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Essays on Credit Spreads, Bank Risk-Taking, and Flight-to-Safety

Li, Ziang

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Essays on Credit Spreads, Bank Risk-Taking, and Flight-to-Safety

Ziang Li

A Dissertation
Presented to the Faculty
of Princeton University
in Candidacy for the Degree
of Doctor of Philosophy

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Abstract

This dissertation consists of three independent chapters in financial economics.

Chapter 1 studies the dynamics of US corporate bond credit spreads. Post-2008, corporate bond credit spreads decline when long-term interest rates increase, particularly for lower-rated bonds. This is true unconditionally but also conditional on monetary policy announcements. In the cross-section, this negative co-movement between long rates and credit spreads is more pronounced for bonds predominantly held by life insurers. I develop a quantitative framework that rationalizes these findings. In the model, life insurers with long-duration liabilities face duration mismatch and, therefore, realize equity gains when long rates increase. As a result, their effective risk aversion declines, driving down equilibrium credit spreads. The model also shows that life insurers' duration mismatch can dampen or even reverse the transmission of unconventional monetary policy to bond markets.

Chapter 2, co-authored with Jihong Song, studies the risk-taking of US banks. Banks with high deposit market power take on significantly less credit risk. The loan portfolios of high-market-power banks are much safer than those of low-market-power banks. This persistent relationship is not driven by the size, funding structure, loan market power, or geography of banks. Consequently, high-market-power banks earn higher profits, are less pro-cyclical, and sustain smaller losses in recessions. We propose a model where deposit market power increases banks' franchise value and induces them to take on less risk to avoid defaults.

Chapter 3, co-authored with Sebastian Merkel, studies the interaction between flight-to-safety behavior and nominal rigidity. We build a New Keynesian model with idiosyncratic risk, incomplete markets, and nominal safe assets to study the transmission of uncertainty shocks through investors' portfolio decisions. In response to an unexpected increase in uncertainty, investors reallocate their resources from productive to safe assets for precautionary reasons. When prices are sticky, the real value of nominal safe assets cannot flexibly adjust. Instead, the adjustment pressure leads to an aggregate demand recession and undershooting in the price of productive assets. Conventional interest rate policy

alone has limited power in influencing household portfolios. Instead, fiscal policy is crucial in price stabilization and optimal policy.

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To Hua.

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Chapter 1

Long Rates, Life Insurers, and Credit Spreads

1.1 Introduction

The US corporate bond market has expanded dramatically in the last three decades, with its total market capitalization reaching 4.4 times GDP in 2023 Q3 from 2.9 times GDP in 1993 Q1 and surpassing the bank loan market as the primary funding source for US corporations. Corporate bond prices are also significant indicators of real investments and aggregate economic activities (Philippon, 2009; Gilchrist and Zakrajšek, 2012). This paper studies the impact of long-term interest rates on the corporate bond market and focuses on credit spreads, a vital component of corporate bond yields. In particular, I find that increases in long-term interest rates have led to declines in credit spreads since the Global Financial Crisis.

The first main contribution of this paper is new empirical evidence on the impact of long rates on credit spreads and the role of life insurers. I document a new *negative* co-movement between the long-term interest rate and corporate bond credit spreads after the Financial Crisis, both unconditionally and conditional on monetary policy announcements. I then attribute this new co-movement to the duration mismatch of life insurers, the largest investor group in the bond market. I provide causal evidence that higher owner-

ship by life insurers leads to more negative co-movement of credit spreads with the long-term interest rate in the cross-section of corporate bonds. I further show that resulting credit spread dynamics have important real implications on bond issuance and investment.

The second main contribution of this paper is a quantitative framework grounded in the new empirical findings. I develop an intermediary asset pricing model featuring life insurers facing duration mismatch. The model quantitatively explains the empirical findings and demonstrates that this duration mismatch channel can dampen or even reverse the effects of unconventional monetary policy on bond yields and issuance.

I begin by documenting novel facts about the co-movement between the long-term interest rate and corporate bond credit spreads. Leveraging detailed microdata on corporate bond prices, I estimate the 10-year Treasury yield pass-through to corporate bonds with different credit ratings. Before the 2007-2008 Financial Crisis, the long-term interest rate and credit spreads exhibited no significant associations. Changes in the long-term interest rate affected all corporate bonds in a similar fashion. However, after the Financial Crisis, there is an economically and statistically significant negative relationship between the long-term interest rate and corporate bond credit spreads. In particular, the yields of low-credit-rating bonds decline relative to high-credit-rating bonds when long-term interest rates increase. In fact, the yields of bonds with the lowest ratings (e.g., single B or lower) even decline in absolute terms when the long-term interest rate increases.

Contrary to conventional wisdom, where high interest rates discourage risk-taking and raise risk premia, increases in the long-term interest rate lead to declines in corporate bond credit spreads, even after controlling for the yield curve and detailed bond characteristics. Moreover, the impact is more significant on bonds with lower credit ratings: when the long-term interest rate declines, the credit spreads of speculative-grade bonds increase significantly more than investment-grade bonds.

High-frequency identifications around monetary policy announcements further demonstrate that increases in long rates reduce corporate bond credit spreads. I construct high-frequency shocks to the 10-year Treasury yield using yield movements around FOMC meetings. Using a local projection method, I find that 10-year Treasury yield shocks did

not cause significant changes in bond credit spreads before the Financial Crisis. After the Crisis, positive shocks to long-term Treasury yields induce large negative credit spread responses. For example, a 1% increase in the 10-year Treasury yield around FOMC meetings leads to an almost 1% reduction in the spread between single B corporate bonds and AAA corporate bonds.

Next, I trace this new negative co-movement to the duration mismatch and bond holdings of life insurers, the largest institutional investor group of US corporate bonds, which owns about 30% of all US corporate bonds. The business model of modern life insurers involves investing in fixed-income securities and issuing long-term annuity products. Before the Financial Crisis, life insurers were hedged against interest rate risk. Their equity value was largely shielded from fluctuations in the long-term interest rate, which suggests that their assets and liabilities had matching duration. However, as the economy entered a low-interest-rate environment post-2008, life insurers began to face a severe duration mismatch, and their market equity values became highly sensitive to the long-term interest rate.[1] In this time period, the market equity of the life insurance sector increased by almost 7.2% when the 10-year Treasury yield rose by 1%.

The negative co-movement between credit spreads and the long-term interest rate only exists in bonds with life insurance ownership and is more pronounced in bonds with higher life insurance ownership. Next, I provide causal evidence that higher life insurance ownership generates stronger co-movement between credit spreads and the long-term interest rate.

To sharpen the identification, I exploit a discontinuity in bond ownership structure stemming from mutual funds' investment mandates (e.g., Li and Yu, 2023). Figure 1.1 visualizes the composition of the US bond market. The bond market is populated by large institutional investors, where the largest investor type is life insurers, followed by mutual funds. Among bond mutual funds, many are "intermediate-term" with fund charters and mandates to invest in bonds whose maturities are less than 10 years, resulting in a discontinuity in investor composition around the 10-year maturity threshold. Bonds with

[1] Lower interest rates increase the insurers' liability duration more than their asset duration. Together with other institutional frictions (e.g., regulatory), it can leave insurers in a persistent duration mismatch. See Section 1.4.1 for detailed discussions on the change in life insurers' hedging behavior.

maturities slightly below 10 years are significantly less likely to be held by life insurers than bonds with maturities slightly above 10 years, as the former face higher demand from mutual funds. I then find that the bonds slightly to the left of the cutoff are much less responsive to the 10-year Treasury yield.

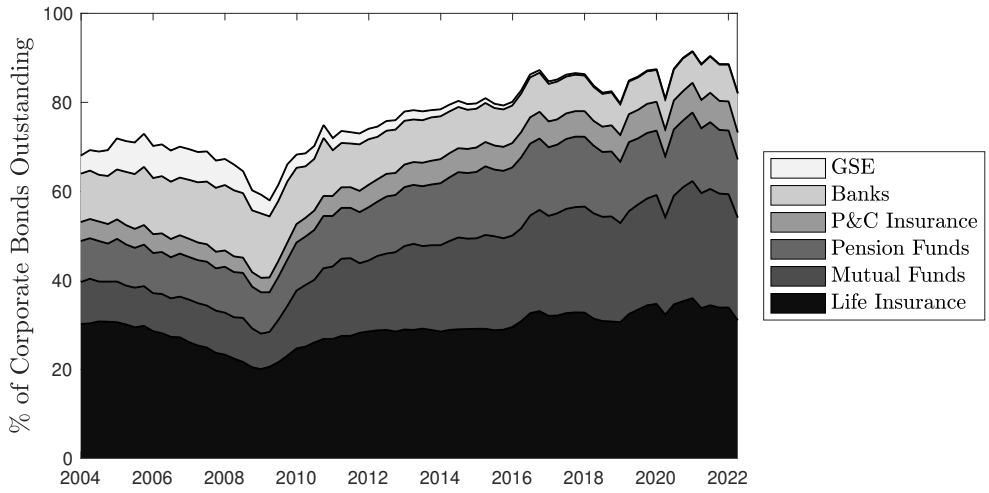


Figure 1.1. **Institutional Investors in the Bond Market.**

This figure plots the ownership structure of US domestic corporate bonds between 2004 and 2022. From top to bottom, the figure shows the fraction of bonds owned by government-sponsored enterprises (GSE), commercial banks, property-casualty insurance companies, pension funds, mutual funds, and life insurance companies. Foreign investors are excluded. The data is obtained from the Financial Accounts of the United States. The black area indicates that life insurers hold 20-35% of all US corporate bonds throughout the last two decades.

The results point to a new channel through which the long-term interest rate affects corporate bond credit spreads — *the duration mismatch channel*. Life insurers' net worth rises following increases in the long-term interest rate. Consequently, their risk-bearing capacity is higher, and they expand their holdings of risky bonds. Furthermore, I show that the bond trading behavior of life insurers supports the duration mismatch channel. Following increases in the 10-year interest rate, life insurers respond by increasing their demand for risky bonds, manifested in the data as more future purchases of risky corporate bonds.

I then show that the credit spread dynamics also generate large real effects on corporate bond issuance and firm investment. Following increases in long-term interest rates, the issuance of investment-grade bonds declines more than the issuance of speculative-grade bonds. The issuance to outstanding amount ratio by investment-grade firms falls by more than 1.5% relative to speculative-grade firms in an average 6-month period when the 10-

year Treasury yield is 1% higher. The finding reveals large credit supply effects from risky firms. Further, I show that life insurers' bond ownership has a significant effect on the transmission of long-term interest rates to firm investment. Firms reduce their capital expenditure when the long-term interest rate increases, but the effect is milder in firms whose bonds are held more by life insurers.

Finally, based on the new empirical evidence, I develop an intermediary asset pricing model centered around the duration mismatch channel to illustrate the impact of duration mismatch facing life insurers and quantify its contribution to the empirical co-movement between long rates and credit spreads. In the model, life insurers hold corporate bonds and Treasuries as assets and issue annuities as liabilities. Life insurers face duration mismatch because the annuities they issue have a much longer duration than their assets. Increases in the Treasury yield cause declines in the price of annuities, which reduce the value of life insurers' liabilities more than their assets and boost their net worth. Life insurers are the main investors of corporate bonds, and their risk-bearing capacity affects equilibrium credit spreads. Life insurers are more averse to bonds with lower credit ratings as they carry greater credit risk and regulatory costs. Therefore, when the long-term Treasury yield rises, life insurers become more willing to hold risky bonds, so the equilibrium credit spreads shrink.

Analytically, I prove that increases in the long-term interest rate depress corporate bond credit spreads in a simplified model. Quantitatively, the model can explain the majority of the observed co-movement between the long-term interest rate and corporate bond credit spreads when matched to the estimated duration mismatch of life insurers. The model can also account for the observations before the Financial Crisis, as the co-movement disappears once life insurers in the model are not subject to duration mismatch.

My findings suggest that policies targeting the long-term interest rate, such as Quantitative Easing and Tightening (QE and QT), have large unintended consequences in the corporate bond market. QE is a policy aimed at boosting the economy by reducing long-term interest rates. However, it may have unintended consequences by heightening credit spreads, especially for companies with higher risk profiles. Conversely, the tightening effects of QT might be dampened as higher long-term interest rates could depress credit

spreads and generate favorable financial conditions for bond-issuing firms. In the model, I show that the duration mismatch channel has large real effects. Quantitatively, the credit spread responses reduce the effectiveness of long-term rate hikes on aggregate bond issuance and firm investment by more than half. The channel even reverses the transmission of long rates to speculative-grade firms, resulting in speculative-grade bond booms after positive long-term rate shocks. These results are particularly relevant today, given the increasing prevalence of unconventional monetary policies such as QE and QT.

Related Literature. My results contribute to the extensive literature on corporate bond credit spreads.[2] Following Fama and French (1993), many have modeled corporate bond yields and returns using factor models (e.g., Gebhardt, Hvidkjaer and Swaminathan, 2005; Lin, Wang and Wu, 2011; Acharya, Amihud and Bharath, 2013; Jostova *et al.*, 2013; Kelly, Palhares and Pruitt, 2023). The factor approach typically views credit risk and the term structure as unconnected orthogonal factors in determining bond yields. In this paper, I show that the pricing of the two factors is interconnected, as the level of long-term interest rates could affect the pricing of credit risk through the risk-bearing capacity of life insurers. Another strand of literature aims to explain the levels and fluctuations of corporate bond credit spreads (see, e.g., recent works by Eom, Helwege and Huang, 2004; Longstaff, Mithal and Neis, 2005; Schaefer and Strebulaev, 2008; Chen, Collin-Dufresne and Goldstein, 2009; Huang and Huang, 2012; Kuehn and Schmid, 2014; Culp, Nozawa and Veronesi, 2018; Feldhütter and Schaefer, 2018; van Binsbergen, Nozawa and Schwert, 2023). I contribute to this literature by documenting a new co-movement between credit spreads and long-term interest rates and providing an explanation centered around life insurance companies.[3]

This paper also belongs to the burgeoning literature focusing on the role of institutional investors in the corporate bond market. My work is most closely connected to Coppola (2022) and Li and Yu (2022, 2023), who, in different contexts, also show that investor

[2] See Huang and Shi (2021) for an overview of the literature on corporate bond returns.

[3] Duffee (1998) finds a negative co-movement between short-term interest rates and spreads between corporate bonds and Treasuries, highlighting the role of corporate bond callability. In this paper, I instead study long-term interest rates and spreads in the cross-section of corporate bonds, focusing on the impact of life insurance companies.

composition matters for bond price dynamics. Using similar empirical frameworks, I show that life insurance ownership induces a negative co-movement between credit spreads and the long-term interest rate after the Financial Crisis. A recent strand of the literature studies the role of mutual funds in liquidity disruptions in crises (e.g., Haddad, Moreira and Muir, 2021; Falato, Goldstein and Hortaçsu, 2021; Jiang *et al.*, 2022; Ma, Xiao and Zeng, 2022). This paper, instead, focuses on life insurers, the largest investor group in the US corporate bond market that currently holds more than 30% of the US corporate market capitalization, to show that their balance sheets are important for bond price dynamics. Recent works such as Bretscher *et al.* (2022) and Darmouni, Siani and Xiao (2022) use demand system approaches to analyze the equilibrium effects of institutional demand. In this paper, I depart from the logit portfolio choices used in the demand system literature to focus on life insurers' duration mismatch.

The findings of my paper echo recent research on the investing behavior of life insurance companies (e.g., Koijen and Yogo, 2022; 2023; Chodorow-Reich, Ghent and Haddad, 2021; Ellul *et al.*, 2022). Several studies, including Berends *et al.* (2013), Hartley, Paulson and Rosen (2016), Domanski, Shin and Sushko (2017), Ozdagli and Wang (2019), Koijen and Yogo (2022), and Huber (2022), have also shown that life insurers' interest rate risk exposure changed after the Financial Crisis. I build on this finding and argue that the duration mismatch can significantly influence bond prices since life insurers, on average, hold more than 25% of all US corporate bonds. Prior works by Ellul, Jotikasthira and Lundblad (2011), Nanda, Wu and Zhou (2019), Girardi *et al.* (2021), Becker, Opp and Saidi (2022), and Murray and Nikolova (2022) have established that the trades of life insurers have potentially large price impacts on corporate bond prices. I confirm that life insurers can considerably influence bond prices in the context of how corporate bond yields respond to long-term interest rate fluctuations. Consistent with Ge and Weisbach (2021) and Bhardwaj, Ge and Mukherjee (2022), I find that insurers tilt their portfolios towards safer investments when they become financially constrained.

Both my empirical and theoretical results add to the recent literature on how the corporate bond market interacts with the corporate sector and the real economy (e.g., Philippon, 2009; Gilchrist, Yankov and Zakrajšek, 2009; Greenwood, Hanson and Stein, 2010; Gilchrist

and Zakrajšek, 2012; López-Salido, Stein and Zakrajšek, 2017; Coppola, 2022; Mota, 2023). In this paper, I study how long-term interest rates affect bond issuance and firm investment through their impacts on life insurers and credit spreads.

The approach of this paper connects to the literature on intermediary asset pricing, which emphasizes the role of the financial health of intermediaries on asset prices (e.g., Brunnermeier and Pedersen, 2009; He and Krishnamurthy, 2013, 2018; Brunnermeier and Sannikov, 2014; Adrian, Etula and Muir, 2014; He, Kelly and Manela, 2017; Haddad and Muir, 2021; Baron and Muir, 2022). My paper finds that the duration mismatch of life insurers, the dominant intermediaries in the US corporate bond market, significantly affects bond credit spreads. Unlike previous works where higher interest rates depress intermediaries' net worth (e.g., Gomez *et al.*, 2021; Kekre, Lenel and Mainardi, 2023), I find that life insurers face the opposite duration mismatch and receive equity gains when long rates increase.

Additionally, this paper contributes to the literature on the impact of monetary policy and interest rates on the bond market. Departing from existing works that focus on short-term monetary policy and mutual funds (e.g., Guo, Kontonikas and Maio, 2020; Daniel, Garlappi and Xiao, 2021; Chen and Choi, 2023; Fang, 2023), I instead focus on the long-term interest rate and life insurers. I document evidence that positive shocks to long-term interest rates significantly depress corporate bond credit spreads and encourage bond issuance by risky firms.

Outline. Section 1.2 describes data sources for the empirical analysis. Section 1.3 discusses evidence on the co-movement between the long-term interest rate and corporate bond credit spreads. Section 1.4 investigates the role of life insurers in shaping the co-movement. Section 1.5 explores the real effects of the long-term interest rate and credit spreads. Section 1.6 builds an intermediary asset pricing model that accounts for the empirical findings and studies policy implications. Section 1.7 concludes.

1.2 Data

In this paper, I combine data from multiple sources to assess the co-movement between the long-term interest rate and corporate bond credit spreads, the significance of life insurers, and their real impacts.

The Long-term Interest Rate. I use the US Treasury yield curve constructed by Liu and Wu (2021) at a daily frequency. In particular, I use the yield on 10-year US Treasury notes as the proxy for the long-term interest rate.

Corporate Bonds. I combine monthly data from the Mergent Fixed Income Securities Database (Mergent FISD), the Trade Reporting and Compliance Engine (TRACE), and the WRDS Bond Returns for corporate bond prices, quantities, and characteristics. The dataset provides comprehensive coverage for US corporate bonds between 2000 and 2019. From Mergent FISD, I obtain information on the bond issuer, maturity, duration, credit ratings, outstanding amount, issuance date, coupons, transaction volume, and default history at a monthly frequency. The WRDS Bond Returns dataset also provides end-of-month transaction prices and yields extracted from TRACE. For any given month, I focus on bonds with at least one observed transaction price.

Mergent FISD reports three "raw" credit ratings from Standard and Poor's (S&P), Moody's Analytics, and the Financial Industry Regulatory Authority (FINRA). For my analysis, I adopt the NAIC system, which consolidates the three ratings into one and sorts them into six NAIC categories. The NAIC rating is the most relevant risk metric for insurance companies, as it determines the capital requirement for each bond. Bonds in NAIC 1 and NAIC 2 are investment-grade, while bonds in NAIC 3-6 are speculative-grade. Table 1.1 replicates Table 2 in Becker and Ivashina (2015), which summarizes the 5-year default rate and capital requirement of each NAIC category. Corporate bonds with lower NAIC ratings have higher default rates and entail more stringent capital requirements.

For part of my empirical analysis, I also use aggregate bond yield indices from the Intercontinental Exchange ("ICE") and bond credit default swaps (CDS) spreads from Markit IHS. In particular, I use the par spreads of credit default swaps with a 5-year tenor, which

NAIC Category	Credit Ratings	Investment Grade	5-year Default Rate (1990-2010)	Capital Requirement
NAIC 1 (highest)	AAA, AA, A	✓	0.00%, 0.09%, 0.69%	0.3%
NAIC 2	BBB	✓	2.62%	0.96%
NAIC 3	BB	x	6.76%	3.39%
NAIC 4	B	x	8.99%	7.38%
NAIC 5	CCC	x	34.38%	16.96%
NAIC 6 (lowest)	CC, C, D	x	n.a.	19.50%

Table 1.1. **The NAIC Rating System.**

This Table summarizes the characteristics of corporate bonds belonging to different NAIC categories. The data on the cumulative 5-year default rates and capital requirements are drawn from Becker and Ivashina (2015).

form the most liquid segment of the CDS market (e.g., Blanco, Brennan and Marsh, 2005). The CDS data has been available since the beginning of 2001.

Life Insurers. I obtain regulatory data on life insurers' end-of-year bond holdings and long-term bond transactions from the National Association of Insurance Commissioners (NAIC). I examine the Schedule D information in life insurers' regulatory reports to NAIC.[4] The NAIC data also contains bond identifiers (CUSIP codes) that allow me to match the bonds held and transacted by life insurers to those in Mergent FISD and WRDS Bond Returns. In addition to the NAIC data, I use data on the aggregate balance sheets of life insurers from the Financial Accounts of the United States and data on life insurers' stock prices from the Center for Research in Security Prices (CRSP).

Investment. To jointly study the life insurers' bond holdings and firm investment, I combine Mergent FISD with Compustat to form a panel of bond-issuing firms. The data include the quarterly capital expenditure and bond ownership structure of all firms in Mergent FISD.

FOMC Meeting Dates. Hillenbrand (2023) summarized the dates of all FOMC meetings since September 1982. In my analysis, I focus on meetings between 1997 and 2022, exclud-

[4]See `https://content.naic.org/sites/default/files/ASB-PCA-22_0.pdf` for the structure and content of the dataset.

ing all unscheduled meetings.

Sample Period. Throughout the paper, I separate my analysis into two time periods: before the Financial Crisis (1997-2007 or 2000-2007) and after the Financial Crisis (2010-2022). The aggregate credit spread data begins in 1997, while the individual bond data in WRDS Bond Returns dates back to January 2000. I remove the Global Financial Crisis (2007-2009), which features large-scale fire sales and liquidity interruptions that potentially confound the mechanism of interest. Similarly, I exclude data from March 2020 in the post-crisis period to avoid capturing the bond market disruptions during the COVID-19 crisis. For analysis involving life insurers' bond ownership or real effects, I shorten the post-crisis sample to 2010-2019 due to data availability.

1.3 The Long-term Interest Rate and Bond Credit Spreads

In this section, I examine the co-movement between the long-term interest rate and corporate bond credit spreads and contrast the findings before and after the 2008 Financial Crisis.

1.3.1 Pass-through of the Long-term Interest Rate

I begin by studying the 10-year Treasury yield pass-through in the cross-section of corporate bonds. I run the following regressions to estimate the pass-through

$$y_{it} = \alpha_i + \sum_{k=1}^{6} \beta_k \cdot \mathbf{1}_{\{\text{NAIC } k\}} \cdot y_t^{(10)} + \Gamma \mathbf{X}_{it} + \varepsilon_{it}, \tag{1.1}$$

where y_{it} is the yield of bond i at time t, $y_t^{(10)}$ is the 10-year Treasury yield, α_i are bond fixed effects, and $\mathbf{X}_{it}$ are additional controls. Here I control for bond characteristics such as bond size (outstanding amount), liquidity (trading volume), maturity, duration, credit ratings, coupon amount, and coupon frequency, as well as the recent default rate of each NAIC category.

The regression coefficient β_k measures the pass-through rate of the 10-year Treasury

yield to the yield of NAIC k corporate bonds. Intuitively, β_k measures the average response of the yields of NAIC k bonds when the 10-year Treasury yield increases by one percentage point. Figure 1.2 shows the estimates of β_k for the sample before the Financial Crisis (2000-2007) and the sample after the Financial Crisis (2010-2022).

