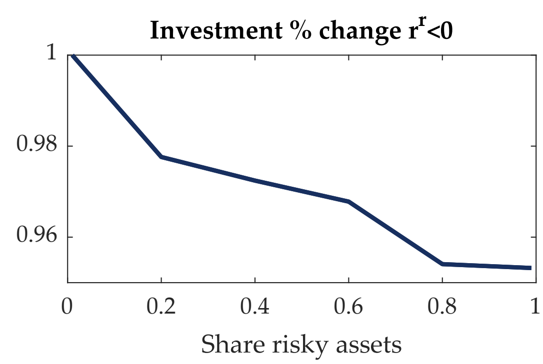

Figure 36: Investment change relative to risk-free only scenario, for different levels of risky savings when r^r falls below 0.

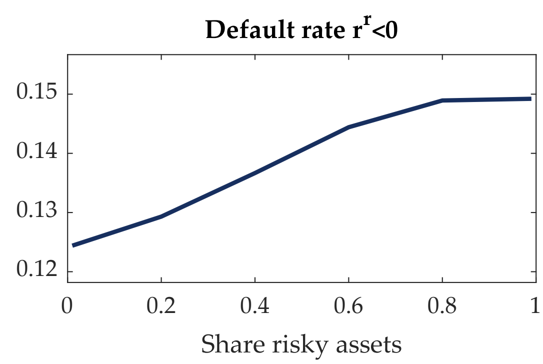

Figure 37: Default rates for different levels of risky savings when r^r falls below 0.

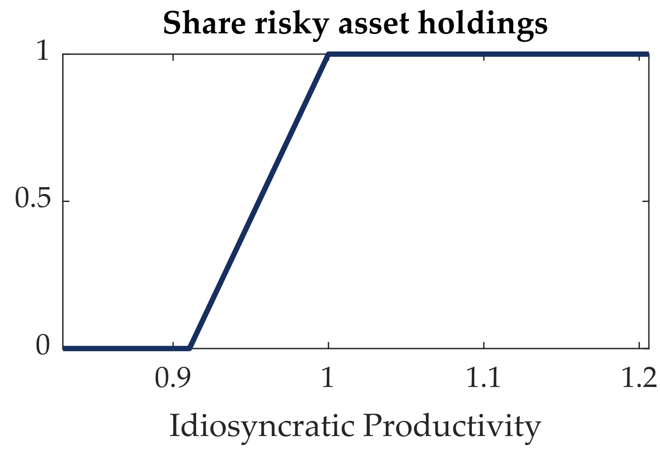

Figure 38: Share of risky asset holdings policy function depending on the idiosyncratic productivity for a given size of the firm and a given aggregate state of the economy.

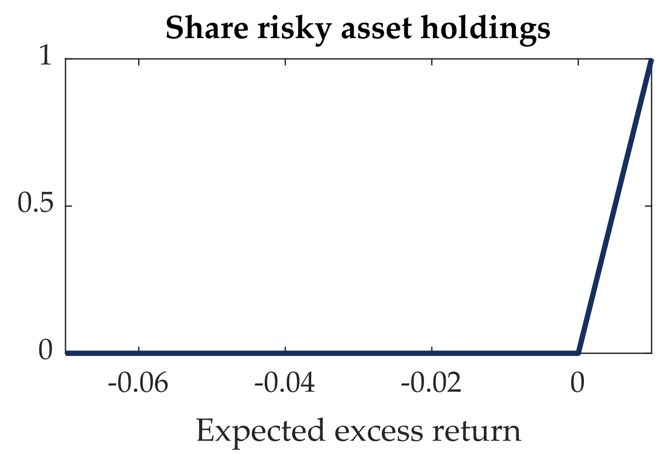

Figure 39: Share of risky asset holdings policy function depending on the expected excess return of risky assets for a firm with zero probability of default.

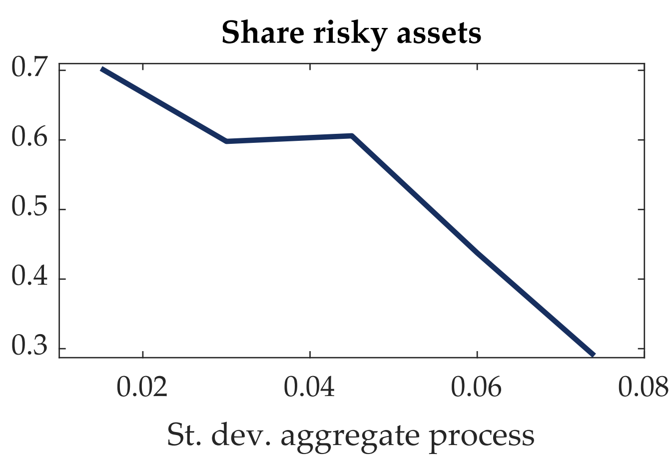

Figure 40: On the left panel, the relation between the standard deviation of the aggregate process and the share of risky assets. While changing σ_z, I change the fixed cost of production to keep the default rate constant and do not change the average return on risky assets. Despite this, the higher potential risk of a recession drives firms away from the risky asset.

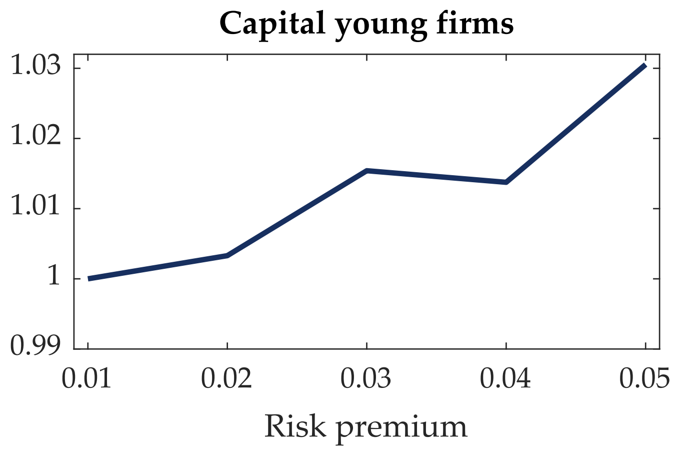

Figure 41: Impact of risk premium on firms' growth rate when compared to the benchmark case of $\omega = 0.01$. A risk premium more in line with the data — between 2% and 3% — could speed up firms growth by 1% to 2% more.

Moment	$\gamma = 1$
Output	0.997
Capital	0.996
Output std	1.024
MPK std	0.999
Capital young firms	1.002
Default rate	1.134

Table 17: Business-cycle statistics relative to a model with $\gamma = 0$. Increasing the share of risky assets causes default rate to increase, which consequently leads to lower values for capital and output.

Moment	$\gamma = 1$	$r^r < r^{rf}$
Output	0.997	1.001
Capital	0.996	1.001
Output std	1.024	1.001
Average recession	0.983	1.000
MPK std	0.999	1.000
Capital young firms	1.002	1.003
Default rate	1.135	1.000

Table 18: Business-cycle statistics relative to a model with $\gamma = 0$. Column 2 and 3 present the results for implementation of the policy that limits losses from risky savings in periods when $r^r < 0$ and when $r^r < r^{rf}$ respectively.