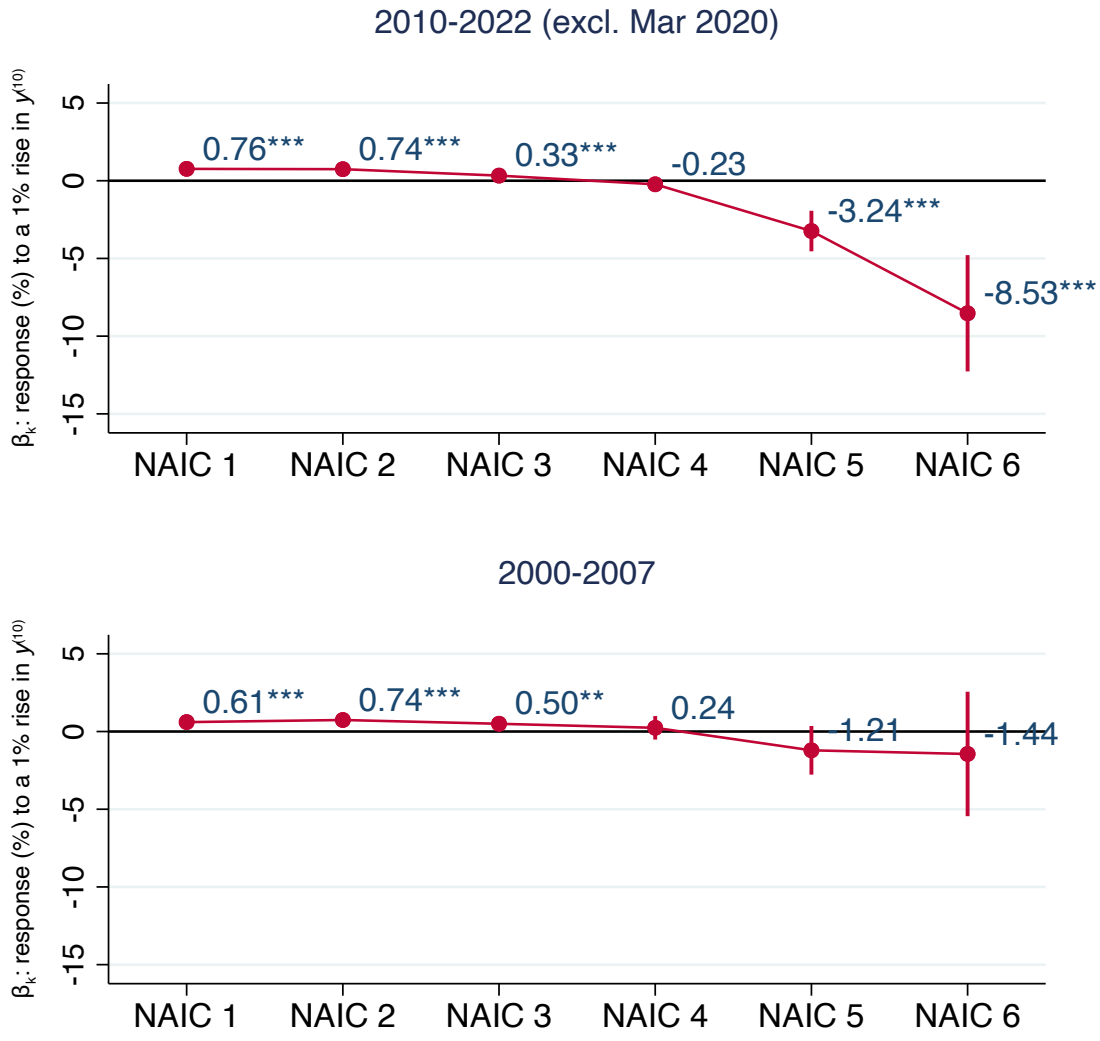


Figure 1.2. **10-year Treasury yield pass-through.**

This figure plots the coefficients β_k estimated from regression (1.1), controlling for the trading volume, outstanding amount, maturity, duration, credit ratings, coupon amount, and coupon frequency of each bond, and the recent default rate of each NAIC category. Both corporate bond yields and the Treasury yield are in percentage points. The top panel shows results for the post-crisis sample, while the bottom panel shows results for the pre-crisis sample. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

After the Financial Crisis, there is a strong relationship between credit ratings and the pass-through of the long-term interest rate. The yields of the safest bonds (i.e., NAIC 1 and 2) move strongly together with the 10-year Treasury yield. However, as the credit rating declines, the sensitivity to the long-term interest rate diminishes and eventually reverses for bonds with the lowest credit ratings (NAIC 5 and 6). The effects are large, especially for bonds in NAIC 5 and 6, whose yields decrease by much more than 1% when the 10-year Treasury yield increases by 1%. Accordingly, the credit spreads between low-rating and high-rating bonds shrink when the 10-year Treasury yield is high.

By contrast, the relationship was much weaker before the financial crisis. Bonds in NAIC 1 and 2 had a strong positive co-movement with the 10-year Treasury yield. However, the responses of lower-rating bonds were much smaller and statistically insignificant from those in NAIC 1 and 2.

Overall, the results indicate a significant increase in the co-movement between the long-term interest rate and corporate bond yields around the Financial Crisis.

1.3.2 Credit Spread Responses to the long-term interest rate

Next, I focus on credit spreads in the cross-section of corporate bonds. To this end, I analyze the spreads between bonds with lower ratings (NAIC k, $k \geq 2$) and the highest credit rating (NAIC 1). Relative to the empirical specification in regression (1.1), I further include maturity-time fixed effects $\alpha_{\tau(i),t}$,

$$y_{it} = \alpha_i + \alpha_{\tau(i),t} + \sum_{k=2}^{6} \beta_k \cdot \mathbf{1}_{\{\text{NAIC } k\}} \cdot y_t^{(10)} + \Gamma \mathbf{X}_{it} + \varepsilon_{it}. \tag{1.2}$$

To construct the maturity-time fixed effects, I sort bonds into small maturity segments with a size of 1 year and interact these maturity dummies with the time variable. The fixed effects thus control for the maturity differences across each NAIC category[5] and variations in the yield curve over time. Additionally, the fixed effects absorb one NAIC category for any given month, which I normalize as NAIC 1. Hence, the coefficient β_k (for $k \geq 2$)

[5]It is important to control for maturity as riskier bonds tend to be of shorter maturity. Figure A.4 and Figure A.5 further confirm that the results also hold when we compare bonds within maturity segments.

measures the average response that changes in the 10-year Treasury yield induce in the *spreads* between NAIC k bonds and NAIC 1 bonds. A negative coefficient indicates that credit spreads move in opposite directions as the long-term interest rate.

Figure 1.3 plots the estimated coefficients and delivers one of the main results of this paper. In the post-crisis sample, corporate bond credit spreads fall when the 10-year Treasury yield increases. The result is significant for all NAIC categories and is stronger for lower ratings.

To understand the significance of the results, it is useful to consider the following decomposition of bond yields

$$y_{t,\text{NAIC } k} = y_{t,\text{NAIC } 1} + (\text{Credit Spread})_{t,\text{NAIC } k}.$$

Effects of the level of the long-term interest rate on total bond yields depend on (1) how it affects the safest segment of the bond market (yields of NAIC 1 bonds) and (2) how it affects credit spreads relative to NAIC 1. In Section 1.3.1, I show that NAIC 1 bond yields co-move positively with the 10-year Treasury yield, with a pass-through coefficient of about 0.76 after the Financial Crisis. For safer bonds (NAIC 2, 3, and 4), the effect on credit spreads partially offsets the changes in NAIC 1 yields, making bond yields less sensitive to the 10-year Treasury yield.

The effects are much larger for the riskiest bonds. For example, when the 10-year Treasury yield increases by 25 basis points, the yields of CCC corporate bonds (NAIC 5) fall by 102 basis points relative to corporate bonds rated A or better (NAIC 1), which is large enough to fully offset the increase in NAIC 1 yields and lower the NAIC 5 yields in absolute terms. As already shown in Figure 1.2, the yields of NAIC 5 and 6 bonds move in opposite directions as the 10-year Treasury yield. Surprisingly, increases in the long-term interest rate lower the funding costs of the riskiest firms.

It is also worth noting that the effects on credit spreads were absent before the Financial Crisis. In the sample before 2007, credit spreads had very small and statistically insignificant responses to the 10-year Treasury yield. Earlier lack of response implies that the co-movement between the long-term interest rate and credit spreads only emerged after

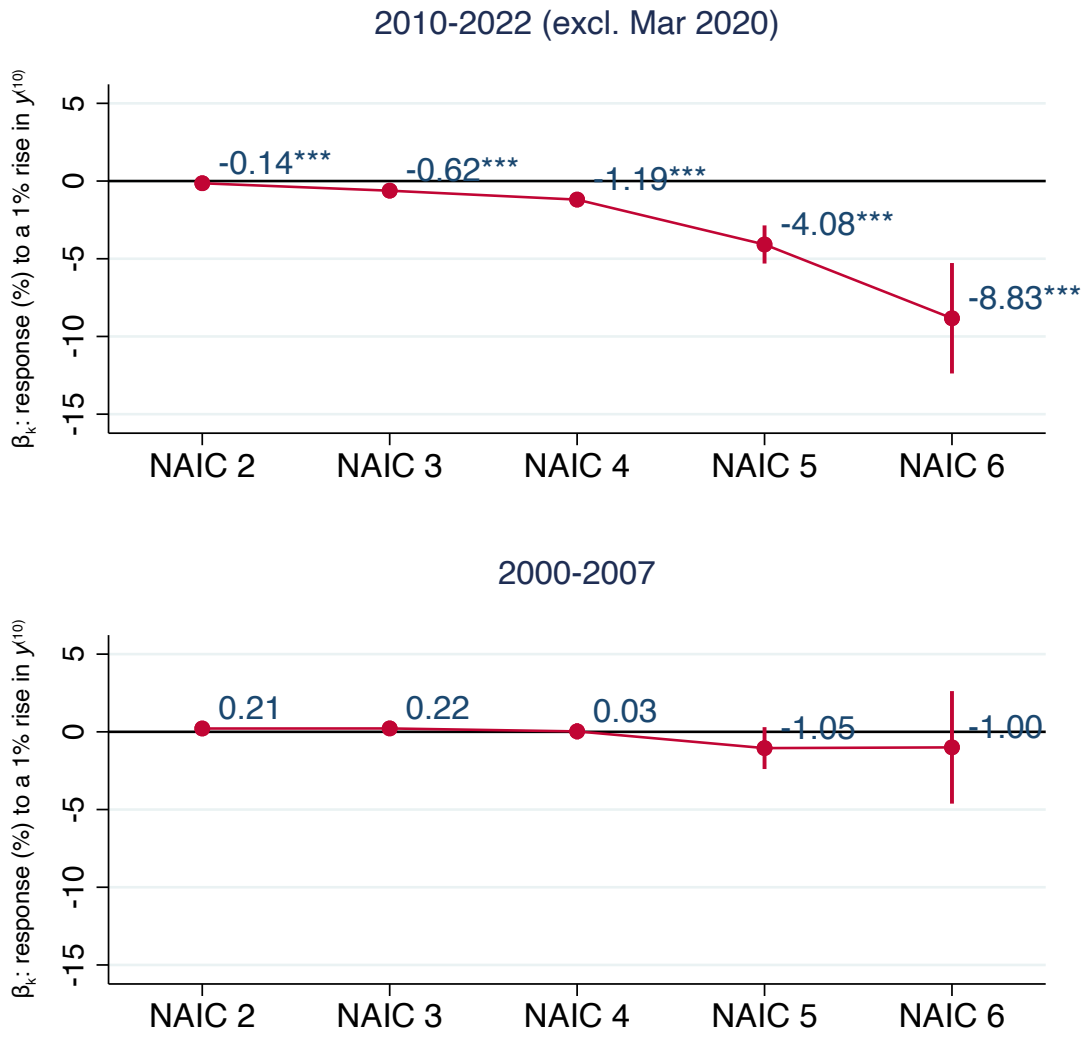


Figure 1.3. **Credit Spread Responses to the Long-term Interest Rate.**

This figure plots the coefficients β_k estimated from regression (1.2), controlling for the trading volume, outstanding amount, maturity, duration, credit ratings, coupon amount, and coupon frequency of each bond, and the recent default rate of each NAIC category. Both corporate bond yields and the Treasury yield are in percentage points. The top panel shows results for the post-crisis sample, while the bottom panel shows results for the pre-crisis sample. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

the Crisis.

Figure A.1 and Figure A.2 in the Appendix visualize the time series of the 10-year Treasury yield and various corporate bond credit spreads. The correlation pattern supports the conclusion of this Section. A strong negative correlation exists between corporate bond

credit spreads and the 10-year Treasury yield after the Financial Crisis but not before the Financial Crisis.

A potential confounding factor in these findings is credit risk movements. For example, stronger economic growth can lower credit risk, which could further lead to both lower credit spreads and increased interest rates (e.g., Wu and Zhang, 2008). To better control for variations in perceived credit risk, I further control the average CDS spread for each NAIC category, which is a direct and real-time measure of the price of default risk (e.g., Longstaff, Mithal and Neis, 2005).[6] By controlling for CDS spreads, we can eliminate the impacts of changing credit risk and more clearly understand how long rates affect credit spreads.[7] Figure A.3 shows the coefficients estimated after controlling for CDS spreads, which exhibit the same pattern as in Figure 1.3 and confirm the validity of the findings.

1.3.3 High-frequency Evidence: FOMC Announcements

Section 1.3.1 and Section 1.3.2 discussed the unconditional co-movements between the long-term interest rate and corporate bond credit spreads. In this section, I strengthen the evidence by showing identified evidence on the impact of 10-year Treasury yields on bond credit spreads using high-frequency shocks around FOMC meetings. A recent study by Hillenbrand (2023) documents that a short window around FOMC meetings explains the majority of the long-run movements in long-term interest rates for the past 30 years. The potential explanation is that FOMC meetings disseminate information concerning the future paths of interest rates. Inspired by Hillenbrand (2023), I construct shocks to the 10-year Treasury yield as the changes in the yield in 2-day windows around FOMC meetings,

$$\Delta y_t^{(10)}\Big|_{\text{FOMC}} = y_{t+1}^{(10)} - y_{t-1}^{(10)},$$

[6] Absent frictions, CDS spreads should coincide with credit spreads. However, empirically, the CDS-bond basis is known to be non-zero and dispersed across bonds (e.g., Bai and Collin-Dufresne, 2019). Following Longstaff, Mithal and Neis (2005) and Mota (2023), I view the CDS spread as a better measure of the market price of credit risk, while credit spreads potentially also reflect other factors, including liquidity, convenience yields, and the risk-bearing capacity of bond investors such as life insurers.

[7] Importantly, life insurers are not the major investors in the CDS market, so the CDS spreads are potentially not affected by the balance sheets of life insurers.

where t is an FOMC announcement day. Using a local projection method (Jordà, 2005), I then estimate the impulse responses of corporate bond credit spreads to the high-frequency 10-year Treasury yield shocks. The regressions are as follows

$$\text{Spread}_{t+h}^{k} - \text{Spread}_{t-1}^{k} = \alpha_h + \beta_h \left(\Delta y_t^{(10)} \Big|_{\text{FOMC}} \right) + \varepsilon_{t,h}. \tag{1.3}$$

Here the left-hand-side variable Spread_t^k is constructed as the difference between the bond yield index for rating k and the bond yield index for the AAA rating. The coefficient β_k measures the cumulative response of Spread_t^k to a 1% positive innovation in the 10-year Treasury yield at a horizon of h trading days.

Figure 1.4 and Figure 1.5 plot the impulse response functions estimated from the local projections (1.3) for the post-crisis sample and the pre-crisis sample, respectively. After the Financial Crisis, positive shocks to the 10-year Treasury yield led to large and significant declines in the credit spreads between AAA bonds and bonds with lower credit ratings. For example, a 1% increase in the 10-year Treasury yield depresses the spread between single B and AAA bonds around 1% at a 10-day horizon. The negative responses of credit spreads are surprising in light of the literature on short-term monetary policy, which typically finds that higher interest rates raise risk premia and corporate bond spreads (e.g., Gertler and Karadi, 2015).

Nevertheless, similar shocks to the 10-year Treasury yield produced statistically insignificant or even the opposite responses before the Crisis. The results suggest that there was a shift in the transmission of policy shocks around the Financial Crisis — the FOMC windows did not influence credit spreads prior to the Financial Crisis.

The results so far focus on credit spreads relative to AAA bonds. Figure A.7 in the Appendix replaces the spreads relative to AAA bonds with the spreads relative to US Treasury securities and finds similar impulse responses. Figure A.8 instead estimates the local projections directly on the yield indices for different credit ratings. The yield of AAA bonds exhibits a persistently positive dependence on the 10-year Treasury yield, while yields of other investment-grade bonds (AA, A, BBB) are less sensitive. Consistent with the findings of Section 1.3.1, the yields of speculative-grade bonds (BB and lower) seem to

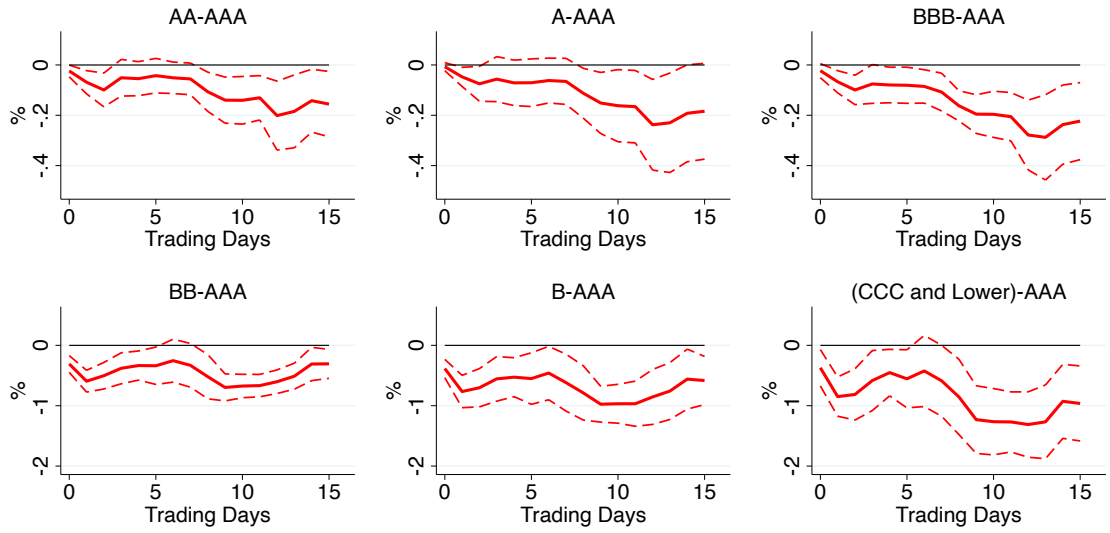


Figure 1.4. **Impulse Responses of Credit Spreads (2010-2022).**

This figure plots the cumulative responses of credit spreads to a 1% increase in the 10-year Treasury yield and 90% confidence intervals based on Newey-West standard errors with a maximum lag of 30 trading days.

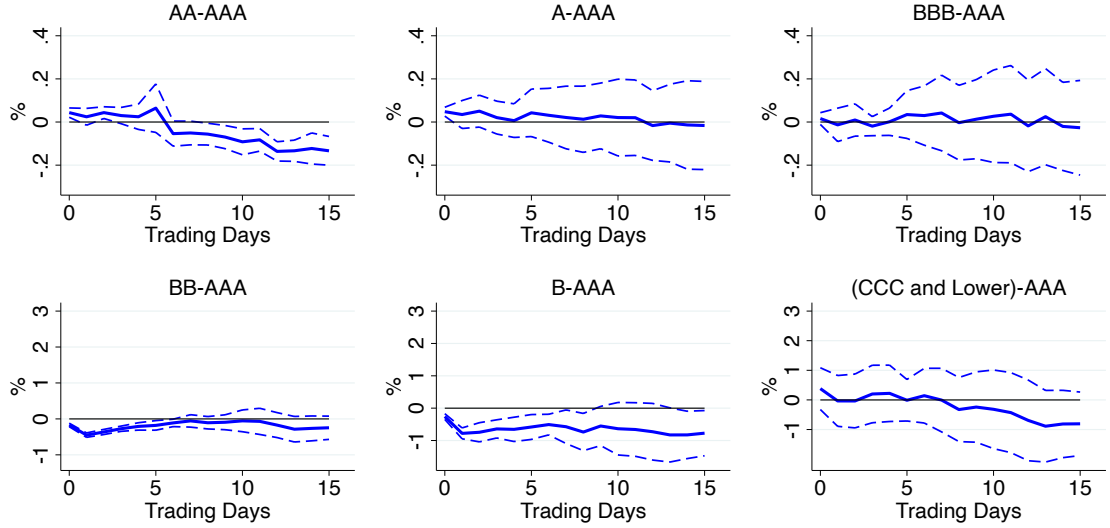


Figure 1.5. **Impulse Responses of Credit Spreads (1997-2007).**

This figure plots the cumulative responses of credit spreads to a 1% increase in the 10-year Treasury yield and 90% confidence intervals based on Newey-West standard errors with a maximum lag of 30 trading days.

move in the opposite direction as the 10-year Treasury yield.

An alternative explanation might be that the effects are mainly due to short rates that move simultaneously with long rates. As a robustness check, I include changes in the 1-month Treasury yield around FOMC meetings as controls for short-term monetary policy.

Further, long-rate movements around FOMC meetings could contain information on the long-run performance of corporate bonds. To distinguish this alternative channel, I include changes in CDS spreads around FOMC windows as controls for credit risk news. Figure A.9-Figure A.12 plot the post-crisis impulses responses estimated after controlling for short rate changes and CDS spreads, which again confirm the patterns shown in Figure 1.4.[8] Figure A.13 further shows that the responses of CDS spreads to long rates are much smaller than the responses of credit spreads.

1.3.4 Discussion on the Mechanism

In this section, I document a negative co-movement between the long-term interest rate and corporate bond credit spreads after the Financial Crisis — credit spreads rise when the 10-year Treasury yield falls. The results might seem counterintuitive relative to the standard macro-finance literature, where low interest rates lower risk premia by enhancing the balance sheets of financial intermediaries or encouraging reaching-for-yield behaviors. While the standard theory has been proven true in the context of bank lending (e.g., Kashyap and Stein, 2000; Jiménez *et al.*, 2014; Whited, Wu and Xiao, 2021), I show there exists an opposite effect in the corporate bond market.

The favored explanation this paper proposes is the impact of life insurers' duration mismatch. In Section 1.4.1, I empirically document a shift in the life insurance sector's duration mismatch and investigate their contribution to the relationship between the long-term interest rate and credit spreads. Under the new duration mismatch, life insurers suffer from equity drawdowns when the long-term interest rate declines, which increase their portfolio exposure to corporate bonds. Since life insurers are the largest investor group in the US bond market, elevations in their effective risk aversion lead to higher equilibrium corporate bond credit spreads.

While life insurers are important for this negative co-movement, there exist other potential channels through which long-term interest rates affect risk premia in the bond market. For example, pension funds have a balance sheet structure similar to life insurers,

[8] Hillenbrand (2023) also argues that the long-rate changes around FOMC meetings $\left(\Delta y_t^{(10)}\Big|_{\text{FOMC}}\right)$ are not driven by short-term economics news or the Fed's policy responses to them.

which makes them susceptible to interest rate fluctuations too. Increases in the long-term interest rate could also result from endogenous monetary policy responses to higher credit spreads. Section 1.6 analyzes a structural model of the corporate bond market to quantify the fraction of the co-movement explained by life insurers. In the model, insurers' duration mismatch can explain a large fraction of the empirical co-movement, while the unexplained fraction is potentially due to other mechanisms discussed above.

1.4 The Role of Life Insurers

Next, I turn to the potential channel through which the long-term interest rate negatively affects corporate bond credit spreads — life insurers' duration mismatch. As shown in Figure 1.1, life insurers are the largest investor group in corporate bonds and own more than 30% of all corporate bonds in the US as of 2022 (see also Koijen and Yogo, 2023).

1.4.1 Duration Mismatch

Modern life insurers issue various life insurance and annuity products while investing primarily in fixed-income markets. For example, variable annuities, which are long-term mutual fund products with minimum return guarantees, have now become the largest component of life insurers' liabilities (Koijen and Yogo, 2022). Maturity transformation is a key component of life insurers' operations, as they invest in fixed-income securities (e.g., corporate bonds) and turn them into longer-term liabilities (e.g., variable annuities). Unlike banks that turn long-term loans into short-term deposits, the maturity transformation of life insurers takes the opposite direction. Hence, life insurers' market equity could be hurt when the long-term interest rate is low.

Table 1.2 summarizes the balance sheet structure of the US life insurance sector. Life insurers' assets are predominantly fixed-income debt securities and mutual fund shares that are ultimately also invested in fixed-income assets. Corporate bonds are an important asset class for life insurers as they make up 80% of all the debt securities they hold. On the liability side, life insurers raise funding mostly by selling life insurance and annuities, which typically have a longer maturity and duration than corporate bonds.

Financial Assets ($ tn)		Liabilities ($ tn)	
Short-term Assets	0.20	Life Insurance Reserves	2.25
Debt Securities	4.43	Annuity Reserves	3.79
– Corporate Bonds	– 3.56	Other Liabilities	2.34
Loans & Equities	1.54		
Mutual Fund Shares	1.70		
Other Financial Assets	1.55		
Total	9.42	Total	8.38

Table 1.2. **The Balance Sheets of the Life Insurance Sector.**

This table summarizes the main financial assets and liabilities of life insurers in the US. The data is from the Financial Accounts of the United States at 2020 Q4.

I then estimate the exposure of life insurers' market equity to the 10-year Treasury yield. In particular, I run the following regressions

$$\text{ExcessReturn}_t = \alpha + \beta \Delta y_t^{(10)} + \text{Controls} + \varepsilon_t. \tag{1.4}$$

Here ExcessReturn_t is the stock return of the life insurance sector in week t in excess of the return on the S&P 500 index, and $\Delta y_t^{(10)}$ is the change in the 10-year Treasury yield in week t. The coefficient β measures the sensitivity of life insurers' market equity to changes in the 10-year Treasury yield. If the duration of life insurers' liabilities exceeds their assets, the coefficient β should be positive, as higher interest rates lower the value of their liabilities more than their assets and thereby boost the value of their equity. Therefore, $(-\beta)$ can also be interpreted as an estimate of the duration of life insurers' market equity, which is defined as $D_E = -\partial E_t / \partial y_t^{(10)}$ (E_t is the market equity of life insurers in week t). A positive estimate of β then indicates that life insurers' equity has a negative duration (e.g., Ozdagli and Wang, 2019; Koijen and Yogo, 2022).

Table 1.3 contrasts life insurers' exposure to the 10-year Treasury yield before and after the Financial Crisis. Before the Financial Crisis, the stock returns of the life insurance sector did not seem to be affected by the long-term interest rate. It implies that life insurers were largely hedged against interest rate fluctuations. However, the estimated β is significantly away from zero in the post-crisis period. The estimated coefficient of 7.179 suggests that

life insurers' equity value grows by more than 7% when the 10-year rate increases by 1%, so life insurers face severe duration mismatch after the 2007-2008 Financial Crisis.

	Dep. Var.: ExcessReturn$_t$	
	1997-2007	2010-2020
$\Delta y_t^{(10)}$	-0.845	7.179***
	[-0.788]	[2.782]
S&P 500 Return	✓	✓
$\Delta y_t^{(1m)}$	✓	✓
Observations	520	520

Table 1.3. **Life Insurers' Duration Mismatch.**

This table shows the coefficients estimated from regression (1.4), controlling for the market return and changes in the one-month Treasury yield. The first column shows the result for the pre-crisis sample, while the second column shows the result for the post-crisis sample. Both the excess return and the 10-year Treasury yield are in percentage points. The t-statistics shown in brackets are based on robust standard errors. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

Figure A.14 in the Appendix shows the evolution of life insurers' duration mismatch over time. In particular, the figure plots the two-year rolling estimates of β. Consistent with existing findings (e.g., Hartley, Paulson and Rosen, 2016; Ozdagli and Wang, 2019; Huber, 2022), the estimated exposure to interest rate risk is small and insignificant from zero before the Financial Crisis, whereas large and persistent deviations from zero are found after the Financial Crisis. Overall, the results suggest that life insurers' duration mismatch increased dramatically after the Financial Crisis.

Figure 1.6 plots the market leverage ratio of the life insurance sector against the 10-year Treasury yield. Consistent with the previous findings, life insurers become less levered when the 10-year Treasury yield is high, as their liabilities become less expensive and their equity declines.

The Source of Duration Mismatch. In this paper, I take a neutral stance on the cause of the shift in life insurers' duration mismatch. Nevertheless, the existing literature typically attributes the new duration mismatch post-2008 to lower interest rates after the Financial Crisis. To illustrate this point, we can write life insurers' equity as $E = A - L$, where A is assets, L is liabilities, and $\ell = L/E$ is the leverage ratio. The duration of equity is then

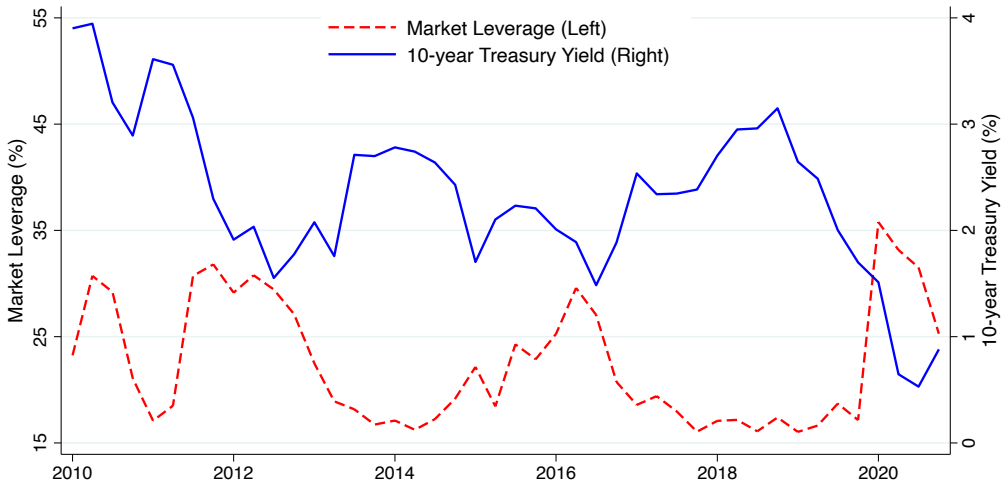


Figure 1.6. **Life Insurers' Market Leverage.**

This figure plots the market leverage ratio of the US life insurance sector and the 10-year Treasury yield. The market leverage ratio is defined as the "fair" value of their liabilities (from Compustat) divided by their market equity value.

$D_E = (AD_A - LD_L)/E = (1+\ell)D_A - \ell D_L$. Before the Crisis, life insurers were hedged against interest rate risk by choosing $D_A \approx [\ell/(1+\ell)]D_L$ so that $D_E \approx 0$. Meanwhile, the assets and the liabilities both have a positive *convexity* as lower interest rates increase bond duration,

$$C_A := -\frac{\partial D_A}{\partial y_t^{(10)}} > 0, \quad C_L := -\frac{\partial D_L}{\partial y_t^{(10)}} > 0.$$

Crucially, the convexity of life insurers' liabilities is greater than the convexity of their assets ($C_L > C_A$), meaning that D_L rises faster than D_A when interest rates fall.[9] As a result, D_E became negative in the low-interest-rate environment after the Crisis.

Furthermore, there exist other market and institutional frictions that prevent life insurers from increasing their asset duration D_A to close the duration gap. Domanski, Shin and Sushko (2017) and Greenwood and Vissing-Jorgensen (2018) argue that large-scale portfolio rebalancing of life insurers towards longer-term assets puts downward pressure on the long-term interest rate, which could further exacerbate the duration mismatch. Ozdagli

[9]One likely explanation is that life insurers' liabilities have a longer maturity than their assets, as the convexity of an asset typically increases in its maturity. It could also be because the embedded options in some of life insurers' variable annuity liabilities are less exercised when interest rates are low (e.g., Ozdagli and Wang, 2019; Koijen and Yogo, 2022).

and Wang (2019) emphasize the role of portfolio adjustment frictions resulting from the cost of large bond trades. Koijen and Yogo (2021) discussed several other reasons why life insurers do not fully hedge their interest rate exposure, including market incompleteness (i.e., the scarcity of long-term assets and options), risk-shifting motives, and regulatory distortions. In particular, Huber (2022) and Sen (2023) argue that the regulatory framework imposed on life insurers might not properly capture the interest rate risk and thus distorts life insurers' hedging incentives.[10]

1.4.2 Life Insurers and Long Rate Pass-through

I further show that life insurers play an important role in shaping the co-movement between the long-term interest rate and corporate bond credit spreads. Section 1.3.1 illustrates that long-term interest rates have heterogeneous impacts on the cross-section of corporate bonds after the Financial Crisis. If life insurers' duration mismatch is the main channel through which the long-term interest rate affects credit spreads, we should expect the pattern to be more pronounced in bonds owned by life insurers, which is indeed confirmed by the following results.

In this Section, I revisit the results of Section 1.3.1. To examine how life insurers affect the pass-through of the long-term interest rate, I modify regression (1.1) in Section 1.3.1 as

$$y_{it} = \alpha_i + \sum_{k=1}^{6} \left(\beta_k^0 + \beta_k^1 \cdot \mathbf{1}_{\{\text{insurance ownership}\}} \right) \cdot \mathbf{1}_{\{\text{NAIC } k\}} \cdot y_t^{(10)} + \Gamma \mathbf{X}_{it} + \varepsilon_{it}. \tag{1.5}$$

Here $\mathbf{1}_{\{\text{insurance ownership}\}}$ is a dummy variable that indicates whether a bond has positive life insurance ownership at the end of the year. The pass-through coefficients are allowed to differ between bonds with no life insurance ownership and bonds with positive life insurance ownership. β_k^0 measures the pass-through of the 10-year Treasury yield to NAIC k bonds *not* held by life insurers, while β_k^1 measures the pass-through to NAIC k bonds that are held by life insurers.

Figure 1.7 plots the estimated coefficients from regression (1.5) for the post-crisis pe-

[10] For more examples of regulatory distortions in the insurance sector, see also Lee, Mayers and Smith (1997), Ellul, Jotikasthira and Lundblad (2011), Becker, Opp and Saidi (2022), and Ellul *et al.* (2022).

riod. Indeed, the relationship between pass-through and credit ratings in Figure 1.2 is only present in bonds with positive life insurance ownership. Bonds with no life insurance ownership exhibit either no significant pass-through (NAIC 1-4) or the opposite pass-through compared to Figure 1.2 (NAIC 5-6). Moreover, the pass-through estimates for bonds with life insurance ownership have comparable magnitudes to those shown in Figure 1.2. Thus, the empirical findings of Section 1.3.1 are driven primarily by life-insurer-owned bonds.[11]

1.4.3 Regression Discontinuity Design

Next, I recover the fraction of each bond owned by life insurers from NAIC regulatory reports and study the role of life insurance ownership in shaping the results of Section 1.3.2.[12]

To further sharpen the identification, I utilize an exogenous discontinuity in investor composition stemming from mutual funds' investment mandates (e.g., Li and Yu, 2023). Bai, Li and Manela (2023) and Li and Yu (2023) document that a large fraction of corporate bond funds are "intermediate-term" and are mandated to only invest in bonds whose maturity is less than 10 years. For a bond with a maturity greater than 10 years at issuance, it will experience a surge in demand from mutual funds once it ages to the point where its maturity drops below 10 years. As a result, the bond's ownership by other investors, such as life insurers, jumps downward.

Figure 1.8 visualizes the discontinuity in life insurers' ownership share around the maturity threshold of 10 years and a quarter. Indeed, we observe a large discontinuous jump in life insurers' ownership shares at the maturity threshold. Bonds whose maturity falls below the threshold are much less likely to be held by life insurers.[13]

I further test the existence of the discontinuity using both OLS regressions and the ro-

[11] Figure A.6 shows that, before the Financial Crisis, the path-through pattern is absent in both insurer-owned bonds and non-insurer-owned bonds. This finding is consistent with the fact that life insurers did not face duration mismatch pre-2008.

[12] In the main regression of this section, I use end-of-year observations as insurance companies' holdings data is only recorded at the end of each year.

[13] The actual maturity cutoff for the discontinuity (10.25 years) is slightly more than 10 years. A likely explanation is mutual funds' window-dressing behavior, meaning that mutual funds only need to comply with their mandates at the end of each quarter when they disclose their bond holdings (Morey and O'Neal, 2006; Agarwal, Gay and Ling, 2014). Therefore, mutual funds could invest in bonds with a maturity between 10 and 10.25 years even if they are mandated to invest in bonds with a maturity of less than 10 years.

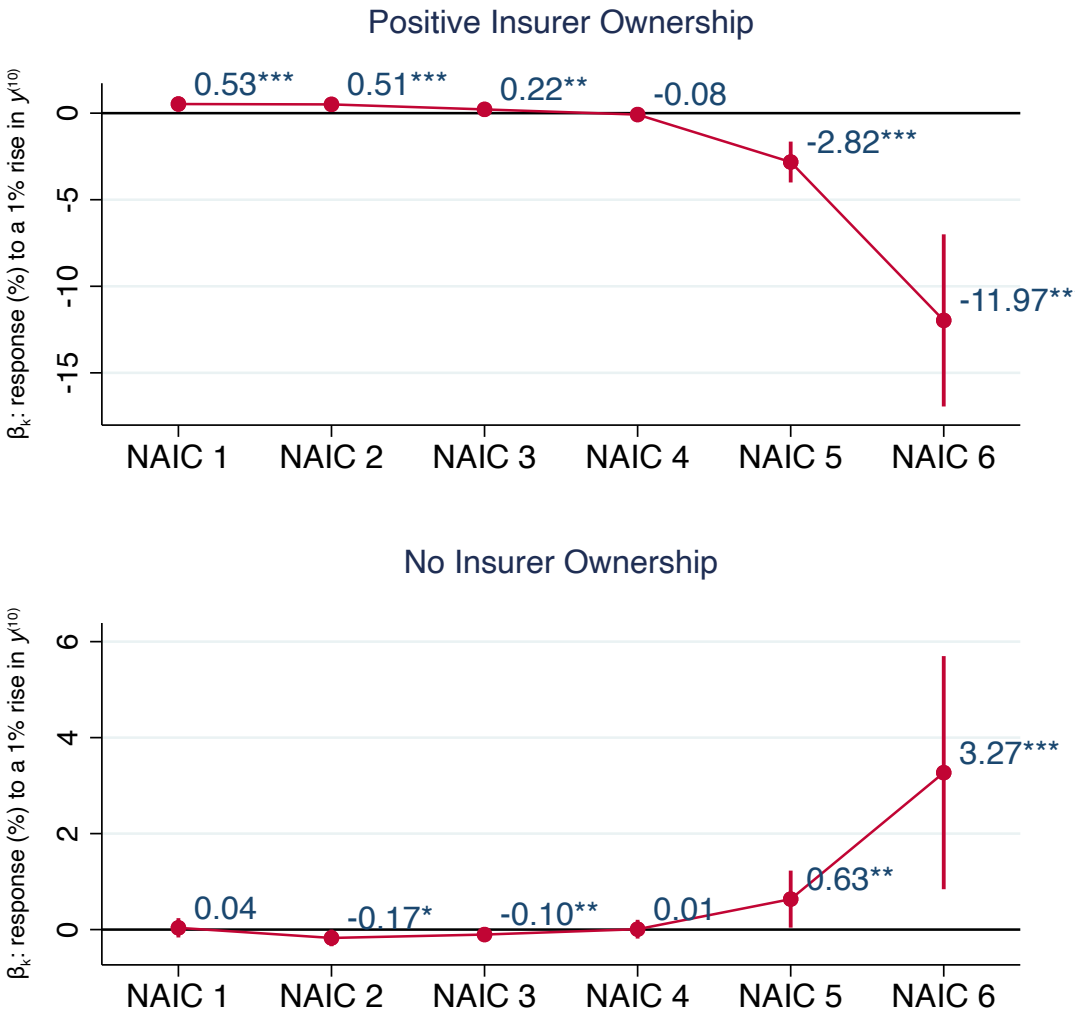


Figure 1.7. **Pass-through by Life Insurance Ownership.**

This figure plots the coefficients β_k estimated from regression (1.5) for the period of 2010-2019, controlling for the trading volume, outstanding amount, maturity, duration, credit ratings, coupon amount, and coupon frequency of each bond, and the recent default rate of each NAIC category. Both corporate bond yields and the Treasury yield are in percentage points. The top panel shows estimates for β_k^1, while the bottom panel shows estimates for β_k^0. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

bust bias-correction method of Calonico, Cattaneo and Titiunik (2014). In the OLS method, I regress the life insurer ownership share on a dummy variable indicating whether a bond's maturity is above the threshold $\mathbf{1}_{\{\text{maturity}_{it} \geq c\}}$ where $c = 10.25$.

$$\varphi_{it}^{\text{Ins}} = \alpha + \beta \cdot \mathbf{1}_{\{\text{maturity}_{it} > c\}} + \Gamma \mathbf{X}_{it} + \varepsilon_{it}.$$

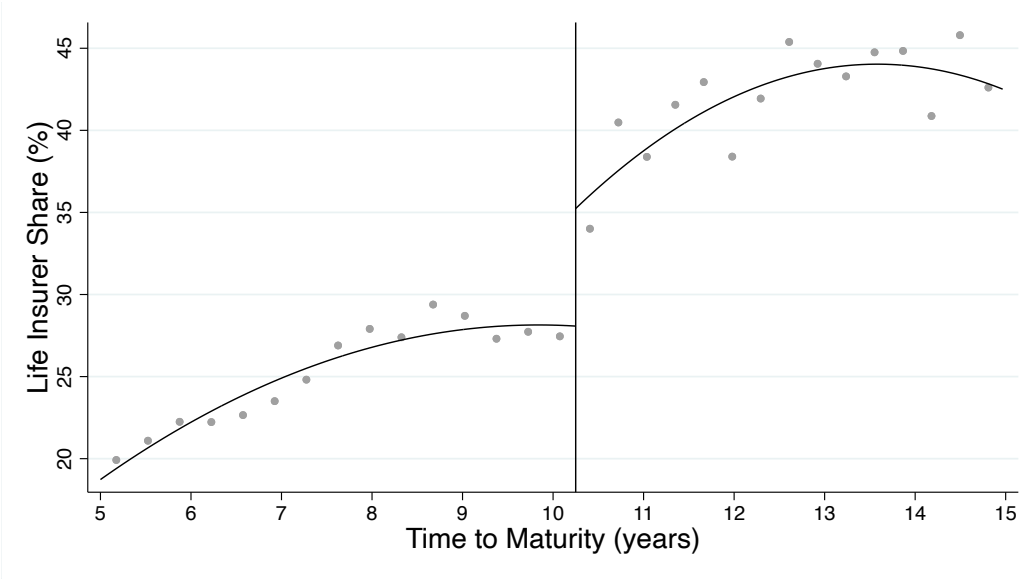


Figure 1.8. **Discontinuity in Investor Composition.**

This figure shows a bin scatter plot of corporate bonds' life insurance ownership share (%) and their maturity. The vertical line indicates the maturity threshold of 10.25 years. The figure also shows the best-fit second-order polynomials for observations on each side of the threshold.

In the robust bias-correction method, I treat the problem as a sharp regression discontinuity design (RDD), where the treatment status is determined by $\mathbf{1}_{\{\text{maturity}_{it} \geq c\}}$ and the outcome variable is the life insurer ownership share.

Table 1.4 summarizes the effect of the maturity threshold on life insurer shares estimated using different methods. All results imply a strong discontinuity in investor composition at the maturity cutoff. The life insurers' ownership share is around 4-5% higher for bonds whose maturity is slightly above the cutoff.

Method	β	p-value	[95% Conf. Interval]
OLS	4.36	0.000	[3.81, 4.91]
RDD, Conventional	4.41	0.000	[2.45, 6.36]
RDD, Bias-corrected	4.58	0.000	[2.63, 6.54]
RDD, Bias-corrected, Robust	4.58	0.000	[2.31, 6.86]

Table 1.4. **Testing the Discontinuity.**

This table shows the coefficient on $\mathbf{1}_{\{maturity_{it} > c\}}$, controlling for the trading volume, duration, maturity, and size for each bond, and the recent default rate in each NAIC category. The first row shows the OLS estimate with robust standard errors, while the other rows show the estimates from various RDD methods discussed in Calonico, Cattaneo and Titiunik (2014).

I then examine the effect of life insurance ownership on the response of a bond's credit spread to the long-term interest rate. I follow a fuzzy RDD approach by instrumenting the life insurer share $\varphi_{it}^{\text{Ins}}$ with the dummy variable $\mathbf{1}_{\{\text{maturity}_{it} \geq c\}}$ for observations near the threshold (e.g., Lee and Lemieux, 2010). The identification relies on the discontinuity of the investor base around the threshold. In other words, I am now comparing the co-movement seen in bonds slightly above the threshold to those seen in bonds slightly below the threshold. Specifically, I estimate the following two-stage regression

$$\begin{aligned}
\varphi_{it}^{\text{Ins}} &= \alpha + \beta \cdot \mathbf{1}_{\{\text{maturity}_{it} > c\}} + \Gamma \mathbf{X}_{it} + \varepsilon_{it} \\
y_{it} &= \left(\beta_2 \cdot \mathbf{1}_{\{\text{NAIC } 2\}} + \beta_{3-6} \cdot \mathbf{1}_{\{\text{NAIC } 3-6\}}\right) y_t^{(10)} + \\
&\quad \left(\gamma_2 \cdot \mathbf{1}_{\{\text{NAIC } 2\}} + \gamma_{3-6} \cdot \mathbf{1}_{\{\text{NAIC } 3-6\}}\right) \varphi_{it}^{\text{Ins}} y_t^{(10)} + \alpha_t + \Gamma \mathbf{X}_{it} + \varepsilon_{it}.
\end{aligned} \tag{1.6}$$

The first stage estimates the effect of the maturity cutoff on the life insurer share $\varphi_{it}^{\text{Ins}}$. The second stage estimates the effect of the life insurer share $\varphi_{it}^{\text{Ins}}$ on the co-movement between the long-term interest rate and credit spreads, using $\mathbf{1}_{\{\text{maturity}_{it} > c\}}$ as an instrumental variable.[14] I choose a small bandwidth of 1 year on both sides of the threshold to create a segment that isolates the impacts of the discontinuity.[15]

Table 1.5 presents the estimates from the RDD regressions above. First, the first-stage *F*-stats both before and after the Financial Crisis are well above the conventional threshold for weak instruments in Stock and Yogo (2005), again confirming the validity of the discontinuity. Second, after the Financial Crisis, we obtained negative and significant coefficients on $\varphi_{it}^{\text{Ins}} y_t^{(10)}$. The results show that life insurer holdings amplify the negative co-movement between the long-term interest rate and credit spreads.[16] It is worth noting that the special role of life insurers began after the Financial Crisis, as the coefficients on $\varphi_{it}^{\text{Ins}} y_t^{(10)}$ were insignificant and positive before the Financial Crisis.

[14] I instrument $\mathbf{1}_{\{\text{NAIC } k\}} \cdot \varphi_{it}^{\text{Ins}} \cdot y_t^{(10)}$ with $\mathbf{1}_{\{\text{NAIC } k\}} \cdot \mathbf{1}_{\{\text{maturity}_{it} > c\}} \cdot y_t^{(10)}$.

[15] Table B.1 in the Appendix offers additional robustness checks with alternative bandwidth choices.

[16] A potential concern is that the results might mostly be driven by new bonds that have different maturities than existing ones. Table B.2 shows the results still hold when we exclude bonds issued less than 3 months ago. Another threat to identification is that firms might strategically issue bonds with a maturity of less than 10 years to attract mutual fund investors. Table B.3 shows the results still hold when we only include bonds whose maturity at issuance is at least 10 years.

	2000-2007	2010-2019
γ_2	0.141	-0.452***
	[0.662]	[-4.745]
γ_{3-6}	0.488	-0.813**
	[0.834]	[-3.229]
Time FE	✓	✓
R^2	.624	.664
First-stage F	173.5	111.2
# Identifying Bonds	1466	3774

Table 1.5. **RDD Regressions.**

This table shows the coefficients estimated from regression (1.6), with the instrument, controlling for the trading volume, duration, maturity, size, coupon amount, and coupon frequency for each bond, and the recent default rate for each NAIC category. The first column shows the result for the pre-crisis sample, while the second column shows the result for the post-crisis sample. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

1.4.4 Bond Transactions

So far, I have shown that declines in the long-term interest rate have a larger impact on bonds held by life insurers after the Financial Crisis. The main hypothesis is that life insurers' risk-bearing capacity becomes more restricted when lower long-term interest rates erode their equity (see Section 1.4.1). To further verify the mechanism, I examine the bond transaction pattern of life insurers following movements in long-term interest rates. Specifically, I expect life insurers to rebalance their bond portfolio towards riskier bonds after the long-term interest rate increases.

I use the following empirical specification to test the hypothesis that life insurers rebalance towards safer bonds after declines in the long-term interest rate,

$$\frac{\text{Net Purchase}_{k,t}^{(m)}}{\text{Market Equity}_t} = \alpha_t + \alpha_k + \sum_{k=2}^{6} \beta_k \cdot \mathbf{1}\{\text{NAIC } k\} \cdot \Delta y_t^{(10)} + \Gamma \mathbf{X}_{kt} + \varepsilon_{kt}. \tag{1.7}$$

Here $\text{Net Purchase}_{k,t}^{(m)}$ is all life insurers' net purchases[17] of NAIC k bonds in a m-month period after month t. The outcome variable is normalized by the aggregate month-end

[17] Net purchases are defined as the total new purchases subtracting the total disposals including bonds sold and matured, using all transactions recorded in NAIC regulatory filings (Schedule D).

market equity of all US life insurers. On the right-hand side, $\Delta y_t^{(10)}$ is the change in the 10-year Treasury yield during month t. After controlling for year-month fixed effects, the coefficients β_k measure the purchases of NAIC k bonds *relative* to NAIC 1 bonds, following a 1% increase in the 10-year Treasury yield. I also include NAIC fixed effects to control market size differences across credit ratings.

Table 1.6 shows the estimated coefficients from regression (1.7) for the post-crisis period. After an increase in the 10-year Treasury yield, life insurers purchase more bonds from NAIC 2-5 relative to NAIC 1, tilting their bond portfolio towards riskier segments of the corporate bond market. The effects are large and significant except for NAIC 6.[18] After a 1% increase in the 10-year Treasury yield, life insurers purchase more lower-rating bonds than NAIC 1 bonds in the following 6 months, and the difference amounts to more than 0.7% of their market equity for bonds in NAIC 2 and more than 2% for bonds in NAIC 3, 4, and 5.

	1 month	3 months	6 months
β_2	0.331***	0.0647	0.723***
	[526.5]	[1.687]	[36.11]
β_3	0.423***	0.988***	2.256***
	[20.17]	[20.44]	[14.92]
β_4	0.522***	1.120***	2.297***
	[25.04]	[27.38]	[14.63]
β_5	0.553***	1.217***	2.433***
	[21.34]	[20.22]	[13.13]
β_6	0.224	-0.225	0.327
	[1.323]	[-0.302]	[0.288]
NAIC FE	✓	✓	✓
Time FE	✓	✓	✓
R^2	.851	.894	.908

Table 1.6. **Insurer Bond Transactions.**

This table shows the coefficients estimated from regression (1.7), controlling for the recent default rate for each NAIC category. The three columns show the results for purchases in different time horizons. The t-statistics shown in brackets are based on standard errors clustered at the NAIC category level. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

[18] NAIC 6 (bonds rated CC and lower) is the smallest segment of the corporate bond market where trading is relatively infrequent. Life insurers also own relatively fewer NAIC 6 bonds.

1.5 Real Effects of the Long-term Interest Rate

A natural question is whether the nexus between the long-term interest rate and credit spreads affects bond-issuing firms' borrowing and investment. In this section, I show that the effects of the long-term interest rate on credit spreads indeed have considerable real consequences on bond issuance and firm investment.

1.5.1 The Long-term Interest Rate and Bond Issuance

In Section 1.3, I documented that a lower long-term interest rate increases credit spreads, especially for speculative-grade bonds. Credit spreads are important indicators of firm borrowing costs — existing studies show that primary market bond prices (i.e., new bond issuance costs) are highly correlated with secondary market conditions (e.g., Coppola, 2022; Flanagan, Kedia and Zhou, 2019). Therefore, the co-movement between the long-term interest rate and corporate bond credit spreads likely affects firms' incentives to issue new bonds.

To investigate the co-movement between the long-term interest rate and corporate bond issuance, I aggregate new bond issuance for each NAIC category in Mergent FISD. I then estimate the following empirical specification

$$\frac{\text{Issuance}_{k,t}^{(6m)}}{\text{Outstanding}_{k,t}} = \alpha_k + \alpha_t + \sum_k \beta_k \cdot \mathbf{1}_{\{\text{NAIC } k\}} \cdot y_t^{(10)} + \Gamma \mathbf{X}_{kt} + \varepsilon_{kt}, \tag{1.8}$$

where $\text{Issuance}_{k,t}^{(6m)}$ is the total NAIC k issuance in the 6-month period between month $t+1$ and month $t+6$, $\text{Outstanding}_{k,t}$ is the total outstanding amount of NAIC k bonds at the end of the month t, $y_t^{(10)}$ is the 10-year yield at the end of the month t, and the controls $\mathbf{X}_{kt}$ include the average maturity of new issues, the average maturity of new issues interacted with the 10-year Treasury yield, and the recent default rates of each NAIC category. The rating fixed effects α_k capture the steady state differences in the growth rates of individual NAIC categories. The time fixed effects α_t capture aggregate fluctuations in bond issuance.

I consider two specifications — one with the time fixed effects α_t and one without. When α_t is not imposed, the coefficient β_k captures the effect of the 10-year Treasury yield

on the *amount* of NAIC k bond issuance. The issuance of NAIC k bonds increases by a β_k fraction of the current outstanding in the next 6 months when the 10-year Treasury yield increases by 1%. When α_t is imposed, the fixed effects absorb the effect on NAIC 1 issuance, so the coefficient β_k measures how the 10-year Treasury yield affects the *difference* in issuance between NAIC k and NAIC 1. The issuance-to-outstanding ratio of NAIC k increases by β_k relative to NAIC 1 when the 10-year Treasury yield increases by 1%.[19]

Table 1.7 contains the estimated coefficients from regression (1.8). The second column reports the results after the Financial Crisis. It suggests that increases in the 10-year Treasury yield boost the issuance of NAIC 2-6 bonds relative to NAIC 1 bonds. Following a 1% increase in the long-term interest rate, the issuance of speculative-grade (NAIC 3-6) bonds grows by more than 1.5% relative to the issuance of NAIC 1 bonds. The results suggest that the long-term interest rate potentially alters the composition of the corporate bond market. Investment-grade bonds make up a larger share of total new issuance when the long-term interest rate is low. After the Financial Crisis, the US economy entered a sustained period of low interest rates accompanied by a large bond market expansion. Consistent with my findings, the post-crisis bond market expansion was concentrated in investment-grade firms (e.g., Mota, 2023).

In contrast, the issuance differences are not correlated with the long-term interest rate before the Financial Crisis. The lack of correlation is expected since the long-term interest rate affected all corporate bonds equally during that period, as demonstrated in Section 1.3.1.

1.5.2 The Long-term Interest Rate and Firm Investment

As demonstrated in the previous section, credit spread responses to long-term interest rates are crucial for long-term interest rates' transmission to bond issuance. Next, I examine whether such credit spread responses affect firms' real investment. I adopt the

[19]The 10-year Treasury yield is highly persistent (e.g., Caporale, Gil-Alana and Yaya, 2022). The current 10-year Treasury yield has strong predictive power for the future path of the 10-year Treasury yield.

	2000-2007	2010-2019
β_2	1.418	0.782^{***}
	[1.585]	[2.900]
β_{3-6}	0.606	1.550^{***}
	[0.864]	[4.712]
NAIC FE	✓	✓
Time FE	✓	✓
R^2	.858	.781

Table 1.7. **Bond Issuance Responses to the Long-term Interest Rate.**

This table shows the coefficients estimated from regression (1.8), controlling for the average maturity of new issues, the average maturity of new issues interacted with the 10-year Treasury yield, and the recent default rates of each NAIC category. The first two columns show results for the post-crisis sample, while the last two columns show results for the pre-crisis sample. Both the responsible variable and the 10-year Treasury yield are in percentage points. The t-statistics shown in brackets are based on standard errors clustered at the NAIC category by year-month levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

following empirical specification

$$\left(\frac{\text{CapEx}}{\text{Asset}}\right)_{jt} = \alpha_j + \sum_k \beta_k \cdot \mathbf{1}_{\{\text{NAIC } k\}} \cdot y_t^{(10)} + \sum_k \gamma_k \cdot \mathbf{1}_{\{\text{NAIC } k\}} \cdot \varphi_{jt}^{\text{Ins}} y_t^{(10)} + \Gamma \mathbf{X}_{jt} + \varepsilon_{jt}. \quad (1.9)$$

The response variable is the investment rate of firm j in quarter t, measured as the firm's capital expenditure to assets ratio. I include the 10-year Treasury yield $y_t^{(10)}$ and the interaction term $\varphi_{jt}^{\text{Ins}} y_t^{(10)}$ as explanatory variables. $\varphi_{jt}^{\text{Ins}}$ is the average life insurance ownership across all bonds issued by firm j measured at the end of the previous year.[20] The coefficient β_k measures how much an NAIC k firm's investment rate reacts to the 10-year Treasury yield if the firm's bonds are not owned by life insurers at all. γ_k, in turn, measures how much life insurance ownership affects the relationship between the 10-year Treasury yield and a firm's investment rate. I also include firm characteristics and firm fixed effects as controls.

Table 1.8 summarizes the estimates from regression (1.9). In the pre-crisis sample, neither the 10-year Treasury yield nor the bond ownership by life insurers had a significant impact on firm investment. Nevertheless, the results indicate that $\beta_k < 0$ and $\gamma_k > 0$

[20] Figure A.15 visualizes the distribution of φ_j^{Ins} across firms.

after the Financial Crisis, suggesting that higher long-term interest rates depress investment, but life insurance ownership dampens or reverses this relationship. This is consistent with the results of Section 1.4 where life insurance ownership induces negative credit spread responses, which offset the effects of elevated long rates. Notably, I find $\gamma_{3-6} > \gamma_2 > \gamma_1$, meaning that the effect of bond ownership by life insurers on investment is the strongest for speculative-grade firms. The result is consistent with the findings of Section 1.3.2, which shows speculative-grade firms exhibit the largest credit spread responses to the long-term interest rate. Since $\beta_{3-6} = -0.653, \gamma_{3-6} = 0.903$, the investment rate of a speculative-grade firm could *increase* with the 10-year Treasury yield if life insurers own more than 72% of its bonds.

	2000-2007	2010-2019
β_1	-0.0427	-0.440***
	[-0.618]	[-9.625]
β_2	0.0381	-0.623***
	[0.353]	[-12.32]
β_{3-6}	0.206*	-0.653***
	[1.925]	[-8.363]
γ_1	0.0372	0.195**
	[0.350]	[2.524]
γ_2	0.185	0.340***
	[1.635]	[4.601]
γ_{3-6}	0.0566	0.903***
	[0.383]	[2.727]
Firm FE	✓	✓
Controls	✓	✓
R^2	.657	.644

Table 1.8. **Firm Investment Responses to the Long-term Interest Rate.**

This table shows the coefficients estimated from regression (1.9), controlling for the average maturity of firms' existing bonds and fixed effects for firms, size deciles, leverage deciles, and NAIC ratings. The first column shows results for the pre-crisis sample, while the second column shows results for the post-crisis sample. Both the responsible variable and the 10-year Treasury yield are in percentage points. The t-statistics shown in brackets are based on standard errors clustered at the firm level. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

1.6 An Intermediary Asset Pricing Model

In the previous sections, I have shown that a negative co-movement between long rates and credit spreads emerged post-crisis and that life insurers' bond holdings matter for this co-movement. In this section, I build an intermediary asset pricing model centered around life insurers to explain the observations. The model illustrates how long rates affect credit spreads through life insurers' duration mismatch and quantifies the strength of this new channel.

As in He and Krishnamurthy (2013), the risk-bearing capacity of intermediaries (life insurers) is key to equilibrium credit spreads. As in Koijen and Yogo (2023), life insurers take on leverage by issuing annuity liabilities and investing in corporate bonds. Importantly, life insurers' portfolios expose them to duration mismatch as found in Section 1.4.1, and their net worth increases with the long-term interest rate. The equity gains reduce life insurers' effective risk aversion and increase their risk-bearing capacity, which leads to lower credit spreads in equilibrium.

1.6.1 Model Setup

Investors. There are two types of corporate bond investors in the model — life insurers and preferred-habitat investors.

The *life insurer* invests its portfolio in corporate bonds and Treasuries while issuing long-term annuities to households. The duration mismatch between the insurer's assets (corporate bonds and Treasuries) and liabilities (annuities) exposes it to interest rate risk. When the interest rate on long-term Treasuries rises, the insurer's liabilities decline more than its assets, so its net worth increases. The insurer's balance sheets are as follows.

Assets	*Liabilities*
Corporate Bonds	Annuities
Treasuries	Net Worth

Preferred-habitat investors include all other investors of corporate bonds (e.g., mutual

funds and pension funds). For simplicity, their demand for corporate bonds is assumed to be reduced-form functions of bond prices, in the spirit of Vayanos and Vila (2021).

Treasuries and Annuities. Time is continuous. *Treasuries* are long-term consol bonds with a geometric maturity structure. The Treasuries have a price P_t^T, coupon rate ϕ^T, and a geometric decaying rate λ^T. Specifically, each bond pays a stream of coupon payments $\phi^T \mathrm{d}t$ and has a face value that decays over time at a constant rate of λ^T. The return rate on Treasuries is

$$\mathrm{d}r_t^T = \frac{(\phi^T - \lambda^T P_t^T)\mathrm{d}t}{P_t^T} + \frac{\mathrm{d}P_t^T}{P_t^T}, \tag{1.10}$$

where $\phi^T \mathrm{d}t$ captures the coupon payments, $\lambda^T P_t^T \mathrm{d}t$ captures the depreciated face value, and $\mathrm{d}P_t^T$ is the capital gain from price fluctuations. Based on the geometric decaying maturity structure, the average maturity of this bond is $\tau^T = 1/\lambda^T$. Each unit of the face value is expected to last a period of length τ^T. I define the Treasury yield as[21]

$$y_t^T := \frac{\phi^T}{P_t^T} - \lambda^T.$$

The Treasury yield has an exogenous law of motion and always reverts to the "natural" level $\overline{y}^T$ at a speed of α_y. Its dynamics is given by

$$\mathrm{d}y_t^T = \alpha_y \left(y_t^T - \overline{y}^T\right) \mathrm{d}t. \tag{1.11}$$

Annuities are similar consol bonds with a price P_t^L, coupon rate ϕ^L, and a geometric decaying rate λ^L. Annuities have a maturity of $\tau^L = 1/\lambda^L$ and a return rate of

$$\mathrm{d}r_t^L = \frac{(\phi^L - \lambda^L P_t^L)\mathrm{d}t}{P_t^L} + \frac{\mathrm{d}P_t^L}{P_t^L}.$$

[21] The yield to maturity is defined as the rate at which future payoffs are discounted and aggregated into the current bond price:

$$P_t^T = \int_t^\infty e^{-(y_t^T + \lambda^T)s} \phi^T \mathrm{d}s.$$

Similar to Treasuries, I define the annuity yield as $y_t^L := \phi^L / P_t^L - \lambda^L$.

No-arbitrage Pricing of Annuities. In this model, both Treasuries and annuities are risk-free assets with deterministic returns, and the life insurer holds both in equilibrium. Therefore, the returns of Treasuries and annuities must be equalized,

$$\mu_t^{r,T} = \mu_t^{r,L}, \tag{1.12}$$

where $\mu_t^{r,T} = \mathrm{d}r_t^T / \mathrm{d}t, \mu_t^{r,L} = \mathrm{d}r_t^L / \mathrm{d}t$ are the return rates of Treasuries and annuities, respectively. This no-arbitrage condition allows us to solve for the annuity price P_t^L and yield y_t^L as functions of the Treasury yield y_t^T.

Corporate Bonds. Corporate bonds are long-term bonds with credit risk. There are N types of corporate bonds corresponding to N credit ratings. The exposure to credit risk varies across different ratings. Investors hold diversified portfolios within each rating. The return rate on rating $n \in \{1, \ldots, N\}$ bonds is

$$\mathrm{d}r_t^n = \frac{\phi^n - \lambda^n P_t^n}{P_t^n}\mathrm{d}t + \frac{\mathrm{d}P_t^n - \nu^n P_t^n \mathrm{d}J_t}{P_t^n}, \tag{1.13}$$

The coupon rate is denoted by ϕ^n, while the rate of decay is represented by λ^n. $\mathrm{d}J_t$ is a Poisson jump process with intensity δ that captures the bonds' credit risk.[22] When a jump is realized, the bond market enters a disrupted period, and a fraction ν^n of rating n bonds default and lose their value. As before, the corporate bond yields are defined as $y^n := \phi^n / P_t^n - \lambda^n$. Further, I define

$$\mathrm{d}r_t^n = \mu_t^{r,n}\mathrm{d}t + \sigma_t^{r,n}(\mathrm{d}J_t - \delta \mathrm{d}t),$$

so that $\mu_t^{r,n}$ is the expected return on bonds n and $\sigma_t^{r,n}$ is the overall risk exposure of bonds n.[23]

[22] The credit risk is correlated across different bonds. This is consistent with the findings of Das *et al.* (2007) and Duffie *et al.* (2009), who show that corporate bond defaults in the US are highly correlated.

[23] $(\mathrm{d}J_t - \delta \mathrm{d}t)$ is a martingale since the process $\mathrm{d}J_t$ drifts upwards in expectation ($\mathbb{E}_t[\mathrm{d}J_t] = \delta \mathrm{d}t$).

Life Insurer's Portfolio Problem. There is one representative life insurer that holds corporate bonds and Treasuries while issuing annuities to households. The quantity of annuities is assumed to be exogenous at L,[24] and the insurer chooses its holdings of corporate bonds and Treasuries. Its portfolio weight in Treasuries, annuities, and corporate bonds are denoted as $w_t^{I,T}, w_t^{I,L}$ and $\left(w_t^{I,n}\right)_{n=1}^N$, respectively. The insurer's net worth A_t^I evolves according to

$$\frac{\mathrm{d}A_t^I}{A_t^I} = \left[w_t^{I,T}\mu_t^{r,T} + \sum_{n=1}^N w_t^{I,n}\mu_t^{r,n} - w_t^{I,L}\mu_t^{r,L} - \sum_{n=1}^N \frac{1}{2}\left(\zeta^n w_t^{I,n}\right)^2 + \psi_t\right]\mathrm{d}t + \sum_{n=1}^N w_t^{I,n}\sigma_t^{r,n}\mathrm{d}J_t.$$

$w_t^{I,L}\mu_t^{r,L}$ enters the net worth evolution negatively because annuities are liabilities. The insurer incurs regulatory cost $\frac{1}{2}\sum_{n=1}^N \left(\zeta^n w_t^{I,n}\right)^2 A_t^I$ for holding corporate bonds, which potentially includes the costs of complying with risk-weighted leverage constraints and passing stress tests.[25] Following Koijen and Yogo (2023), the regulatory cost is assumed to be quadratic in the bond holdings, while the parameter ζ^n governs the marginal regulatory cost of holding bonds in rating n. The process $\psi_t\mathrm{d}t$ captures an exogenous process of equity injection and dividend payout, which ensures that net worth A_t^I is stationary. In particular, I assume

$$\psi_t = \psi(A_t^I - \overline{A}^I), \quad \psi < 0,$$

so the insurer pays out dividends (raises equity) at the rate of ψ when its net worth is greater (less) than the reference level $\overline{A}^I$.

The insurer has a mean-variance preference over the return on its net worth:

$$\mathbb{E}_t\left[\frac{\mathrm{d}A_t^I}{A_t^I}\right] - \frac{a}{2}\mathrm{Var}_t\left[\frac{\mathrm{d}A_t^I}{A_t^I}\right].$$

[24] In practice, the quantity of life insurers' liabilities is stable as they are typically long-term products with few early withdrawals (e.g., Chodorow-Reich, Ghent and Haddad, 2021).

[25] Life insurers also face other potential costs, such as transaction and informational costs, which are conceptually similar to the regulatory cost from the modeling perspective.

The portfolio problem can then be written as[26]

$$\max_{\{w_t^{I,n}\}_{n=1}^N,\, w_t^{I,T},\, w_t^{I,L}} \quad \underbrace{w_t^{I,T}\mu_t^T + \sum_{n=1}^N w_t^{I,n}\mu_t^{r,n} - w_t^{I,L}\mu_t^{r,L}}_{\text{expected return}} - \underbrace{\frac{a}{2}\delta\left(\sum_{n=1}^N w_t^{I,n}\sigma_t^{r,n}\right)^2}_{\text{risk aversion}} - \underbrace{\frac{1}{2}\sum_{n=1}^N \left(\zeta^n w_t^{I,n}\right)^2}_{\text{regulatory cost}}, \tag{1.14}$$

$$\text{s.t.} \quad w_t^{I,T} + \sum_{n=1}^N w_t^{I,n} - w_t^{I,L} = 1, \tag{1.15}$$

The objective function (1.14) can be decomposed into three components: expected portfolio return, exposure to credit risk, and additional regulatory costs. The parameter a symbolizes the degree of risk aversion. (1.15) is the insurer's balance sheet constraint, which simply states that the portfolio weight in assets (Treasuries and corporate bonds) minus the portfolio weight in liabilities (annuities) equals one, the portfolio weight in net worth.

Preferred-Habitat Investors. The preferred-habitat investors also participate in the corporate bond market. I denote the shares of rating n bonds held by the preferred-habitat investors as $D_t^{P,n}$. I assume that the preferred-habitat investors have the following demand functions

$$\log D_t^{P,n} = \alpha^n - \beta \log P_t^n. \tag{1.16}$$

In this specification, β is the price elasticity of demand, and the intercept α^n captures the average propensity to hold bonds of rating n by the preferred-habitat investors.

Firms. There are N sectors. Each sector consists of a continuum of ex-ante identical firms with a mass of one. Let K_t^n denote both the total and average capital stock of sector n firms. Each firm in sector n produces the following stream of output

$$Y_t^n \mathrm{d}t = \frac{(K_t^n)^{1-\theta}}{1-\theta}\mathrm{d}t.$$

[26] It follows from the fact the $\mathrm{Var}_t(\mathrm{d}J_t) = \delta \mathrm{d}t$.

The production function features decreasing returns to scale. Firms issue corporate bonds to finance their capital. Capital is elastically supplied at a price of one. For simplicity, I assume that the firms can freely adjust capital stock and debt quantity but are not allowed to accumulate capital. As a result, their balance sheet constraint is simply $K_t^n = P_t^n B_t^n$, i.e., the value of their assets K_t equals the value of their debt $P_t^n B_t^n$.

In normal times (i.e., when jumps $\mathrm{d}J_t$ do not realize), all firms operate normally, and no bond defaults. However, when the bond market is disrupted (i.e., when a jump arrives), a fraction ν^n of sector n firms are destroyed. The affected firms lose all their capital, default on the bonds, exit the economy, and get replaced by new firms after the market disruption is over. Therefore, as in equation (1.13), a diversified portfolio in rating n bonds loses a ν^n fraction of its value when a jump materializes.

Myopic firms solve a static profit maximization problem where they choose capital stock and bond supply to maximize their expected profits subject to the balance sheet constraint.

$$\max_{K_t^n, B_t^n} \ \mathbb{E}_t \left[\mathbf{1}_{\{\text{survive}_t\}} \left(\frac{(K_t^n)^{1-\theta}}{1-\theta} - \phi^n B_t^n \right) \right] \quad \text{s.t.} \quad K_t^n = P_t^n B_t^n.$$

The firms' profits equal their outputs subtracting the coupon payments on bonds, conditional on survival. The firm problem leads to a tractable bond supply function

$$B_t^n = \left[\frac{(P_t^n)^{1-\theta}}{\phi^n} \right]^{\frac{1}{\theta}}. \tag{1.17}$$

The bond supply B_t^n is increasing in the bond price P_t^n, implying that firms borrow more when their debt is more valuable.

Market Clearing. Recall that the Treasury yield y_t^T follows the exogenous law of motion (1.11). Treasuries are supplied perfectly elastically to clear the market, given the exogenous yield.

The supplies of corporate bonds are B_t^n. The market for rating n bonds clears when

$$w_t^{I,n} A_t^I + P_t^n D_t^{P,n} = P_t^n B_t^n. \tag{1.18}$$

Market clearing requires that the demand from the life insurer $w_t^{I,n} A_t^I$ and the demand from preferred-habitat investors $P_t^n D_t^{P,n}$ add to the total market cap $P_t^n B_t^n$. The annuity market clears when the insurer's portfolio weight in annuities equals the exogenously fixed annuity demand.

$$w_t^{I,L} A_t^I = P_t^L L. \tag{1.19}$$

Equilibrium. An *equilibrium* is a mapping from the Treasury yield and insurer net worth $\{y_t^T, A_t^I\}$ to insurer portfolio weights $\{w_t^{I,n}\}$ and asset prices $\{P_t^L, P_t^n\}$ that satisfy the insurer's portfolio choice problem (1.14)-(1.15), the habitat demand function (1.16), the bond supply function (1.17), and the market clearing conditions (1.18)-(1.19).

1.6.2 Analytical Insights

In this section, I analyze the effects of an unexpected shock on the long-term Treasury yield on credit spreads. I focus on a simplified version of the model that permits analytical solutions and illustrates the mechanism. To this end, I make two simplifying assumptions.

Assumption 1 *The Treasury yield is constant $y_t^T \equiv y$.*

Assumption 2 *Corporate bonds are short-term bonds with independent default risks.*

Since the Treasury yield is constant, the prices of Treasuries and annuities are constant (so $\mathrm{d}P_t^T = \mathrm{d}P_t^L = 0$). From equations (1.10) and (1.12), the return rates on Treasuries and annuities are simply

$$\mu_t^{r,T} = \mu_t^{r,L} = y.$$

The prices of Treasuries and annuities are given by the following Gordon growth formulas,

$$P_t^T = \frac{\phi^T}{y + (1/\tau^T)}, \quad P_t^L = \frac{\phi^L}{y + (1/\tau^L)}. \tag{1.20}$$

Corresponding to the standard Gordon formula,[27] the current dividend rate of the Treasuries is ϕ^T, the required return rate is y, and the dividend growth rate is minus the depreciation rate $-\lambda^T = -1/\tau^T$.

When the government (unexpectedly) raises the Treasury yield, it also raises the annuity yield of the same magnitude. According to (1.20), the increase in y lowers the price of annuities P_t^L, making life insurers' liabilities less expensive. The results are intuitive — for the same stream of coupon payments, the price of the annuities must decline to be consistent with a higher equilibrium yield.

Next, I consider a scenario where the government unexpectedly increases the Treasury yield from y to $\widehat{y} > y$, focusing on how the Treasury yield shock affects the life insurer's net worth and bond prices.

When the Treasury yield changes, long-term assets, such as the Treasuries and annuities, are repriced according to the Gordon formula (1.20). I denote the price of Treasuries before and after the shock as P^T and $\widehat{P}^T$, respectively. Similarly, the price of annuities before and after the shock is written as P^L and $\widehat{P}^L$. As a result, the life insurer's net worth could also change. Denote the insurers' net worth before and after the shock as A and $\widehat{A}$, respectively. The change in net worth follows

$$\begin{aligned} \widehat{A} - A = & \overbrace{T\left(\widehat{P}^T - P^T\right)}^{\text{Repricing of Treasuries}} - \overbrace{L\left(\widehat{P}^L - P^L\right)}^{\text{Repricing of Annuities}} \\ = & T\left[\frac{\phi^T}{\widehat{y} + (1/\tau^T)} - \frac{\phi^T}{y + (1/\tau^T)}\right] - L\left[\frac{\phi^L}{\widehat{y} + (1/\tau^L)} - \frac{\phi^L}{y + (1/\tau^L)}\right]. \end{aligned} \tag{1.21}$$

Here $T := Aw^{I,T}/P^T$ is the quantity of Treasuries held by the insurer before the shock.

[27] The Gordon growth formula gives the price of an asset whose dividend growth rate and required return rate are constant:

$$\text{Price} = \frac{D}{r - g} = \frac{\text{Dividend Rate}}{\text{Required Return Rate} - \text{Dividend Growth Rate}}.$$

A higher Treasury yield depresses the values of Treasuries and annuities ($\widehat{P}^T < P^T, \widehat{P}^L < P^L$). The change in the insurer's net worth, $\widehat{A} - A$, is determined by the extent to which Treasuries and annuities are repriced. Consider a simple case where the Treasury and the annuity have the same coupon rate ($\phi^T = \phi^L = \phi$), where

$$\widehat{A} - A = \phi(\widehat{y} - y)\left[\frac{L}{(\widehat{y} + (1/\tau^L))(y + (1/\tau^L))} - \frac{T}{(\widehat{y} + (1/\tau^T))(y + (1/\tau^T))}\right].$$

Since, in the scenario of interest, annuities have a longer maturity than Treasuries ($\tau^L > \tau^L$) and the insurer issues more annuities than the Treasuries it holds ($L > T$), then the insurer's net worth increases with the Treasury yield (i.e., $\widehat{A} > A$), which corresponds to the situation after the Financial Crisis (Section 1.4.1).

Since the corporate bonds are short-term with independent credit risks, their return rates (1.13) simply become

$$\mathrm{d}r_t^n = \frac{\phi^n}{P_t^n}\mathrm{d}t - \nu^n \mathrm{d}J_t^n,$$

where $\{\mathrm{d}J_t^n\}$ are independent from each other. To understand how the insurer's net worth affects bond credit spreads, it is useful to characterize the solution to the portfolio problem (1.14)-(1.15). In this simplified model, the first-order condition for rating n bonds is given by

$$\underbrace{\mu_t^{r,n} - \mu_t^T}_{\text{credit spread}} = \underbrace{a\delta w_t^{I,n}\nu^n}_{\text{risk premium}} + \underbrace{\zeta^n w_t^{I,n}}_{\text{regulation premium}} = \gamma^n w_t^{I,n}, \tag{1.22}$$

where $\mu_t^{r,n} := \mathbb{E}_t[\mathrm{d}r_t^n]/\mathrm{d}t = \phi^n/P_t^n - \nu^n\delta$ is the expected return on rating n bonds and $\gamma^n := a\delta\nu^n + \zeta^n > 0$ measures the total cost of holding rating n bonds for the insurer. We can write equation (1.22) as

$$w_t^{I,n} = \frac{\mu_t^{r,n} - \mu_t^T}{\gamma^n}, \tag{1.23}$$

which is the standard portfolio choice condition under mean-variance preferences. $w_t^{I,n}$, the insurer's portfolio weight in rating n bonds, equals the risk premium $\mu_t^{r,n} - \mu_t^T$ divided

by the cost parameter γ^n.[28]

Equation (1.23) allows us to express $A_t^I w_t^{I,n}$, the (dollar) amount of corporate rating n bonds demanded by the life insurer, as

$$A_t^I w_t^{I,n} = \frac{\mu_t^{r,n} - \mu_t^T}{\gamma^n / A_t^I}.$$

The demand is given by the credit spread divided by the insurer's *effective risk aversion*, which I define as γ^n / A_t^I, the total holding cost γ^n divided by net worth A_t^I. Under duration mismatch, the increase in the Treasury yield boosts the insurer's net worth, lowering the insurer's effective risk aversion. As a result, the insurer increases its demand for risky bonds, putting downward pressure on equilibrium credit spreads.

I make two further assumptions before presenting the analytical results. The first assumption states that the life insurer is subject to a duration mismatch of the same kind found in Section 1.4.1. In Appendix A.3.1, I provide a sufficient condition for this assumption to hold in equilibrium. The second assumption is that the preferred-habitat demand is downward-sloping. The assumption is standard in the literature of institutional bond demand and supported by various empirical estimates (Bretscher *et al.*, 2022; Darmouni, Siani and Xiao, 2022).

Assumption 3 *The life insurer is subject to duration mismatch (i.e.,* $\dfrac{\partial \widehat{A}}{\partial \widehat{y}} > 0$ *for* $\widehat{y} \geq 0$*).*

Assumption 4 *The preferred-habitat demand functions are downward-sloping (i.e.,* $\beta \leq 0$*).*

The next Proposition summarizes the main analytical results from this model.

Proposition 1 *Under assumptions 1-4, the following predictions hold when the Treasury yield increases from* y *to* $\widehat{y} > y$*:*

1. *the insurer's net worth increases*
2. *the insurer's exposure to credit risk* $w_t^{I,n}$ *declines for all* $n > 1$
3. *the credit spread* $\mu_t^{r,n} - \mu_t^{r,T}$ *declines for all* $n > 0$

[28] In the absence of the regulatory cost ζ^n, the parameter $\gamma^n = a\delta\nu^n$ equals the risk aversion coefficient a times the default risk $\delta\nu^n$, which is exactly the solution of a standard mean-variance portfolio problem.

In addition, the magnitudes of predictions 2-3 increase in the duration mismatch (i.e., $\frac{\partial \widehat{A}}{\partial \widehat{y}}$).

Proof. *See Appendix A.3.2.*

Proposition 1 shows that when the yield on long-term Treasuries rises, the insurer's balance sheet net worth rises as it faces duration mismatch. The insurer's portfolio becomes less concentrated in risky bonds, and the insurer is less exposed to the credit risks and regulatory burdens of corporate bonds. Consequently, the equilibrium credit spreads decline. Moreover, the impact of a Treasury yield shock is larger when the life insurer's duration mismatch is more severe, and its net worth is more sensitive to the Treasury yield.

1.6.3 Quantitative Model

In the following sections, I match the model to empirical estimates and key moments in data in order to quantify the contribution of life insurers' duration mismatch to the observed empirical patterns and the transmission of unconventional policy.

Calibrated Parameters. Table 1.9 discusses model calibration. I consider two corporate bond ratings ($N = 2$) where $n = 1$ represents investment-grade bonds (NAIC 1-2), and $n = 2$ represents speculative-grade bonds (NAIC 3-6). Both types of corporate bonds have a maturity of 8.55 years, which is the average time to maturity of all corporate bonds in Mergent FISD. The parameter of firm production function θ is set to 0.34, matching the usual Cobb-Douglas capital share in the literature.[29]

I normalize all the coupon rates and the life insurer's reference net worth as 1 ($\phi^T = \phi^L = \phi^n = 1$). I set $\tau^T = 10$ and $\tau^L = 20$, so the maturity of Treasuries is 10 years, and the maturity of annuities is 20 years. I let the steady-state value of the 10-year Treasury yield be 2.5%, which is roughly the average observed 10-year US Treasury yield between 2010 and 2020. I set the speed of mean-reversion as $\alpha_y = \psi = 2$, in which case the half-life of Treasury yield shocks is about 3 quarters. I normalize the insurer's reference net worth to

[29] To map the production function into a Cobb-Douglas form, we can assume that every firm has a single unit of labor supply $L_t^n = 1$ and the production function is $Y_t^n = \frac{1}{1-\theta}(K_t^n)^{1-\theta}(L_t^n)^{\theta}$.

$\overline{A}^I = 1$. I use a standard value of risk aversion $a = 2$.

Parameter	Target
Treasuries and Annuities	
$\tau^T = 10$, $\tau^L = 20$	Treasury maturity = 10 yrs, Annuity maturity = 20 yrs
$\phi^T = \phi^L = 1$	Normalization
$\overline{y}^T = 2.5\%$	Average 10-year Treasury yield (2010-2020)
$\alpha_y = \psi = -2$	Half-life of shocks $\approx$ 3 qtrs
Corporate Bonds	
$\tau^1 = \tau^2 = 8.55$	Corporate bond maturity = 8.55 yrs
$\phi^1 = \phi^2 = 1$	Normalization
$\delta = 1.635$	Variance of speculative-grade default rates
$\theta = 0.34$	Standard Cobb-Douglas capital share ($1 - \theta = 0.66$)
Life Insurer	
$\overline{A}^I = 1$	Normalization
$a = 2$	Standard

Table 1.9. **Calibrated Parameters.**

Estimated Parameters. I estimate a few other key parameters using empirical data. The estimated parameters are summarized in Table 1.10.

Parameter	Estimation Strategy
Corporate Bonds	
$\nu^1 = 0.001,\ \nu^2 = 0.017$	Average default rates
$\delta = 1.635$	Variance of speculative-grade default rates
Life Insurer	
$\zeta^1 = 2.85$	Relative portfolio share $(w^{I,2}/w^{I,1})^{ss} = 0.059$
$\zeta^2 = 7.21$	Relative bond supply $(P^2B^2/P^1B^1)^{ss} = 0.195$
$L = 8.79$	Empirical duration mismatch
Habitat Investor	
$\beta = 1.106$	Mutual fund demand elasticity (Darmouni et al., 2023)
$\alpha^1 = 0.47,\ \alpha^2 = 0.12$	Life insurers' share in each category (35.7%, 10.3%)

Table 1.10. **Estimated Parameters.**

I estimate the loadings on credit risk ν^1, ν^2 and the intensity of the credit risk process δ from the average annual default rates of both investment-grade and speculative bonds and the variance of speculative-grade default rate. The average one-year default rate between 2003 and 2019 is 0.156% for investment-grade bonds and 2.829% for speculative-grade bonds. The standard deviation of the one-year investment-grade bond default rate is 0.004. In the model, these three moments are given by $\delta\nu^1, \delta\nu^2$ and $\sqrt{\delta}\nu^1$. I estimate values of ν^1, ν^2, δ from the data by equating the model moments to the empirical counterparts.

I estimate regulatory cost parameters ζ^1, ζ^2 using two moments: the insurer's relative portfolio share investment-grade and speculative-grade bonds and the relative market cap of the two types of bonds (see Table B.4). I choose the values of ζ^1, ζ^2 so the model replicates the two empirical moments in the steady state.

The annuities supply L is obtained from the empirically estimated duration mismatch (see Section 1.4.1). Under my parametrization, the insurer's duration mismatch is more severe when they are more levered (i.e., larger L). The L parameter is chosen such that the insurer's net worth increases by 7.18% in response to a 1% positive Treasury yield shock starting from the steady state.

For the habitat investors' demand elasticity β, I adopt the demand elasticity of mutual funds estimated by Darmouni, Siani and Xiao (2022). I then estimate the demand intercepts α^1, α^2 using the market share of life insurers in each risk category at the end of 2010.[30] In the steady state, the insurer owns 35.7% of investment-grade bonds and 10.3% speculative-grade bonds, which match the empirical observation.

Model Performance. The model is successful at matching a number of important untargeted empirical responses. I consider an unexpected 1% positive shock to the 10-year Treasury yield from the steady state. Table 1.11 summarizes both the model-implied and empirical responses of three key variables relating to credit spreads, the insurer's portfolio adjustments, and bond issuance.[31] The model generates a 0.92% reduction in the credit spread between investment-grade bonds and speculative-grade on impact, which amounts

[30] In Section 1.4.2, I show that the co-movement of interest only exists in bonds held by life insurers. Therefore, I calibrate α^n to those bonds with life insurance ownership (see column 2 of Table B.4).

[31] See Table B.5 for details on the empirical estimates.

to 86% of the empirical estimate. The model also implies that the insurer increases its portfolio weight in speculative-grade bonds by 1.06% relative to investment-grade bonds in a quarter after the shock, matching the 1.00% empirical counterpart. In the model, the one-quarter issuance of speculative-grade bonds outpaces that of investment-grade bonds by 0.92%, which is reasonably close to the empirical estimate of 0.63%.

Definition	Description	Model	Empirical
$\Delta(y_t^2 - y_t^1)\vert_{t=0}$	Immediate Credit Spread Response	-0.92%	-1.06%
$\left(\Delta w_t^{I,2} - \Delta w_t^{I,1}\right)\vert_{t=0.25}$	1-qtr Portfolio Adjustment	1.06%	1.00%
$\left(\frac{\Delta B_t^2}{B^{2,ss}} - \frac{\Delta B_t^1}{B^{1,ss}}\right)\vert_{t=0.25}$	1-qtr Bond Issuance Response	0.92%	0.63%

Table 1.11. **Untargeted Responses.**

To understand these responses intuitively, it is useful to examine the insurer's trading and the induced bond price changes. In response to the 1% positive Treasury yield shock, the insurer lowers its portfolio weight in investment-grade bonds by 1.06% and leaves its portfolio weight in speculative-grade bonds largely unchanged by $t = 0.25$. Again, the difference in portfolio adjustments is because higher interest rates boost the insurer's net worth and its demand for risky bonds relative to safe bonds. The insurer sells investment-grade bonds that amount to 0.48% of the total steady-state outstanding. In contrast, it purchases speculative-grade bonds that are 0.84% of the total steady-state outstanding. The trading then lowers the price of investment-grade bonds by about 0.2% and increases the price of speculative-grade bonds by about 0.69%. The price changes trigger further supply responses, inducing less investment-grade bond supply and greater speculative-grade bond supply. Finally, the price movements translate to a 0.25% increase in the investment-grade yield and a 0.66% decline in the speculative-grade yield, thus generating a 0.91% decline in the credit spread.[32]

[32]Under my parametrization, a 1% corporate bond price change generates yield movements between 0.75% and 1.25%. The result suggests that the bonds' have a duration close to 1, which is consistent with the empirical price-yield sensitivity from observed market transactions, albeit less than the usual measure of average bond duration. This is because I target the duration of shorter-term bonds, which are traded more frequently and have larger weights in the bond price dataset and my empirical results.

1.6.4 The Duration Mismatch Channel and Policy Implications

The model has several new implications for unconventional monetary policy. In recent years, the Federal Reserve has adopted policies aiming to control long-term interest rates (e.g., Quantitative Easing and Tightening). For example, since 2022, the Federal Reserve has conducted Quantitative Tightening (QT) to shrink its balance sheets and control inflation, which increases the long-term interest rate.

Next, I investigate the model implications of a positive shock to the 10-year Treasury yield, which I view as a result of a QT policy.[33] The goal of this section is to quantitatively examine the policy's impacts on corporate bond yields, spreads, and issuance, as well as the role of the duration mismatch channel in the transmission.

Specifically, I analyze the responses of key model variables to an unexpected shock that moves the 10-year Treasury yield from $y_t^T = 2.5\%$ to $y_t^T = 3.5\%$. In the following analysis, I study a situation where the default shocks J_t are not realized, so the yield change is the only shock to the system.

In particular, I consider two scenarios: (1) the full model and (2) the model with no duration mismatch. In the full model, the insurer's duration mismatch is calibrated to the empirical estimate of Section 1.4.1, meaning that the insurer's net worth increases by 7.18% as the Treasury yield increases by 1%. In the model with no duration mismatch, I assume that the equity injection and dividend payout process $\psi_t \mathrm{d}t$ is chosen such that the insurer's net worth A_t^I always stays constant. In this case, the net worth does not respond to the Treasury yield shock. In the broad context, we can use the full model to represent the post-crisis scenario and the model without duration mismatch to represent the pre-crisis scenario. By contrasting these two scenarios, I aim to quantitatively assess the consequences of the duration mismatch channel on the transmission of long-term interest rates.

Figure 1.9 visualizes the shock and the response of insurer net worth A_t^I. The left panel plots the path of the Treasury yield, which jumps from 2.5% to 3.5% at $t = 0$ and gradu-

[33] In this paper, I view the unexpected Treasury yield shock as the end product of a QT policy and do not model the details regarding the implementation of the QT policy. See, for example, Krishnamurthy and Vissing-Jorgensen (2011), D'Amico and King (2013) and Vayanos and Vila (2021) for mechanisms of how unconventional monetary policies influence long-term interest rates.

ally reverts back to the steady state level 2.5%. The right panel shows the change in the insurer's net worth as a percentage of its steady-state value for the two different scenarios. In the full model, the insurer's net worth rises on impact and slowly returns to the steady state value. In the model without duration mismatch, the insurer's net worth stays constant.

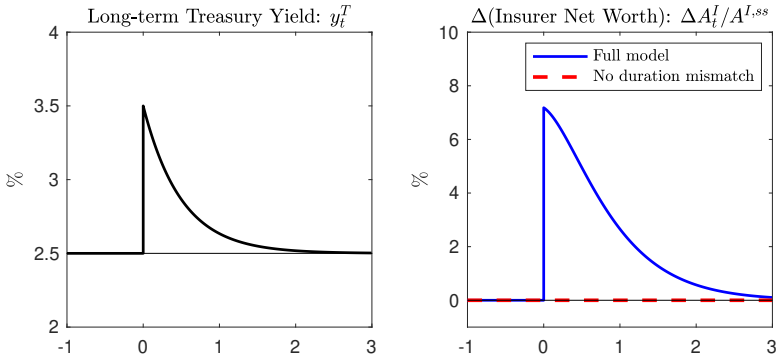


Figure 1.9. **Treasury Yield Shock and the Insurer's Net Worth Responses.**

Figure 1.10 plots the responses of corporate bond yields relative to the steady state. In the model without duration mismatch, yields of both bonds 1 and bonds 2 increase with the Treasury yield. This is due to the standard portfolio rebalancing channel — the insurer reduces demand for corporate bonds as Treasuries become more attractive. In addition, higher interest rates raise risk premia, as the credit spread between bonds 1 and bonds 2 widens as the Treasury yield increases. This is consistent with the empirical results of Figure 1.3, where higher long-term interest rates weakly increased the credit spreads for NAIC 2 and NAIC 3 bonds before the Crisis.

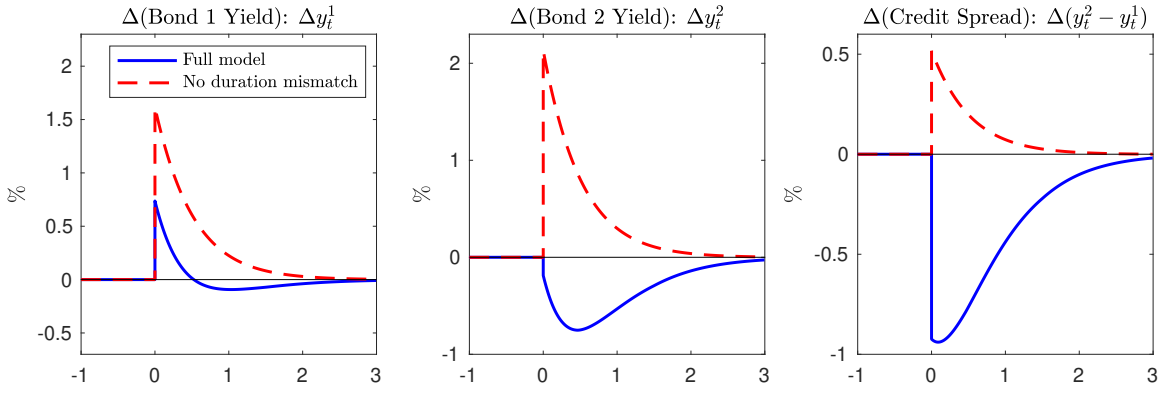


Figure 1.10. **Responses of Bond Yields and Credit Spreads.**

In the full model, there is an additional duration mismatch channel, where a higher Treasury yield increases the insurer's net worth, thereby boosting its demand for corporate bonds. Quantitatively, on impact, the duration mismatch channel dampens the investment-grade bond yield response by half while reversing the speculative-grade bond yield response slightly. Over time, the dampening and reversing effects become stronger before the yields revert to the steady state. Further, the duration mismatch channel has a larger effect on the speculative-grade yield, and the credit spread between the two bonds falls sharply as the Treasury yield rises. Thus, the QT policy unintentionally tightens the credit spread of corporate bonds. Notably, we can only generate large negative credit spread responses that are in line with Section 1.3.2 when the insurer faces duration mismatch.

I then study whether such credit spread responses can dampen or reverse the transmission of QT to real outcomes, including bond issuance and firm investment.

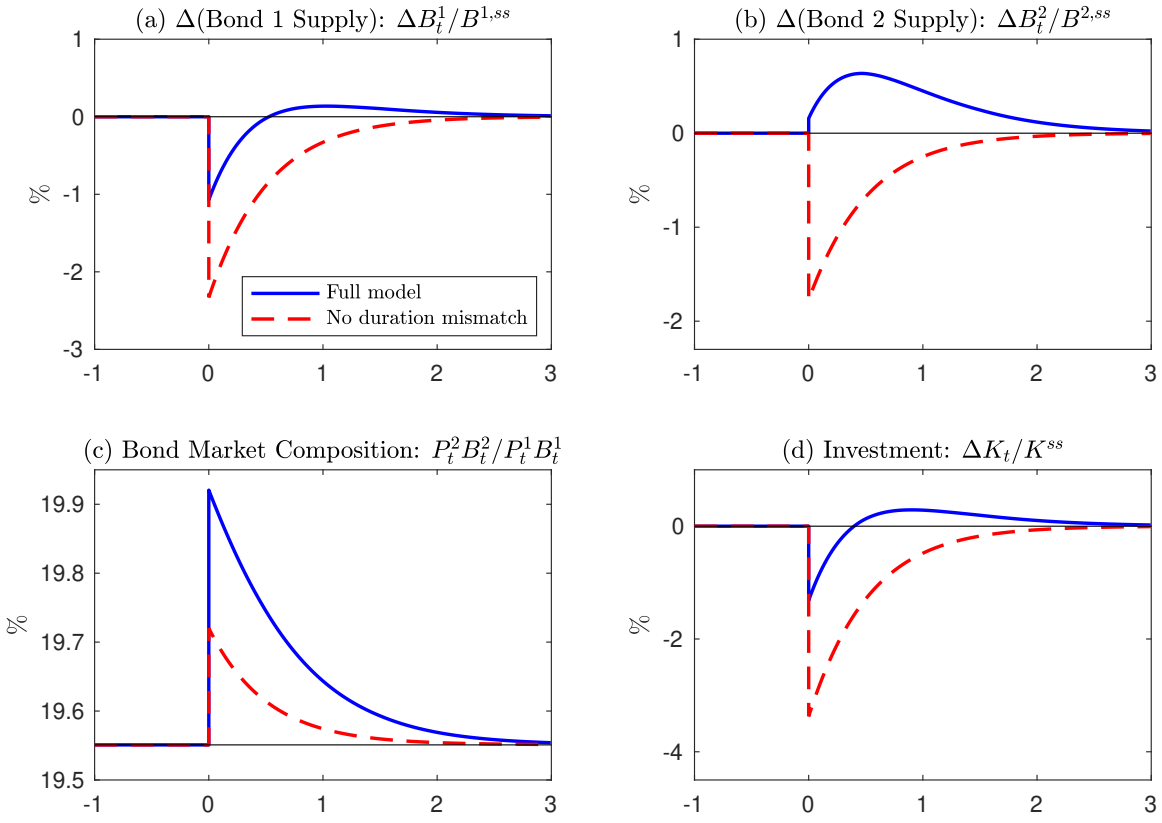


Figure 1.11. **Responses of Bond Supply and Investment.**

Panels (a) and (b) of Figure 1.11 plot the responses of the supply of bonds 1 and 2. In

the model without duration mismatch, the surge in the Treasury yield drives up corporate bond yields. In response, firms borrow less, showing that the policy is effective at cooling the bond market, at least when the life insurer is not subject to duration mismatch. In the full model, the duration mismatch channel counteracts the increase in corporate bond yields. Quantitatively, the results demonstrate that the duration mismatch channel can offset half of the contraction in investment-grade bond supply and even generate an unintended expansionary effect on speculative-grade bond supply.

Panel (c) of Figure 1.11 shows the relative market cap of bond 2 relative to bond 1. The QT policy tilts the market towards the speculative-grade segment, even more so in the full model, where credit spreads fall in response to the positive long-term interest rate shock. The results demonstrate that QT potentially alters the composition of the bond market, favoring risky issuers over safe ones.

Panel (d) of Figure 1.11 displays the aggregate investment response. Absent the duration mismatch channel, firms disinvest 3% of their capital following the Treasury yield increase. The investment response is also heavily muted in the full model, at about 1/3 of that in the model without duration mismatch.

Quantitative Easing (QE) is the opposite of QT, where the Fed purchases long-term Treasuries and lowers long-term interest rates. Empirical evidence shows that QE and central bank asset purchases can effectively lower long rates (e.g., Krishnamurthy and Vissing-Jorgensen, 2011; D'Amico and King, 2013; Vayanos and Vila, 2021), which potentially boosts economic activities. However, my results show that the effects of QE are achieved at the cost of increased corporate bond credit spreads, which offsets some of the postulated economic benefits of QE. Similar to QT, the duration mismatch channel could dampen the transmission of QE to the yields and issuance of investment-grade bonds and even reverse the effects of QE on the yields and issuance of speculative-grade bonds. Overall, the results of this section suggest that unconventional monetary policies that target the long-term interest rate could have large unintended effects in the corporate bond market due to life insurers' duration mismatch.

1.7 Conclusion

In this paper, I document a shift in the co-movement between the long-term interest rate and corporate bond credit spreads. In particular, declines in the long-term interest rate led to large increases in credit spreads only after the Financial Crisis. This is important given the long-run trend of the falling long-term interest rate and unconventional monetary policies that specifically target the long-term interest rate. I further establish that the new co-movement is caused by life insurers' bond holdings. Life insurers, the largest institutional investor group in the corporate bond market, comprise 20-35% of the bond market on average. After the Financial Crisis, they faced a large duration mismatch, and their equity value declined sharply with the long-term interest rate. I present causal evidence that this co-movement is more pronounced in bonds held by life insurers. This mechanism also has significant real effects on bond issuance and investment in the cross-section of firms. I build an intermediary asset pricing model with life insurers to account for the empirical findings. In the model, declines in the long-term interest rate squeeze life insurers' balance sheet equity and increase their effective risk aversion, resulting in higher equilibrium credit spreads. The model explains more than 80% of the observed co-movement between the long-term interest rate and corporate bond credit spreads as a result of the *duration mismatch channel*. The model implies large real effects and shows that life insurers' balance sheets can play an important role in the transmission of unconventional monetary policy to bond yields, issuance, and investment.

Chapter 2

Deposit Market Power and Bank Risk-Taking

2.1 Introduction

Commercial banks issue safe deposits against risky loans. As of September 2022, banks in the US hold $12.0 trillion loans (47% of GDP) and issue $19.4 trillion deposits (75% of GDP). It has been argued that safety transformation is one of the main business models of modern commercial banks, and the associated risk-taking is an important driver of fragility within the banking sector (e.g., Calomiris and Mason, 2003; Admati and Hellwig, 2014; Brunnermeier and Sannikov, 2014; Baron, Verner and Xiong, 2021). Naturally, it is of great importance to understand the drivers of bank risk-taking.

In this paper, we identify a new cross-sectional pattern of bank risk-taking — banks that enjoy greater market power in deposit markets take on significantly less credit risk. As a result, high-market-power banks have lower regulatory asset risk weight and leverage ratio. On average, a one standard deviation increase in deposit market power is associated with a 7.2% decrease in a bank's risk-weighted assets to tier-1 capital ratio, one of the most widely adopted measures of bank soundness.

Importantly, high-market-power banks shed away from risk by reducing their portfolio weights on the riskiest loans. Consequently, they suffer from fewer loan losses, especially

in recessions. In the Great Recession, banks in the top tercile of the deposit market power distribution sustained loan losses amounting to 0.83% of their assets. In contrast, banks in the bottom tercile experienced a loan loss rate of 1.33%. Moreover, the loan loss of high-market power banks is less exposed to business cycle fluctuations.

These findings have important implications for credit provision and the stability of the banking sector. In particular, they hint at a *competition-stability* trade-off. In more competitive markets, banks have less deposit market power and take on more risk by supplying more risky loans. However, the increased intermediation activities come at the cost of greater risk and more defaults on the asset side of the banks' balance sheets, which undermine the stability of those banks.

It is a well-studied fact that banks exhibit imperfect pass-through of the policy rate to retail deposit rates, and the degree of pass-through is tightly linked to concentration and market power.[1] Following Drechsler, Savov and Schnabl (2021), our baseline specification uses the banks' interest expense–federal funds rate (FFR) beta as the measure of deposit market power. Intuitively, a high beta means that the bank's deposit rate is more sensitive to the policy rate, indicating that the bank has little market power over depositors. We obtain bank balance sheet information from U.S. Call Reports and use the banks' asset risk weight and leverage ratio as measures of bank risk-taking.[2] Using data covering the period between 1996 and 2020, we show that the negative relationship between deposit market power and risk-taking is persistent over time and robust after controlling for bank size, funding structure, fee income, loan market power, and geographical distribution.

To address the measurement challenge that a bank's interest expense beta may reflect other unobserved characteristics than deposit market power, we further follow Drechsler, Savov and Schnabl (2021) to instrument the bank-level interest expense–FFR beta with a county-level retail deposit rate-FFR beta constructed from actual deposit rates, which measures the competitiveness of the local deposit markets each bank operates in. This

[1] See, e.g., Hannan and Berger (1991), Neumark and Sharpe (1992), Driscoll and Judson (2013), Drechsler, Savov and Schnabl (2017, 2021), Polo (2021), Gödl-Hanisch (2022), and Wang *et al.* (2022).

[2] In this work, we focus on *credit risk* as it is one of the largest sources of risk facing modern commercial banks (e.g., Begenau, Piazzesi and Schneider, 2015). Complementary to this paper, a number of existing studies have investigated the relationship between deposit market power and *interest rate risk* (e.g., Li, Loutskina and Strahan, 2023; Whited, Wu and Xiao, 2021; Drechsler, Savov and Schnabl, 2021).

instrument is based on the assumptions that the geographical distribution of banks and the competitiveness of county-level deposit markets are correlated with banks' deposit market power and that they only affect bank risk-taking through market power. Our main results remain robust in the two-stage least squares regression based on this instrument.

An obvious identification challenge is that risk-taking is affected by banks' investment opportunities, which might be correlated with their deposit market power as both can depend on their locations. We address this concern by examining one-county banks within the same county. After controlling for county-time fixed effects, we can compare banks that operate in the same location but differ in their deposit market power. The identification assumption is that banks in the same geographic area face the same borrowers and thus have similar investment opportunities. We show that the negative relationship between market power and risk-taking remains robust under this more restrictive specification.

We also present a second identification scheme by examining the zero lower bound (ZLB) period. In practice, banks benefit from deposit market power as they can choose a deposit rate below the federal funds rate and earn a positive deposit premium (Drechsler, Savov and Schnabl, 2017). Hence, we expect that deposit market power becomes less relevant when the economy is at the zero lower bound where all banks must supply deposits at a rate of almost zero. Indeed, we find that the risk-taking gap between high-market-power banks and low-market-banks shrank substantially after 2009 when the federal funds rate hit zero.

We then build a model of bank franchise value to explain our empirical findings. Consistent with our measurements, high-market-power banks in the model charge higher deposit spreads and earn more profits. Banks also choose the amount of risk to take on. A riskier asset portfolio yields a higher risk premium but also increases the bank's default probability. Banks have limited liability in the event of default. Deposit market power boosts the banks' franchise value, the value of remaining in the market for the future. Thus, banks with high market power choose to take on less risk to avoid a potential default. The model has direct implications for bank competition and stability. In a highly competitive market, banks have low franchise value and are more willing to take on risk. In equilibrium, low market power results in more fragility in the form of greater default

probability.

Related Literature. Our paper belongs to the burgeoning literature on bank deposit market power. Following Drechsler, Savov and Schnabl (2017), a number of studies have investigated the role of bank deposit market power in the transmission of monetary and fiscal policy (e.g., Xiao, 2020; Polo, 2021; Wang, Whited, Wu and Xiao, 2022; Li, Ma and Zhao, 2021; Gödl-Hanisch, 2022; Wang, 2022). However, such studies mostly focus on the liability side of bank balance sheets to study the pass-through of government policy to deposit rate and deposit quantity. Instead, we show that there exist important interactions between deposit market power and bank asset choice. In this regard, we share the same focus with Li, Loutskina and Strahan (2023), which emphasizes the maturity of bank assets and argues that deposit market power encourages banks to engage in long-term lending by reducing their funding risk. Similarly, Drechsler, Savov and Schnabl (2021) argues that deposit market power increases the duration of bank liabilities and that banks choose the duration of their assets to match the duration of their liabilities. In this paper, we instead focus on the risk of bank assets and show that deposit market power leads banks to behave more cautiously when choosing credit risk and leverage.

In a broad sense, our paper connects with the literature on the interactions between bank assets and bank liabilities. The seminal contributions of Diamond and Dybvig (1983) and Kashyap, Rajan and Stein (2002) have pointed out the fragility and synergy caused by lending and deposit-taking. Recently, Bolton *et al.* (2021) and Granja, Leuz and Rajan (2022) show that deposit inflows might depress bank lending and increase bank risk-taking. In this project, we demonstrate that risk-taking and deposit-taking can become substitutes when deposit market power elevates bank franchise value. That is, when banks earn high profits from deposit market power, they curb risk-taking to lower their likelihood of default.

We provide new insights into the long debate on the relationship between bank competition and financial stability.[3] Some have argued that a more competitive banking industry is also more fragile (e.g., Keeley, 1990; Demsetz, Saidenberg and Strahan, 1996; Beck,

[3]See Vives (2016) for an overview of the literature.

Demirgüç-Kunt and Levine, 2006; Jiménez, Lopez and Saurina, 2013; Berger, Klapper and Turk-Ariss, 2017; Carlson, Correia and Luck, 2022), while some suggest that competition does not necessarily lead to risk build-up in the banking sector (e.g., Allen and Gale, 2004; Boyd and De Nicolo, 2005; Boyd, De Nicolo and Jalal, 2006; Martinez-Miera and Repullo, 2010). Our paper provides new evidence that is supportive of the first view where competition leads to instability. However, instead of using bank valuation (e.g., Tobin's q) or profit markups (e.g., the Lerner index) as proxies for competition, we directly test the role of deposit market power. Further, we go beyond the overall level of bank risk (e.g., as measured by stock volatility and Z-scores) and examine the *source* of risk using bank balance sheet information. Our results suggest that low-market-power banks primarily take on more credit risk through loan issuance.

Our results also contribute to the emerging literature on the effect of a low-interest-rate environment on bank risk-taking. Existing research (e.g., Altunbas, Gambacorta and Marques-Ibanez, 2010; Maddaloni and Peydró, 2011; Jiménez, Ongena, Peydró and Saurina, 2014; Heider, Saidi and Schepens, 2019; Whited, Wu and Xiao, 2021) suggests that low nominal rates led to increased bank risk-taking, while we show that low rates can nullify the effect of deposit market power, reducing the difference in risk-taking between high-market-power banks and low-market-power banks.[4]

Outline. Section 2.2 describes the data used in the empirical analysis. Section 2.3 presents time series evidence, the empirical specification, main regression results, and various robustness checks. Section 2.4 examines the cross-sectional relationship between deposit market power and risk-taking in the zero lower bound period. Section 2.5 explains the findings with a tractable model of bank franchise value. Section 2.6 concludes.

[4]Using a sample of Japanese banks, Balloch and Koby (2022) show that low rates weaken deposit market power and depress loan growth.

2.2 Data and Measurement

2.2.1 Data Sources and Sample Selection

Our main source of data at the bank level is the quarterly U.S. Call Reports provided by Wharton Research Data Services. All U.S. commercial banks are required to file the report with balance sheet and income statement information. We use data from March 1996[5] to March 2020. For banks owned by bank holding companies, we aggregate the data to the holding company level.

For information at the bank branch level, our main source of data is the FDIC Summary of Deposits which reports the address and total deposits for each U.S. bank branch at the end of each June. We use the Summary of Deposits data from 1996 to 2020 and merge it to Call Reports using FDIC bank identifiers. For a part of our analysis, we also use deposit rate data from Ratewatch, which provides weekly branch-level deposit rates from 1998 to 2019 for a subset of bank branches.[6]

We limit our main analysis sample to banks that have deposit-taking branches in at least two counties (at least one must be among the top 1000 counties by population) for at least five years from 1996 to 2019. We further require each bank-quarter observation to have at least $10 million of total assets, $1 million of loans, and $1 million of deposits, and we require each bank to have at least 20 quarters of data for interest expense, risk-weighted assets, and tier-1 capital. The main analysis sample consists of 3437 banks (2969 bank holding companies and 468 non-BHC banks) and 195225 bank-quarter observations from 1996Q1 to 2020Q1. For the average quarter during this period, our main sample covers 72% of assets reported by all banks filing Call Reports. In Section 2.3.2, we examine a separate sample of one-county banks to address the identification challenge raised by the potential correlation between a bank's geographical distribution and its investment opportunities.

[5]Banks were required to report asset risk weight and risk-weighted leverage on section RC-R of call report starting in 1996Q1.

[6]Ratewatch provides deposit rates data for 63% of all U.S. bank branches in 2019. The majority of branches follow the rates set by a small number of "rate-setting branches." Among covered branches in 2019, only 11% set deposit rates by themselves.

2.2.2 Measuring Bank Market Power

We follow the approach of Drechsler, Savov and Schnabl (2021) and use the sensitivity of a bank's interest expense to federal funds rate changes to measure the bank's deposit market power. Banks with higher market power can charge higher deposit spreads when the federal funds rate increases. Therefore, a low sensitivity of interest expense to the federal funds rate indicates high market power.

For each bank i, we estimate the response of the interest expense rate to the federal funds rate as follows:

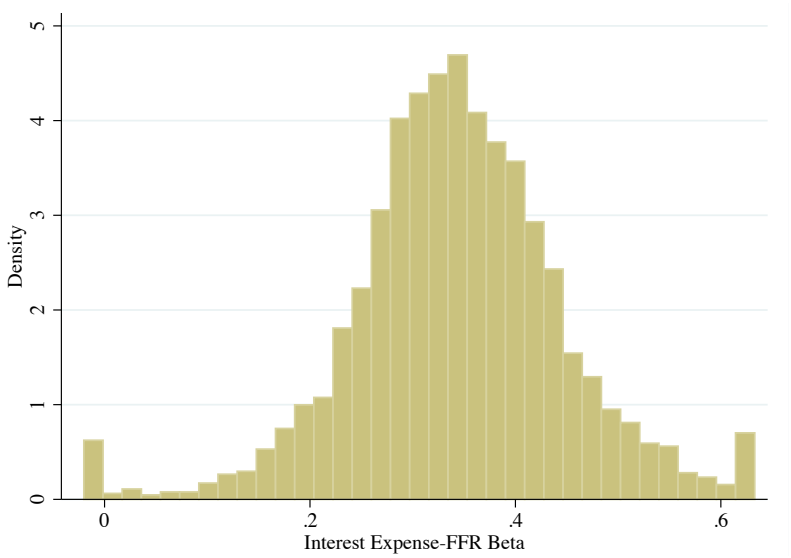
$$\Delta \text{IntExp}_{i,t} = \alpha_i + \sum_{\tau=0}^{3} \gamma_{i,\tau} \Delta \text{FFR}_{t-\tau} + \varepsilon_{i,t} \tag{2.1}$$

$$\text{IntExpBeta}_i := \sum_{\tau=0}^{3} \gamma_{i,\tau} \tag{2.2}$$

where $\text{IntExp}_{i,t}$ is bank i's interest expense rate in quarter t and FFR_t is the average of month-end federal funds rates in quarter t. We define the interest expense rate for a bank-quarter as quarterly interest expense divided by quarterly average total assets and multiplied by 4. The interest expense to FFR beta IntExpBeta_i (hereafter "interest expense beta") captures the total response of a bank's interest expense rate to changes in federal funds rate over the past year.

We require at least 20 observations for estimating equation (2.1) and winsorize the interest expense beta at 1% and 99% percentiles to avoid the impact of outliers. Figure 2.1 plots the histogram of interest expense beta across banks, and Table 2.1 provides summary statistics. Across 3437 banks in our main sample, the average interest expense beta is 0.343, and the standard deviation is 0.105 — i.e., the average bank in our sample increases its deposit rate by 0.343% in response to a 1% increase of federal funds rate over a year.

Figure 2.1. Distribution of Interest Expense to FFR Beta



Note: The interest expense-FFR beta at bank level estimated from Equations (2.1-2.2) for 3437 banks in the main sample and winsorized at 1% and 99% percentiles.

2.2.3 Measuring Bank Risk-Taking

Our main metric for bank risk-taking is risk-weighted leverage, defined as a bank's risk-weighted asset divided by tier-1 capital. It is the product of a bank's asset risk weight and leverage and thus summarizes a bank's risk-taking on both margins. The inverse of risk-weighted leverage is the Tier-1 Capital Ratio commonly used by regulators to judge a bank's capital adequacy.

$$\underbrace{\frac{\text{Risk-Weighted Assets}}{\text{Tier-1 Capital}}}_{\text{Risk-Weighted Leverage}} = \underbrace{\frac{\text{Risk-Weighted Assets}}{\text{Assets}}}_{\text{Asset Risk Weight}} \times \underbrace{\frac{\text{Assets}}{\text{Tier-1 Capital}}}_{\text{Leverage}}. \tag{2.3}$$

Each bank classifies its assets by four risk weight categories of 0%, 20%, 50%, and 100% on the call report and computes the risk-weighted asset by applying these risk weights and adjusting for off-balance-sheet exposure.[7] The instructions for call reports define the risk weight categories for each type of asset.[8] For example, the risk weight guidelines for

[7]The reported off-balance sheet exposure is 3% of total assets for an average bank in the period from 2001Q1 to 2014Q4. This is very small compared to the on-balance-sheet risk-weighted asset, which is 68% of total assets for an average bank in the same period.

[8]According to the June 2007 call report instructions, risk weight categories 20%, 50%, and 100% can be considered as long-term credit rating AAA/AA, A, and BBB, respectively (`https://www.ffiec.gov/PDF/`

loans in the June 2007 call report instructions are as follows:

- 0% for the guaranteed portion of SBA loans purchased in the secondary market.
- 20% for loans to other depository institutions, the guaranteed portion of FHA and VA mortgage loans, the guaranteed portion of SBA loans originated by the bank, and student loans insured by the U.S. government.
- 50% for loans fully secured by first liens on residential properties that are "prudently underwritten"[9] and not past due for more than 90 days.
- 100% for all other loans on the balance sheets (i.e., riskier mortgages and all commercial loans).

Table 2.1 provides summary statistics for risk-weighted leverage and its two components. For all of our analyses, we winsorize all three variables at 1% and 99% levels in each quarter to mitigate the impact of outliers. The average risk-weighted leverage in our main sample is 7.89, corresponding to a tier-1 capital ratio of 12.6%. The average asset risk weight is 70.8%, and the average raw leverage is 11.2. Risk-weighted leverage and its components all vary substantially across banks and over time.

For a part of our analysis, we also use loan loss provision as a measure of a bank's ex-post loss due to loan defaults. We calculate banks' loan loss rate as the quarterly loan loss provision divided by quarterly average assets, averaged across the past four quarters to adjust for seasonality. Table 2.1 shows that the average annual loan loss to asset ratio is 0.328% in our sample.

Table 2.1. Summary Statistics: Main Sample

Variable	Level	*N*	Mean	SD	Q10	Q50	Q90
Interest Expense Beta	Bank	3437	0.343	0.105	0.226	0.341	0.469
Risk-Weighted Leverage	Bank-Quarter	195225	7.89	2.19	5.17	7.92	10.36
Asset Risk Weight (%)	Bank-Quarter	195225	70.8	11.4	55.7	71.6	84.9
Leverage	Bank-Quarter	195225	11.2	2.64	8.17	11.1	14.0
Annual Loan Loss Rate (%)	Bank-Quarter	194149	0.328	0.531	0	0.175	0.772

`FFIEC_forms/FFIEC031_041_200706_i.pdf`).

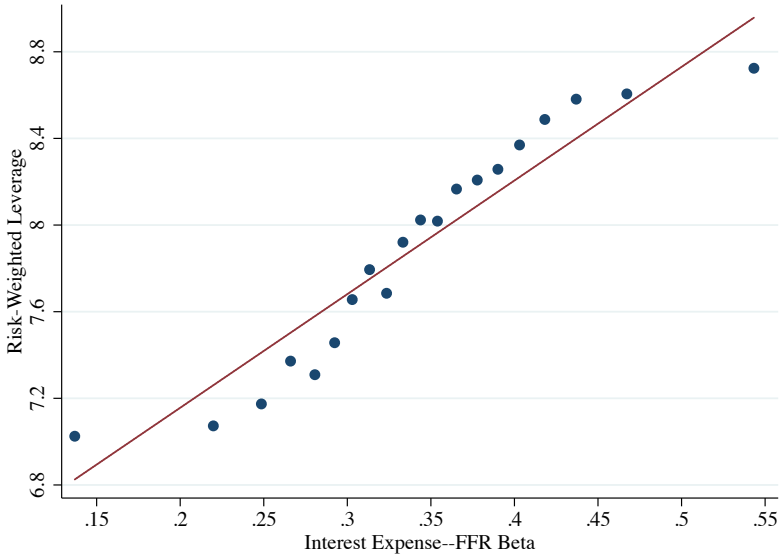
[9]Prudent underwriting typically requires a loan-to-value ratio not exceeding 80% (75% for floating-rate loans).

2.3 Main Results

2.3.1 Market Power and Risk-Taking Metrics

In this section, we examine the relationship between interest expense beta and risk-taking metrics in the cross-section of banks. To begin with, Figure 2.2 shows a binned scatter plot of risk-weighted leverage against interest expense beta. The plot shows a clear relationship where banks with lower interest expense beta — i.e., higher deposit market power — have lower risk-weighted leverage.

Figure 2.2. Risk-Weighted Leverage and Interest Expense to FFR Beta



Note: 20-point binned scatter plot with year-quarter fixed effects taken out. Data from 1996Q1 to 2020Q1 for 3437 banks.

We use the regression below to formally test the relationship between interest expense beta and risk-taking metrics:

$$\text{Risk}_{i,t} = \alpha_t + \beta \cdot \text{IntExpBeta}_i + \boldsymbol{\gamma}' \boldsymbol{x}_{i,t} + \varepsilon_{i,t} \tag{2.4}$$

where $\text{Risk}_{i,t}$ is one of the risk-taking metrics for bank i in quarter t, α_t is a year-quarter fixed effect that ensures comparison in the cross-section of banks, $\boldsymbol{x}_{i,t}$ are control variables, and IntExpBeta_i is the interest expense beta for bank i. The parameter of interest is β, which

measures the change of risk-taking behavior per one unit increase of interest expense beta.

Risk-Weighted Leverage

The regression results for risk-weighted leverage are presented in Table 2.2. Column (1) shows the regression results without controls, with log risk-weighted leverage as the risk metric. The coefficient β is 0.720 with a large t-statistic: in the cross-section of banks, 0.1 unit lower interest expense beta (one standard deviation) is associated with 7.2% lower risk-weighted leverage. Column (2) shows that the coefficient β is 0.570 after controlling for basic bank characteristics, including log assets, deposit-to-liability ratio, log total number of branches, and an indicator for having branches in multiple states. Column (3) shows that the coefficient is 0.557 after further controlling for two measures of non-interest income[10]: domestic deposit fee income and other non-interest income[11].

One potential omitted variable for our regression analysis is bank-specific investment opportunities related to geographical distribution. For example, banks with higher deposit market power might be located in high-income counties with an older population, where lending opportunities are safer. To address this concern, we construct bank-level measures about the riskiness of the counties in which the bank operates. We first compute a "county business cycle beta" CountyBusBeta_c for each county c by regressing the county's real per-capita income growth $g_{c,t}$ onto the U.S. real per-capita income growth G_t using annual data from 1969 to 2019, as shown in Equation (2.5).

$$g_{c,t} = \alpha_c + \text{CountyBusBeta}_c \cdot G_t + \varepsilon_{c,t}. \tag{2.5}$$

We then aggregate this measure to the bank level by taking the average of county business cycle beta across all counties a bank operates in, weighted by the number of branches the

[10]Domestic deposit fee income is the service charges on domestic deposit accounts (RIAD4080) divided by a bank's total assets. Other non-interest income is all non-interest income minus the deposit fees (RIAD4079 minus RIAD4080), divided by a bank's total assets. We use annualized rolling 4-quarter averages of these two fee measures to adjust for seasonality.

[11]Notably, banks that earn high service fees from domestic deposit accounts also tend to have lower risk-weighted leverage and asset risk weight, as shown in columns 4 and 5 in Table 2.2. One can interpret the deposit fee income as an alternative measure of deposit market power, as banks with high market power over their depositors could charge higher service fees. Therefore, the negative association between deposit fee income and risk-taking is consistent with our main results.

bank has in each county, as shown in Equation (2.6).

$$\text{BankBusBeta}_{b,t} = \frac{\sum \#\ \text{Branch}_{b,c,t} \times \text{CountyBusBeta}_{c}}{\sum \#\ \text{Branch}_{b,c,t}}. \tag{2.6}$$

Similarly, we also construct the weighted average of per-capita income across counties a bank operates in, as shown in Equation (2.7).

$$\text{BankIncome}_{b,t} = \frac{\sum \#\ \text{Branch}_{b,c,t} \times \text{Per-Capita Income}_{c,t}}{\sum \#\ \text{Branch}_{b,c,t}}. \tag{2.7}$$

Column (4) of Table 2.2 shows the regression results after controlling for the two bank-level measures defined above. Adding the controls does not meaningfully change our main coefficient β (from 0.557 to 0.554). As shown in columns (5-6), the average county business cycle beta is positively correlated with asset risk weight but not significantly correlated with bank leverage. Conditioning on county business cycle beta, average county per-capita income is also positively correlated with risk-taking, which might indicate that high-income counties offer more lending opportunities.

Table 2.2. Risk-Taking and Interest Expense Beta: Main Regression Results

	Dependent Variable: Risk Metrics					
	Log Risk-Weighted Leverage				Risk Weight	Log Leverage
	(1)	(2)	(3)	(4)	(5)	(6)
IntExp-FFR Beta	0.720**	0.570**	0.557**	0.554**	0.221**	0.217**
	[12.70]	[10.28]	[10.04]	[10.03]	[10.81]	[5.341]
Log Assets		0.00807	0.00108	-0.0121	-0.00328	-0.00528
		[0.913]	[0.120]	[-1.297]	[-0.860]	[-0.760]
Deposit/Liability		-0.372**	-0.374**	-0.378**	0.00112	-0.362**
		[-5.818]	[-5.846]	[-5.966]	[0.0430]	[-8.134]
Log(# Branches)		0.0375**	0.0501**	0.0625**	0.0140**	0.0380**
		[3.298]	[4.260]	[5.201]	[2.900]	[4.324]
Multi State		-0.0114	-0.0114	-0.0134	-0.00150	-0.00869
		[-1.083]	[-1.119]	[-1.314]	[-0.335]	[-1.127]
Deposit Fee Income			-0.0777**	-0.0610**	-0.0556**	0.0194
			[-4.373]	[-3.359]	[-8.093]	[1.352]
Other Non-Interest Income			-0.00588	-0.00827	0.000700	-0.00801+
			[-0.906]	[-1.293]	[0.249]	[-1.764]
Log(County PC Income)				0.0763*	0.0336**	0.0354
				[2.616]	[2.989]	[1.587]
County Bus. Cycle Beta				0.0426**	0.0339**	-0.00342
				[2.812]	[5.478]	[-0.290]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Within R^2	.055	.104	.11	.117	.102	.066
# Banks	3437	3437	3437	3437	3437	3437
Observations	195225	195225	195225	195225	195225	195225

Note: Regressions based on Equation (2.4). "IntExpBeta" is the interest expense to FFR beta defined in Equations (2.1-2.2). "Multi State" is an indicator for having branches in multiple states. "County PC Income" is the average per-capita income in counties a bank operates in, defined by Equation (2.7). "County Bus. Cycle Beta" is the average county business cycle beta in counties a bank operates in, defined by Equation (2.6). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Breakdown of Risk Components

To further examine which component of risk-taking is related to market power, we run the main regression (2.4) separately with asset risk weight and log leverage as dependent variables. Column (5-6) of Table 2.2 shows that with all the control variables, 0.1 unit lower interest expense beta is associated with 2.21 percentage point lower asset risk weight (3.1% compared to the overall average risk weight of 70.8 percent) and 2.17% lower raw leverage. Therefore, banks with higher market power choose both a safer asset portfolio and lower leverage; these two margins have a similar contribution to the overall relationship between

market power and risk-weighted leverage.

Table 2.3 uses data from 2000Q1 to 2014Q4[12] to examine further breakdowns of asset composition. In columns (1-2), we separately examine the off-balance-sheet and on-balance-sheet asset risk weights, where the sum of these two equals the overall asset risk weight. For 0.1 unit lower interest expense beta across banks, off-balance-sheet risk weight reduces by 0.11 percentage points (compared to the average of 3%), and on-balance-sheet risk weight reduces by 2.43 percentage points (compared to the average of 68%). Therefore, both the average asset risk weight and its relationship with market power are mainly driven by the composition of on-balance-sheet assets.

Finally, we further separate on-balance-sheet assets into two categories: loans with 100% risk weight and all other assets. According to the June 2007 call report instructions, loans in the 100% risk category include all mortgages not secured by first-lien or not "prudently underwritten" and all commercial-industrial loans. Loans in this category are, on average, 51% of the total assets in our subsample from 2000Q1 to 2014Q4, so they contribute the most towards overall asset risk weights. Column (3) of Table 2.3 shows that banks with higher market power allocate less of their portfolio in loans with 100% risk weight: 0.1 unit lower interest expense beta is associated with 3.48 percentage point lower portfolio weight in this category. Therefore, the relationship between market power and asset risk is primarily driven by portfolio allocation between risky, unsecured loans and other assets (non-loan assets and secured or guaranteed loans).

[12]This subsample period is limited by data availability. A detailed breakdown of assets into risk weight categories was only available since 2000Q1. Schedule RC-R of the call reports was substantially changed after 2015Q1, making some of the variables non-comparable.

Table 2.3. Interest Expense Beta and Asset Composition

	Dependent Variable: Risk Metrics			
	Off-Bal Risk Weight (1)	On-Bal Risk Weight (2)	100% Wgt Loan to Assets (3)	Avg. Risk Weight Other Assets (4)
IntExp-FFR Beta	0.0114*	0.243**	0.348**	0.0417**
	[2.016]	[11.17]	[11.33]	[3.199]
Log Assets	0.0115**	-0.0116**	-0.000644	-0.0203**
	[8.275]	[-2.957]	[-0.126]	[-9.491]
Deposit/Liability	-0.0252**	0.0458+	0.189**	-0.147**
	[-3.201]	[1.812]	[5.818]	[-8.253]
Log(# Branches)	-0.00368*	0.0151**	0.00743	0.0188**
	[-2.168]	[3.099]	[1.163]	[7.593]
Log(County PC Income)	0.0168**	0.0147	0.0553**	-0.0454**
	[5.463]	[1.317]	[3.549]	[-5.328]
County Bus. Cycle Beta	-0.000543	0.0347**	0.0609**	-0.00904+
	[-0.335]	[5.724]	[7.619]	[-1.885]
Multi State	0.000269	-0.00721	-0.00394	-0.00984**
	[0.213]	[-1.627]	[-0.655]	[-3.236]
Deposit Fee Income	-0.000240	-0.0529**	-0.0647**	-0.0181**
	[-0.128]	[-7.871]	[-7.125]	[-3.990]
Other Non-Interest Income	0.00477**	-0.00593*	-0.0123**	0.00499**
	[5.791]	[-2.013]	[-3.215]	[2.826]
Year-Quarter FE	✓	✓	✓	✓
Within R^2	.235	.093	.142	.058
# Banks	3395	3395	3395	3395
Dep. Var. Mean	.03	.68	.51	.36
Observations	124377	124377	124377	124377

Note: Regressions based on Equation (2.4). "Off-Bal Risk Weight" is off-balance sheet risk exposure divided by assets. "On-Bal Risk Weight" is the average risk weight of all assets reported on the balance sheet. "100% Wgt Loan to Assets" is the fraction of assets in the "100% risk-weight loan" category. "Avg. Risk Weight Other Assets" is the average risk weight of all assets excluding 100% risk-weight loans. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

2.3.2 Robustness

The previous section shows our main result, which is that banks with higher market power take less risk both by choosing a safer asset portfolio and by taking on less leverage. In this section, we first show that our results are robust to controlling for loan market power. We also show that our results hold for both small and large banks. We then use a two-stage least squares specification based on variations of retail deposit rates across

counties to address concerns about measurement error. We finally examine a separate sample of one-county banks to address identification concerns regarding the unobserved geographical distribution of investment opportunities. Appendix B.2 provides more robustness results.

Loan Market Power

One potential concern for our main results in Table 2.2 might be driven by banks' loan market power instead of deposit market power. Holding borrower characteristics constant, a bank with higher loan market power could charge higher loan spreads and thus earn higher interest income. If deposit market power and loan market power are positively correlated, as both could be driven by a bank's geographical distribution, then the negative relationship between deposit market power and risk-taking might be confounded by loan market power.

To address this concern, we construct a proxy for loan market power based on the HMDA data for mortgage originations[13] from 1996 to 2019. For each county in each year, we compute the county-level HHI based on the loan amounts originated by each bank. We then aggregate the county-level HHI to the bank level by taking a loan-amount-weighted average of HHI across all counties in which a bank originates mortgages. We use the resulting bank-level measure of *mortgage HHI* as a proxy for a bank's loan market power[14]. A high mortgage HHI indicates that a bank issues more mortgages in counties with concentrated mortgage markets.

In our analysis sample, mortgage HHI can be computed for 87.4% of banks (constituting 98.8% of total assets) in an average quarter. The correlation between mortgage HHI and interest expense beta is 0.04, and the correlation between mortgage HHI and the deposit HHI measure of Drechsler, Savov and Schnabl (2017) is 0.39. These results show that the correlation between loan market power and deposit market power is moderate at best.

[13]The HMDA data provides loan-level origination records for mortgages. We include all mortgages for home purchasing or refinancing that originated from all lenders reporting to HMDA. We require the loans to have a FIPS code within the 50 U.S. states and require the loan amount to be between 10,000 and 10,000,000 dollars.

[14]We use a 5-year rolling average of mortgage HHI in regression analysis in order to mitigate the issue of missing data. The rolling average also takes into account the fact that HMDA captures the flow of mortgage originations rather than the stock of all outstanding mortgages held by each bank.

Table 2.4 shows the results of our main regression with mortgage HHI as an additional control. Comparing with results in Table 2.2, we find that the coefficient on interest expense beta only reduces slightly after the control. For example, the coefficient for interest expense beta in the regression for log risk-weighted average decreases from 0.554 ($t = 10.0$) to 0.519 ($t = 9.2$) after adding the control. The results are similar for the two components of the risk-weighted average.

Table 2.4 also shows that mortgage HHI is positively associated with risk weight, negatively associated with log leverage, but not significantly associated with risk-weighted leverage. However, we note that the coefficients on mortgage HHI in Table 2.4 are very small in magnitude: for example, 1-standard deviation higher mortgage HHI is only associated with 0.5 percentage point higher risk weight and 0.8% lower leverage. Overall, these results suggest that mortgage market power has a small impact on banks' risk-taking and franchise value.[15]

Finally, Table B.4 in the appendix shows that our results based on deposit HHI as a measure of deposit market power are also robust after controlling for mortgage HHI.

[15]We note that there are at least two potential reasons why high mortgage market power may not translate into high bank franchise value. On the one hand, banks may not have much pricing power over conforming mortgages sold to GSEs. On the other hand, mortgages may be more nationally priced than deposits (e.g., Hurst *et al.*, 2016).

Table 2.4. Robustness: Controlling for Mortgage Market Power

	Dependent Variable: Risk Metrics		
	Log Risk-Wgt Lev. (1)	Risk Weight (2)	Log Lev. (3)
IntExp-FFR Beta	0.519**	0.206**	0.208**
	[9.205]	[9.672]	[5.036]
Log Assets	-0.00967	-0.00272	-0.00456
	[-0.921]	[-0.644]	[-0.595]
Deposit/Liability	-0.359**	0.0140	-0.361**
	[-5.514]	[0.522]	[-7.885]
Log(# Branches)	0.0547**	0.0122*	0.0345**
	[4.128]	[2.341]	[3.590]
Log(County PC Income)	0.0677*	0.0346**	0.0236
	[2.202]	[2.885]	[1.001]
County Bus. Cycle Beta	0.0434**	0.0354**	-0.00500
	[2.696]	[5.293]	[-0.406]
Multi State	-0.00539	-0.000249	-0.00342
	[-0.544]	[-0.0565]	[-0.441]
Deposit Fee Income	-0.0806**	-0.0570**	0.00194
	[-4.096]	[-7.676]	[0.125]
Other Non-Interest Income	-0.00467	0.00242	-0.00767
	[-0.761]	[0.926]	[-1.629]
Mortgage HHI (STD)	0.000109	0.00557**	-0.00806*
	[0.0240]	[3.592]	[-2.297]
Year-Quarter FE	✓	✓	✓
Within R^2	.112	.099	.064
# Banks	3197	3197	3197
Observations	171501	171501	171501

Note: Regressions based on Equation (2.4) with additional control of mortgage HHI defined in the text. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Subsample by Bank Size

One potential concern is that the results in Table 2.2 might mostly be driven by small banks that only constitute a small portion of the banking sector. In this subsection, we examine the samples of large banks and small banks separately and show that the relationship between deposit market power and bank risk-taking holds for both types of banks.

We first rank the 3437 banks in our main sample by size, defined as a bank's share

of total assets average across time. We then estimate the main regression (Equation 2.4) separately for the 500 largest banks and the rest. The 500 largest banks constitute 94.0% percent of all assets on average in our sample period, which reflects the high concentration of the banking industry.

Columns (1-2) of Table 2.5 show that the main coefficient of interest expense β for risk-weighted leverage is 0.251 for the top 500 banks and 0.613 for the rest, smaller banks. Therefore, the negative relationship between market power and risk-taking holds for both large and small banks but is stronger among small banks. Columns (3-4) show that the coefficient for asset risk weights is similar for large and small banks (0.173 and 0.228), and columns (5-6) show that the coefficient for log leverage is only positive and statistically significant for small banks. These results indicate that higher market power is associated with a safer asset portfolio across both large and small banks, although the relationship with raw leverage is only present for small banks.[16]

[16]It has been documented that large banks and small banks have different leverage dynamics (e.g., Kalemli-Ozcan, Sorensen and Yesiltas, 2012; Coimbra and Rey, 2024). A handful of factors might lead to these differences, including regulatory burdens, access to government bailouts, and (decreasing) return to scale for banks.

Table 2.5. Robustness by Bank Size: 500 Largest and Other Banks

	Dependent Variable: Risk Metrics					
	Log Risk-Weighted Lev.		Asset Risk Weight		Log Leverage	
	Top 500	Other	Top 500	Other	Top 500	Other
	(1)	(2)	(3)	(4)	(5)	(6)
IntExp-FFR Beta	0.251*	0.613**	0.173**	0.228**	-0.000484	0.265**
	[2.384]	[10.10]	[3.630]	[10.46]	[-0.00592]	[5.889]
Log Assets	-0.0183	0.0115	-0.0158*	0.00988*	0.00474	-0.00155
	[-1.073]	[1.119]	[-2.019]	[2.479]	[0.307]	[-0.207]
Deposit/Liability	-0.128	-0.490**	0.104+	-0.0690*	-0.290**	-0.360**
	[-1.316]	[-5.993]	[1.921]	[-2.257]	[-3.666]	[-6.497]
Log(# Branches)	0.0710**	0.0541**	0.0259**	0.00433	0.0301	0.0434**
	[3.411]	[4.285]	[3.111]	[0.889]	[1.624]	[4.679]
Log(County PC Income)	-0.0200	0.108**	-0.0523	0.0582**	0.0670	0.0298
	[-0.321]	[3.378]	[-1.605]	[5.077]	[1.514]	[1.202]
County Bus. Cycle Beta	0.0522	0.0387*	0.0651**	0.0268**	-0.0372	0.00293
	[1.427]	[2.391]	[3.392]	[4.240]	[-1.190]	[0.232]
Multi State	0.00210	-0.00869	0.0177*	-0.00563	-0.0199	0.00104
	[0.116]	[-0.727]	[2.115]	[-1.086]	[-1.297]	[0.119]
Deposit Fee Income	-0.0664+	-0.0425*	-0.0598**	-0.0456**	0.0193	0.0228
	[-1.721]	[-2.272]	[-4.038]	[-6.541]	[0.554]	[1.512]
Other Non-Interest Income	-0.0106	-0.00670	-0.00216	0.00208	-0.00512	-0.00873
	[-0.879]	[-0.965]	[-0.284]	[0.804]	[-0.818]	[-1.604]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Within R^2	.103	.104	.085	.117	.091	.044
# Banks	500	2937	500	2937	500	2937
Observations	31074	164151	31074	164151	31074	164151

Note: Regressions based on Equation (2.4). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Instrument with County-Level Retail Deposit Beta

The sensitivity of a bank's interest expense to federal funds rate may be driven not only by the bank's market power in deposit markets but also by factors including the bank's funding structure, depositor composition (institutional v.s. retail), types of deposit products the bank offers, and other unobserved bank characteristics. In addition, the estimation of interest expense beta on at most 24 years of quarterly data also introduces measurement error. In order to address these concerns, we follow Drechsler, Savov and Schnabl (2021) to construct an instrument using the sensitivity of retail deposit rate to federal funds rate at the county level and banks' geographical distribution across counties,

based on recent empirical findings that local markets are important for bank deposit rate setting (e.g., Drechsler, Savov and Schnabl, 2017; Levine *et al.*, 2021; Dlugosz *et al.*, 2023; Gödl-Hanisch, 2022).

Methodology. For this exercise, we use published rates of $25,000 money market savings accounts at the branch level provided by RateWatch.[17] We aggregate the original weekly RateWatch data to the monthly level in order to reduce noise from reporting delays. First, we estimate a "county-level retail deposit beta" using data for all bank branches in a county:

$$R_{i,c,t} = \alpha_{i,c} + \text{RetailBeta}_c \cdot \text{FFR}_t + \varepsilon_{i,c,t} \tag{2.8}$$

where $R_{i,c,t}$ is the deposit rate for branch i in county c in month t, $\alpha_{i,c}$ are branch fixed effects, and the regression is estimated separately for each county. We winsorize the reported deposit rates $R_{i,c,t}$ at 99% percentile for each month to mitigate the impact of outliers, and we limit our sample to counties with at least two banks and 60 months of data and to branches with at least 20 months of data. The coefficient RetailBeta_c is the "county-level retail deposit beta," which measures the sensitivity of deposit rates in county c to the federal funds rate. We interpret counties with lower RetailBeta_c as having less competitive deposit markets, which enable banks to charge higher deposit spreads when the federal funds rate increases.

Second, we aggregate the county-level retail deposit beta RetailBeta_c to the bank level by taking a branch-weighted average across all counties for each bank:

$$\text{RetailBeta}_{b,t} = \frac{\sum \#\,\text{Branch}_{b,c,t} \times \text{RetailBeta}_c}{\sum \#\,\text{Branch}_{b,c,t}}. \tag{2.9}$$

Finally, we compute the time series average RetailBeta_b for each bank to use as our instrument for bank-level interest expense beta.

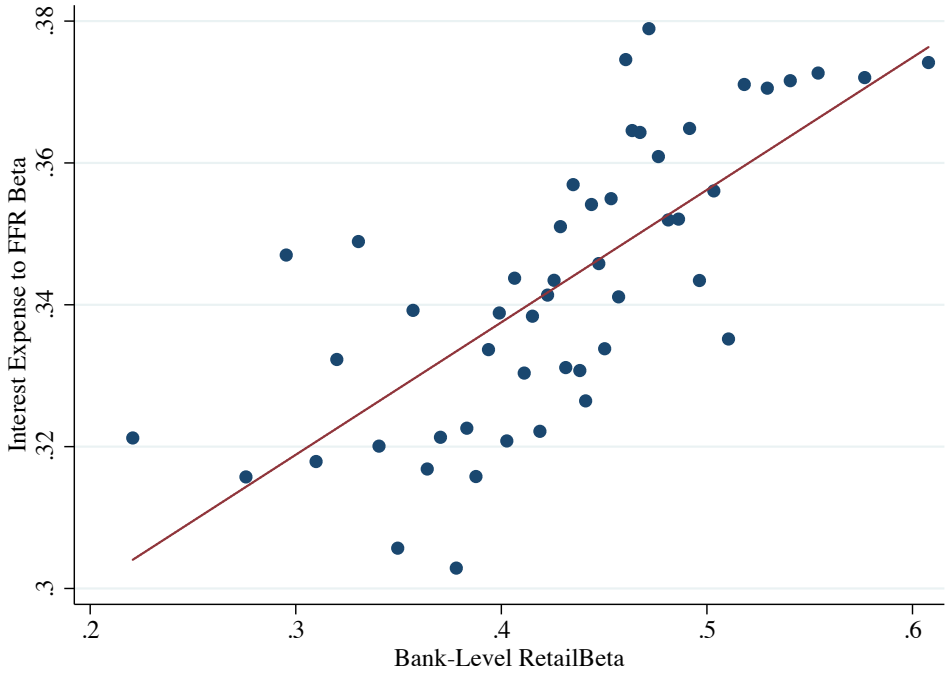
[17] We only use data for "rate-setting branches" that set deposit rates on their own.

Identification Assumptions. A bank's retail deposit beta RetailBeta_b is determined by two sources: the bank's distribution across counties and the competitiveness of the retail deposit market in each county. The relevance assumption for this instrument is that banks operating in counties with less competitive deposit markets have higher market power and, thus, a lower interest expense beta. The exclusion restriction is that both the geographical distribution of banks and the competitiveness of local deposit markets only affect bank risk-taking through market power.

We note that the exclusion restriction relies on the strong assumption that the bank's geographical distribution is exogenous to risk-taking. The assumption is violated if investment opportunities in high-market-power counties are inherently less risky. Therefore, the retail beta instrument does not address this specific threat to the identification. However, we address this issue in two ways: first, by controlling for county-level riskiness defined in Section 2.3.1, and second, by examining a separate sample of one-county banks in Section 2.3.2 below.

Results. We first show the first-stage relationship between our instrument RetailBeta_b and interest expense beta IntExpBeta_b as a binned scatter plot in Figure 2.3, which shows a positive correlation between the two variables. A bank-level regression of IntExpBeta_b onto RetailBeta_b has a coefficient of 0.186 with F-statistic of 63.44 under robust standard errors, which exceeds the conventional threshold values of Stock and Yogo (2005).

Figure 2.3. First Stage: Interest Expense Beta and Bank Retail Beta



Note: 50-point binned scatter plot on data for 3430 banks.

Table 2.6 shows the 2SLS regression results. Column (1) shows that the 2SLS estimation for our main coefficient of interest (β of Equation 2.4) is 1.711 for log risk-weighted leverage: i.e., 0.1 unit lower interest expense beta is associated with 17% lower risk-weighted leverage. The coefficient is statistically significant with $t = 6.56$ with clustered standard errors at the bank and quarter level and is much larger than the OLS estimate of 0.554 in Table 2.2. Columns (2-3) show that the 2SLS coefficient of 0.793 for asset risk weight and 0.489 for log leverage are both statistically significant and larger than the OLS point estimates in Table 2.2.

Table 2.6. Risk Regression: 2SLS Results

	Dependent Variable: Risk Metrics		
	Log Risk-Wgt Lev. (1)	Risk Weight (2)	Log Lev. (3)
IntExp-FFR Beta	1.711**	0.793**	0.489*
	[6.555]	[7.529]	[2.614]
Log Assets	-0.0428**	-0.0185**	-0.0124
	[-3.440]	[-3.497]	[-1.456]
Deposit/Liability	-0.265**	0.0561*	-0.335**
	[-3.829]	[2.005]	[-6.843]
Log(# Branches)	0.0860**	0.0257**	0.0433**
	[5.906]	[4.249]	[4.479]
Log(County PC Income)	0.122**	0.0564**	0.0460*
	[3.830]	[4.388]	[1.989]
County Bus. Cycle Beta	0.0122	0.0190**	-0.0108
	[0.682]	[2.643]	[-0.833]
Multi State	-0.0289*	-0.00930^{+}	-0.0122
	[-2.432]	[-1.790]	[-1.470]
Deposit Fee Income	-0.0326	-0.0417**	0.0264^{+}
	[-1.625]	[-5.367]	[1.739]
Other Non-Interest Income	-0.00972	0.0000541	-0.00846^{+}
	[-1.445]	[0.0178]	[-1.848]
Year-Quarter FE	✓	✓	✓
1st Stage F	149.097	149.097	149.097
# Banks	3430	3430	3430
Observations	194930	194930	194930

Note: Two-staged least squared regression based on Equation (2.4), with IntExpBeta instrumented by RetailBeta. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

One-County Banks with County-Time Fixed Effects

In order to further address the threat to identification due to the unobserved variation of investment opportunities and bank characteristics across geographical areas, we examine a separate sample of 2232 banks (1444 BHCs, 788 non-BHC banks) that only have deposit-taking branches in one county from 1996 to 2019. With the assumption that the one-county banks mainly take deposits and lend in the same county, we can add county-times-quarter fixed effects to the main regression (2.4) to absorb the unobserved county-level investment opportunities.

To begin with, Table 2.7 shows summary statistics for the one-county banks. These banks are generally smaller, accounting for 4.5% of total call report assets in an average quarter. Compared to the main-sample banks (Table 2.1), the one-county banks take slightly less risk: the average risk-weighted leverage is 6.32 for the one-county banks and 7.89 for the main sample banks, and the one-county banks also have a lower average loan loss rate. The one-county banks have a slightly lower average interest expense beta (0.318) compared to the main-sample banks (0.343).

Table 2.7. Summary Statistics: One-County Sample

Variable	Level	*N*	Mean	SD	Q10	Q50	Q90
Interest Expense Beta	Bank	2232	0.318	0.135	0.181	0.317	0.471
Risk-Weighted Leverage	Bank-Quarter	123333	6.32	2.49	3.28	6.15	9.48
Asset Risk Weight (%)	Bank-Quarter	123333	64.9	14.5	45.9	65.1	83.5
Raw Leverage	Bank-Quarter	123333	9.69	3.06	6.01	9.61	13.2
Annual Loan Loss Rate (%)	Bank-Quarter	122042	0.285	0.572	0	0.107	0.721

Table 2.8 shows the regression results for one-county banks. Among the control variables we use, only log assets and deposit-to-liability ratio vary within counties; we also control for an indicator of having only one branch. Column (1) shows the regression results for log risk-weighted leverage with only quarter fixed effects, and column (2) shows the results with county-times-quarter fixed effects. Comparing columns (1) and (2), we find that adding county-times-quarter fixed effects only reduces the main coefficient from 0.796 to 0.730, and the coefficient in column (2) is still highly significant with a t-statistic of 9.56. The results for asset risk weight and leverage in columns (3-6) show the same finding for these two components of risk.

Therefore, our results show that among the one-county banks, the relationship between market power and risk-taking is not driven by county-specific investment opportunities. We note two limitations of this analysis: first, the county-time fixed effects approach relies on the assumption that banks that take deposits in the same county also lend to clients in the same county; second, we cannot apply this approach to the main-sample banks that operate in multiple counties due to the lack of county-level asset-side data with risk metrics, and the results for one-county banks may not necessarily generalize to multi-county banks.

Table 2.8. Risk Regression: One-County Banks

	Dependent Variable: Risk Metrics					
	(1) Log Risk-Wgt Lev.	(2) Log Risk-Wgt Lev.	(3) Risk Wgt	(4) Risk Wgt	(5) Log Lev.	(6) Log Lev.
IntExp-FFR Beta	0.796**	0.730**	0.214**	0.182**	0.468**	0.442**
	[10.61]	[9.556]	[8.174]	[7.376]	[8.460]	[7.293]
Log Assets	0.0462**	0.0447**	0.0151**	0.00856*	0.0246**	0.0302**
	[5.229]	[4.557]	[4.348]	[2.315]	[3.604]	[3.626]
Deposit/Liability	-0.590**	-0.448**	-0.180**	-0.0870*	-0.325**	-0.354**
	[-5.163]	[-4.472]	[-3.982]	[-2.238]	[-3.978]	[-4.561]
Deposit Fee Income	0.0661*	0.127**	-0.0414**	-0.00632	0.124**	0.118**
	[2.566]	[4.247]	[-4.934]	[-0.580]	[6.445]	[5.802]
Other Non-Interest Income	0.00149	-0.0178	0.0173**	0.00500	-0.0240*	-0.0252**
	[0.121]	[-1.590]	[4.189]	[1.270]	[-2.331]	[-2.673]
Only One Branch	-0.150**	-0.136**	-0.0159**	-0.0206**	-0.116**	-0.0991**
	[-9.561]	[-9.438]	[-2.977]	[-4.021]	[-10.03]	[-8.642]
Time FE	✓		✓		✓	
County-Time FE		✓		✓		✓
Within R^2	.139	.116	.101	.046	.105	.09
# Banks	2232	2232	2232	2232	2232	2232
Observations	123333	123333	123333	123333	123333	123333

Note: Regressions based on Equation (2.4). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

2.3.3 Market Power and Ex-Post Loan Loss

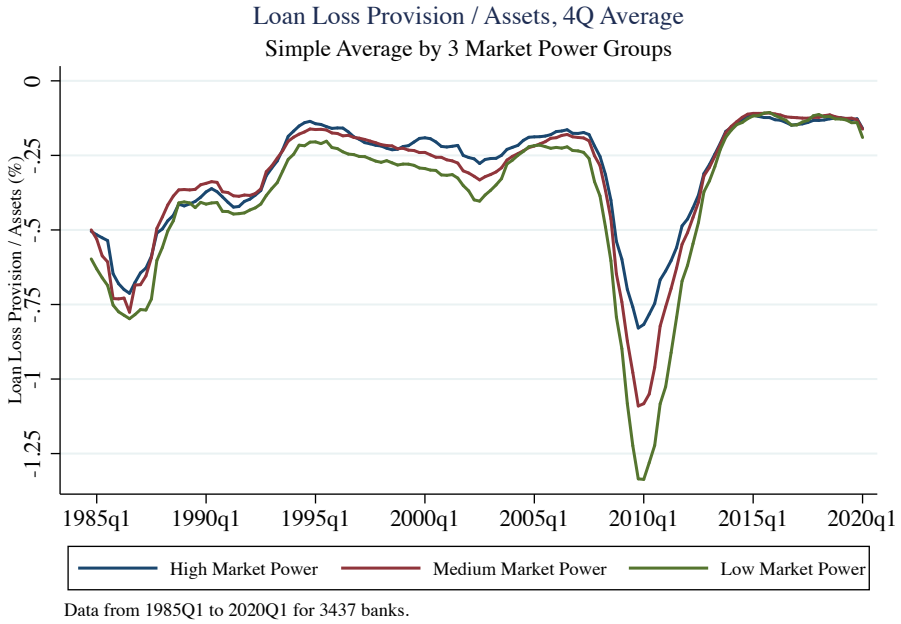
In this section, we examine the relationship between market power and ex-post loan loss and show that banks with higher market power have both lower levels and lower cyclicality of loan loss. These results complement our main finding on asset risk weight, which is an ex-ante measure of risk. Our results here also augment the similar findings of Li, Loutskina and Strahan (2023) with a different specification and different measure of market power.

We use the item "provision for loan and lease losses" on call reports (hereafter loan loss provision) to measure a bank's loss due to default. For each bank-quarter, we compute the ratio of loan loss provision to quarterly average assets and then take its average over the past 4 quarters to account for seasonality in the reporting of loan losses. Table 2.1 shows that for observations in our main sample, the average annual loan loss is 0.328% of total assets.

To begin with, we sort the 3437 banks in our main sample by their interest expense beta into 3 equal-sized groups and compute the average loan loss to asset ratio for each group

and quarter, as plotted in Figure 2.4. The comparison between groups shows that banks with high market power had significantly less loan loss during the financial crisis. From 2009Q1 to 2009Q4, the average loan loss is 0.83% of assets for the high market power banks and 1.33% of assets for the low market power banks. Moreover, the negative relationship between loan loss and market power is persistent over time.

Figure 2.4. Loan Loss Provision Rate and Market Power



Note: We sort banks into 3 equal-sized groups by interest expense beta. For each group-quarter, we compute the average loan loss to asset ratio and plot the rolling 4-quarter averages. Negative values indicate loan losses. Data covers 3437 banks in the main sample from 1985Q1 to 2020Q1.

We then formally test how market power is related to the level of loan loss. Table 2.9 shows results from running the main regression (2.4) with loan loss rate as the dependent variable (signed so that the losses are negative values). Column (2) of the table shows that after including all the main control variables—including measures of risk related to geographical distribution—a 0.1 unit lower interest expense beta is associated with 2.7 basis points lower loan loss, which is sizable compared to the average loan loss level of 32.8 basis points. In addition, columns (3-4) of the table show regression results using data from 1996Q1 to 2006Q4, which shows that our results are persistent over time and are not simply driven by the financial crisis.

Table 2.9. Market Power and Loan Loss Level

	Dependent Variable: Loan Loss / Asset (%, Negative = Loss)			
	(1) 1996-2020	(2) 1996-2020	(3) 1996-2006	(4) 1996-2006
IntExp-FFR Beta	-0.418**	-0.269**	-0.332**	-0.321**
	[-5.606]	[-4.899]	[-6.363]	[-6.277]
Log Assets		-0.0284**		-0.00148
		[-2.739]		[-0.179]
Deposit/Liability		-0.0826		-0.0376
		[-1.390]		[-0.747]
Log(# Branches)		0.00956		0.00660
		[0.791]		[0.601]
Log(County PC Income)		0.185**		0.121**
		[6.065]		[4.874]
County Bus. Cycle Beta		-0.154**		-0.0522**
		[-5.487]		[-3.690]
Multi State		-0.0260*		0.00132
		[-2.312]		[0.123]
Deposit Fee Income		0.0472+		-0.0550**
		[1.778]		[-3.548]
Other Non-Interest Income		-0.0123		-0.0599**
		[-1.136]		[-5.444]
Sample Period	1996-2020	1996-2020	1996-2006	1996-2006
Year-Quarter FE	✓	✓	✓	✓
Within R^2	.007	.02	.011	.04
# Banks	3437	3437	2682	2682
Observations	194149	194149	78665	78665

Note: Regressions based on Equation (2.4). The dependent variable is the loan loss provision divided by assets, signed so that negative values represent losses. The sample period is 1996Q1-2020Q1 for columns (1-2) and 1996Q1-2006Q4 for columns (3-4). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Finally, we use the following regression to test how market power is related to the cyclicality of loan loss:

$$\text{Loss}_{i,t} = \alpha_i + \delta_t + \beta \cdot \text{IntExpBeta}_i \cdot \Delta_4 y_t + \boldsymbol{\gamma}_1' \boldsymbol{x}_{i,t} + \boldsymbol{\gamma}_2' \boldsymbol{x}_{i,t} \cdot \Delta_4 y_t + \varepsilon_{i,t} \tag{2.10}$$

where $\Delta_4 y_t$ is the real GDP growth rate from $t-4$ to t, α_i are bank fixed effects, and δ_t are quarter fixed effects. With bank fixed effects, the coefficient β captures how the *co-movement* between a bank's loan loss and GDP relates to the bank's interest expense beta:

a higher β means banks with lower market power have more cyclical loan losses. The control variables $\boldsymbol{x}_{i,t}$ are both directly included and interacted with GDP growth. Note that the GDP growth $\Delta_4 y_t$ and interest expense beta IntExpBeta_i are not included in the regression because they are absorbed by the fixed effects.

The estimates for β from regression (2.10) are reported in Table 2.10. Column (1) shows that the loan loss to GDP beta is increasing in interest expense beta, which confirms that banks with higher market power have less cyclical loan loss. Column (2) shows that the relationship survives direct and interacted controls, and columns (3-4) show that the result is robust in the 1996-2006 period and thus not purely driven by the financial crisis of 2007-2008.

Table 2.10. Market Power and Loan Loss Cyclicality

	Dependent Variable: Loan Loss / Asset (%, Negative = Loss)			
	(1) 1996-2020	(2) 1996-2020	(3) 1996-2006	(4) 1996-2006
$\Delta_4 y_t \times \text{IntExpBeta}_i$	0.176**	0.0533*	0.0687**	0.0585*
	[5.018]	[2.079]	[2.862]	[2.461]
Sample Period	1996-2020	1996-2020	1996-2006	1996-2006
Year-Quarter FE	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓
Basic Controls		✓		✓
Within R^2	.004	.036	.001	.009
# Banks	3437	3437	2672	2672
Observations	194149	194149	78655	78655

Note: Regressions based on Equation (2.10). Only the core coefficient of interest β is reported. The sample period is 1996Q1-2020Q1 for columns (1-2) and 1996Q1-2006Q4 for columns (3-4). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

In summary, this section shows that banks with higher market power have lower levels and lower cyclicality of loan loss. These results show that the relationship between deposit market power and risk-taking is not limited to the ex-ante regulatory risk measure but has a real impact on banks' financial performance and, therefore, the overall stability of the banking sector.

2.4 Zero Lower Bound

Banks benefit from deposit market power by charging a deposit rate lower than the market short rate. During the zero lower bound period from 2009Q1 to 2015Q4, the federal funds rate was kept at 0-0.25%, and the 1-year treasury yield was also near zero. Deposit market power becomes less relevant in this environment because there is little room for banks to charge positive deposit spreads. If banks expect the low-rate environment to persist, we should find a weakened link between deposit market power and risk-taking.

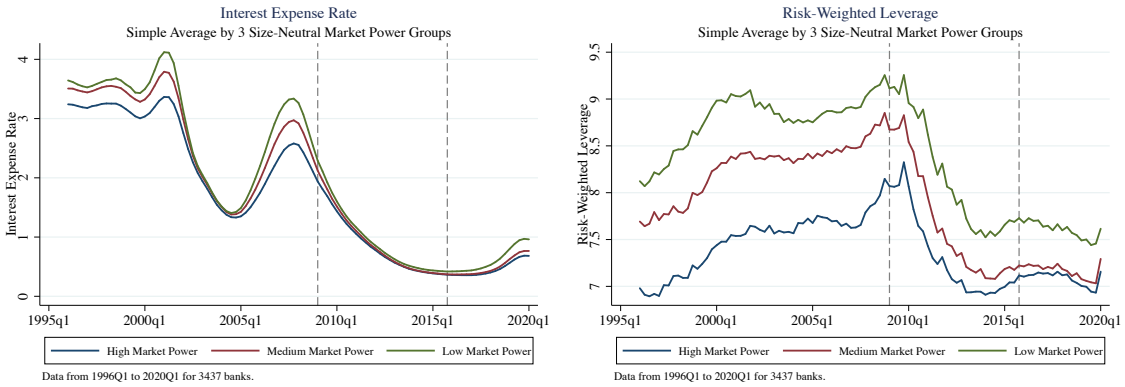
In this section, we show that the relationship between market power and risk-taking is indeed stronger when the interest rate is higher. In particular, the regression coefficient of log risk-weighted leverage on interest expense beta is 35% lower during the ZLB period compared to the non-ZLB period. These results support our main findings by showing that the market short rate — which determines the effectiveness of bank market power — plays an important role in the relationship between market power and risk-taking.

Motivating Evidence. To begin with, we sort the 3437 banks in our main sample into 3 size-neutral groups[18] by interest expense beta. For each of the 3 market power groups, we compute the average interest expense rate and average risk-weighted leverage for each quarter.

The left panel of Figure 2.5 plots the interest expense rates. The plot shows clearly that high market power banks could only charge significantly higher deposit spreads (i.e., lower interest expense rates) when the interest rate is higher. During the ZLB periods, the interest expense rates for all banks are near zero, and there is little difference between high- and low-market-power banks. The right panel of Figure 2.5 then shows that the difference of risk-weighted leverage between high and low market power banks also shrinks during the ZLB period.

[18]We first sort the banks by their average assets into 5 groups. Within each size group, we then sort by interest expense beta into 3 groups. Each of the 3 groups by interest expense beta thus contains both small and large banks.

Figure 2.5. Market Power and Interest Expense (Left) / Risk-Weighted Leverage (Right)



Note: We sort banks into three size-neutral groups by interest expense beta. For each group-year, we compute the average interest expense rate (left, four-quarter averages) and risk-weighted leverage (right). Data covers 3437 banks in the main sample from 1996Q1 to 2020Q1.

Regression Analysis. We then formally test the difference between non-ZLB and ZLB periods by adding an interaction term to our main regression in Equation (2.4):

$$\begin{aligned} \text{Risk}_{i,t} = \alpha_t + \beta_1 \cdot \text{IntExpBeta}_i + \beta_2 \cdot \text{IntExpBeta}_i \times 1\{\text{ZLB}\}_t \\ + \gamma_1' \boldsymbol{x}_{i,t} + \gamma_2' \boldsymbol{x}_{i,t} \times 1\{\text{ZLB}\}_t + \varepsilon_{i,t} \end{aligned} \tag{2.11}$$

where $1\{\text{ZLB}\}_t$ is an indicator for the ZLB period from 2009Q1 to 2015Q4. Coefficient β_1 captures the relationship between interest expense beta and risk-taking in the non-ZLB period. Coefficient β_2 captures the additional relationship during the ZLB period. $\boldsymbol{x}_{i,t}$ includes the full set of control variables listed in Table 2.2. To ensure the interaction effect between ZLB and interest expense beta is not driven by other bank characteristics, we also include interacted controls $\boldsymbol{x}_{i,t} \times 1\{\text{ZLB}\}_t$ in some specifications.

Table 2.11 shows the coefficients β_1 and β_2 from the regression. Column (2) shows that in the specification with interacted controls, $\beta_1 = 0.654$ and $\beta_1 + \beta_2 = 0.386$ for risk-weighted leverage. That is, 0.1 unit lower interest expense beta is associated with 6.54% lower risk-weighted leverage in non-ZLB periods but only 3.86% lower risk-weighted leverage in ZLB periods. Therefore, the relationship between market power and risk-taking is significantly muted during the ZLB period (by $\beta_2/\beta_1 = -41\%$).

Columns (4) and (6) further show that the ZLB interaction effect is present for both asset risk weight and leverage. In fact, the effect is stronger for leverage. Figure A.1 in Appendix B.1 shows that the difference in leverage between high and low market power banks gradually disappeared during the ZLB period. One explanation of this result might be that leverage is easier to adjust than the riskiness of long-term assets.

Table 2.11. Risk Regression: ZLB Interaction

	Dependent Variable: Risk Metrics					
	(1) Log Risk-Wgt Lev.	(2) Log Risk-Wgt Lev.	(3) Risk Wgt	(4) Risk Wgt	(5) Log Lev.	(6) Log Lev.
IntExp-FFR Beta	0.654**	0.645**	0.250**	0.252**	0.282**	0.271**
	[10.37]	[9.984]	[11.32]	[11.12]	[6.163]	[5.857]
IntExp-FFR Beta × 1{ZLB}	-0.268**	-0.233**	-0.0770**	-0.0800**	-0.174**	-0.133*
	[-4.192]	[-3.422]	[-3.530]	[-3.367]	[-3.448]	[-2.589]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Interaction Ctrls		✓		✓		✓
Within R^2	.119	.125	.103	.107	.067	.071
Observations	195225	195225	195225	195225	195225	195225

Note: Regressions based on Equation (2.11). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Further, the role of the market short rate in mediating the market power and risk-taking relationship is not limited to the ZLB period. To show this, we run the regression (2.11) with 4-quarter average federal funds rate FFR_t instead of the ZLB indicator. Columns (1-3) of Table 2.12 show the regression results for the entire main sample, and columns (4-6) show the regression results *outside* the ZLB period. For example, column (1) shows that the baseline association between interest expense beta and log risk-weighted leverage is 0.362, and this coefficient increases by 0.099 per 1 percentage point increase of federal funds rate; and column (4) shows that this result is robust over the non-ZLB period.

Table 2.12. Risk Regression: FFR Interaction

	Dependent Variable: Risk Metrics					
	Full Sample			Excluding ZLB (09Q1-15Q4)		
	(1) Log Risk-Wgt Lev.	(2) Risk Wgt	(3) Log Lev.	(4) Log Risk-Wgt Lev.	(5) Risk Wgt	(6) Log Lev.
IntExp-FFR Beta	0.362**	0.179**	0.0825+	0.306**	0.204**	0.00272
	[6.212]	[7.426]	[1.829]	[3.715]	[5.819]	[0.0543]
IntExp-FFR Beta × FFR	0.0985**	0.0216**	0.0696**	0.111**	0.0159*	0.0873**
	[6.985]	[3.654]	[6.287]	[6.277]	[2.099]	[7.682]
Year-Quarter FE	✓	✓	✓	✓	✓	✓
Controls	✓	✓	✓	✓	✓	✓
Interaction Ctrls	✓	✓	✓	✓	✓	✓
Within R^2	.128	.107	.073	.159	.117	.104
Observations	195225	195225	195225	130283	130283	130283

Note: Regressions based on Equation (2.11), with a 4-quarter average federal funds rate in place for the ZLB indicator. The sample period is 1996Q1-2020Q1 for columns (1-3) and is 1996Q1-2008Q4 and 2016Q1-2020Q1 (i.e., excluding the ZLB period) for columns (4-6). t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

In summary, we show in this section that the relationship between market power and risk-taking is strongly driven by the short-term interest rate. In a higher-rate environment, banks benefit more from their market power by charging higher deposit spreads. At the same time, they make more prudent risk-taking decisions. These results provide further support that our results are driven by banks' deposit market power rather than other potential forces.

2.5 Model

In this section, we use a static model of bank franchise power to explain the relationship between deposit market power and bank risk-taking. In the model, deposit market power reduces the sensitivity of household deposit demand to deposit rate, allowing banks to charge higher deposit spreads and earn more profits. Banks face limited liability in the event of a default, and deposit market power raises their franchise value. Expecting higher future profits, high-market-power banks choose to reduce their exposure to default risk by holding safer assets.

2.5.1 Model Setup

Deposit Demand. The deposit market consists of I identical depositors indexed by $i \in \{0, 1, ..., I\}$ and N banks indexed by $j \in \{0, 1, ..., N\}$. Bank j offers a deposit rate r_j^d and has other characteristics x_j. Deposit i receives utility $u_{i,j}$ if she deposits her wealth with bank j where

$$u_{i,j} = \eta_j r_j^d + (1 - \eta_j)x_j + \xi_{i,j}.$$

Depositors put a weight η_j on the deposit rate and a weight $(1 - \eta_j)$ on the bank's other characteristics (e.g., quality of service). The demand shocks $\xi_{i,j}$ are independent and follow a type-I generalized extreme value distribution with the cumulative distribution function $F(\xi) = \exp(-\exp(-\xi))$. By standard arguments, the probability of depositor i choosing bank j is given by the following logit choice model

$$s_j(r_j^d; \eta_j) = \frac{\exp(\eta_j r_j^d + (1 - \eta_j)x_j)}{\sum_k \exp(\eta_k r_k^d + (1 - \eta_k)x_k)}.$$

We consider the case where the number of depositors is large (i.e., $I \to \infty$) so that we can interpret $s_j(r_j^d; \eta_j)$ as the market share of bank j. The depositors' demand elasticity is given by

$$\frac{\partial s_j}{\partial r_j^d} \frac{r_j^d}{s_j} = \eta_j r_j^d (1 - s_j).$$

All else equal, depositors are less sensitive to bank j's deposit rate if η_j is low. Hence, we identify banks with lower η_j as having greater deposit market power.

Bank Risk-Taking. In addition, banks choose the riskiness of their asset portfolio. The return on bank j's assets is $(r + \theta_j)$ where r is the Fed Funds rate and θ_j is the risk premium earned by holding riskier assets.

However, risk-taking increases the likelihood of bank failures. The *survival* probability of bank j is given by the function $p(\theta_j)$. As in Allen and Gale (2004) and Boyd and

De Nicolo (2005), we impose the following restrictions on $p(\cdot)$,

$$p'(\cdot) < 0, \;\; p''(\cdot) \leq 0, \;\; p(0) = 1, \;\; p(\bar{\theta}) = 0.$$

First, $p(\cdot)$ is a decreasing function, as risk-taking increases the probability of bank failure. Second, $p(\cdot)$ is concave, which signifies a "decreasing return to risk-taking." As the risk premium θ_j rises, the bank needs to entail greater default risk in exchange for an additional risk premium. This condition is necessary to ensure that banks do not take on an infinite amount of risk. Third, if the bank invests all of its deposits in fed funds, it is free from default risk. Lastly, there exists an upper bound of risk-taking $\bar{\theta}$ such that the bank fails with certainty if $\theta_j \geq \bar{\theta}$. Importantly, these requirements imply that $-p'(\cdot)/p(\cdot)$ is an increasing function. For tractability, we will assume the following functional form of $p(\cdot)$ for some of the results proven in Section 2.5.2.

Assumption 5 *The survival probability is given by* $p(\theta_j) = 1 - \psi \left[\exp(\kappa\theta_j) - 1\right]$.

It is easy to verify that this function satisfies the four requirements on $p(\cdot)$ for positive values of ψ and κ. In this case, the risk-taking limit is $\bar{\theta} = \frac{1}{\kappa}\ln(1 + \frac{1}{\psi})$.

Bank's Problem. Bank j chooses its deposit rate r_j^d and risk-taking θ_j to maximize its expected profit

$$\max_{r_j^d,\, \theta_j} \;\; p(\theta_j)(r + \theta_j - r_j^d)s_j(r_j^d; \eta_j), \tag{2.12}$$

which is the product of the bank's survival probability $p(\theta_j)$, its profit margin $(r + \theta_j - r_j^d)$, and its market share $s_j(r_j^d; \eta_j)$.

Banks face two trade-offs. First, by offering a higher deposit rate, the bank captures a larger share of the deposit market, but the profit margin shrinks. Second, by taking on more risk, the bank earns a higher risk premium on its deposit base, but the probability of default also heightens, in which case it has to forfeit profit $(r + \theta_j - r_j^d)s_j(r_j^d; \eta_j)$.

Market Power and Market Share. One might expect that high-market-power banks also have larger market shares, as market share and franchise value typically move in the same direction. Indeed, as shown in Table B.1 in Appendix B.1, banks' market share and deposit market power are strongly and positively correlated in our sample. In the model, the market share of bank j is related to its deposit market power by

$$\frac{\mathrm{d}s_j(r_j^d;\eta_j)}{\mathrm{d}\eta_j} = s_j(1-s_j)\left(r_j^d + \eta_j\frac{\partial r_j^d}{\partial \eta_j} - x_j\right).$$

To replicate the empirical relationship between market power and market share, we assume that x_j is large enough so that $\mathrm{d}s_j/\mathrm{d}\eta_j < 0$.

Assumption 6 *The value of x_j is large enough so that $\mathrm{d}s_j/\mathrm{d}\eta_j < 0$ for all banks.*

2.5.2 Model Results

Deposit Rate. Now, we illustrate the key implications of deposit market power. Solving problem (2.12), the first-order condition with respect to the deposit rate r_j^d is,

$$(r + \theta_j - r_j^d)\eta_j(1-s_j) = 1. \tag{2.13}$$

The right-hand side represents the interest expense saved per unit of deposit when the bank lowers the deposit rate by a marginal unit. The left-hand side is the revenue lost because the bank's deposit base shrinks when it lowers the deposit rate. In particular, $\eta_j(1-s_j) = (\partial s_j/\partial r_j^d)/s_j$ is the response of depositors' demand to a decline in the deposit rate, divided by the deposit stock. In equilibrium, we have the following results regarding bank deposit rate setting.

Proposition 2 (Deposit Spread) *Bank j's deposit spread is increasing in its market power*

$$\frac{\partial(r - r_j^d)}{\partial \eta_j} < 0.$$

Proposition 3 (Interest Expense Beta) *Bank j's interest expense-FFR beta is decreasing in its market power*

$$\frac{\partial}{\partial \eta_j}\left(\frac{\partial r_j^d}{\partial r}\right) > 0.$$

High-market-power banks exploit depositors' insensitivity to their deposit rates and charge higher deposit spreads in equilibrium. In turn, the deposit rates they set are less sensitive to changes in the Fed Funds rate, which justifies our use of the interest expense-FFR beta as a measure of deposit market power. In this sense, deposit market power grants banks *franchise value* — if the bank does not fail, it can enjoy high profits derived from the market power.

Bank Risk-Taking. The first-order condition with respect to risk-taking is

$$p'(\theta_j)(r + \theta_j - r_j^d) + p(\theta_j) = 0. \tag{2.14}$$

The first term reflects the fact that default is more likely when the bank takes on more risk, in which case it forgoes the profit $(r + \theta_j - r_j^d)$. The second term is the extra profit earned through risk-taking, which only materializes if the bank does not fail. Intuitively, when a bank has greater deposit market power, its profit margin widens as the deposit spread $(r - r_j^d)$ is high. In this case, the first term in (2.14) becomes more dominant, and banks take on less risk to preserve their franchise value.

Formally, we have the following result that explains the cross-sectional relationship between deposit market power and bank risk-taking presented in Section 2.3.

Proposition 4 (Bank Risk-Taking) *Banks take on less risk when they have greater deposit market power*

$$\frac{\partial \theta_j}{\partial \eta_j} > 0.$$

Zero Lower Bound. We are also able to incorporate a zero lower bound on the deposit rate into the model. In practice, bank deposit rates are almost always between zero and the Fed Funds rate. In the model, it translates to the following constraint

$$1 \leq r_j^d \leq r.$$

When the Fed Funds rate approaches zero, all banks have to offer a deposit rate that is almost zero. In this case, deposit market power no longer matters. Plugging $r - r_j^d = 0$ into (2.12), the banks' problem becomes

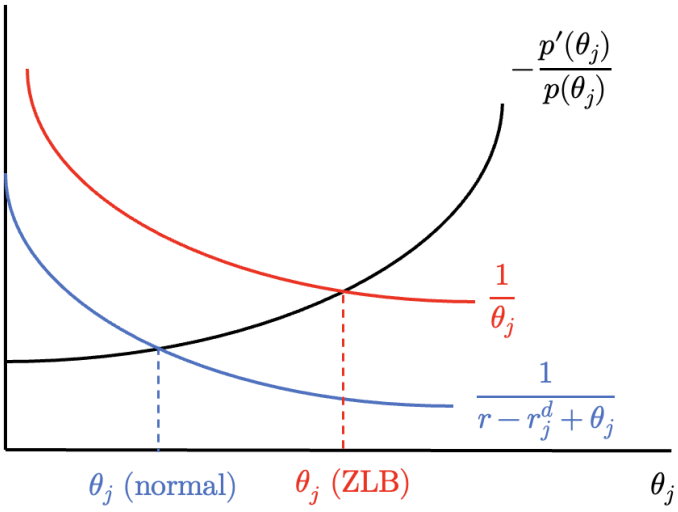
$$\max_{\theta_j} \quad p(\theta_j)\theta_j.$$

The optimal risk-taking now satisfies

$$p'(\theta_j)\theta_j + p(\theta_j) = 0. \tag{2.15}$$

Comparing the first-order conditions (2.14) and (2.15), it is clear that the zero lower bound forces the banks to charge a zero deposit spread, which depresses their franchise value and encourages risk-taking. We can immediately see the effect of a zero lower bound in Figure 2.6, a graphic representation of the equilibrium conditions (2.14) and (2.15).

Figure 2.6. Equilibrium Risk-Taking



Proposition 5 (Zero Lower Bound) *Banks take on more risk at the zero lower bound. Further, deposit market power has no predictive power of bank risk-taking at the zero lower bound.*

Ceteris paribus, a low-rate environment stimulates bank risk-taking, which is in line with existing studies (e.g., Whited, Wu and Xiao, 2021).[19] Furthermore, consistent with the empirical evidence presented in Section 2.4, deposit market power has less predictive power of bank risk-taking when the Fed Funds rate reaches zero.

In practice, the effect of the zero lower bound will also depend on its duration, as banks base their risk-taking decisions on the present value of their future deposit market power. As shown in Section 2.4, low rates attenuated rather than completely nullified the effect of deposit market power. A potential explanation is that banks expect the low-rate environment to be persistent but not permanent, which is a distinction that we omitted in this static model.

Market Structure. Our theory suggests that deposit market power plays a disciplinary role in shaping bank risk-taking. Apart from the cross-sectional relationship between deposit market power and bank risk-taking, we can also leverage the model to examine the relationship between the competitiveness of the deposit market and the aggregate level of bank risk. To do so, we consider a symmetric equilibrium where banks are identical.

Assumption 7 *All banks have the same market power and other characteristics. That is,* $\eta_j = \eta, x_j = x$ *for all* j.

In this case, the market share of every bank is $s_j = 1/N$. We can consolidate the first-order conditions (2.13) and (2.14) into

$$-\frac{p'(\theta)}{p(\theta)} = \frac{N-1}{N}\eta.$$

[19] As shown in Figures 2.4 and 2.5, banks' risk-weight leverage and loan default rate have declined during the zero lower bound period. This is not necessarily contradictory to Proposition 5 as it is important to notice that banks also faced more stringent regulations and worse lending opportunities after the Great Recession, which we abstracted away in the model. Instead, we view the fact that deposit market power has less predictive power in this period as supportive evidence for the franchise value channel of deposit market power.

Since $-p'(\cdot)/p(\cdot)$ is an increasing function, we see that banks take on more risk when their deposit market power is low or when the number of banks is large (e.g., when η or N increases). Both forces reduce banks' franchise value — a higher η indicates that depositors are more sensitive to deposit rates, and a higher N lowers the market share of the banks.

Proposition 6 (Market Competitiveness) *A more competitive deposit market is associated with greater bank risk and higher bank default probability (i.e., θ is increasing in η and N).*

Therefore, our model implies a *competition-stability* trade-off. When the deposit market is more competitive, banks charge a lower deposit spread, and the pass-through of monetary policy to deposit rate is higher. In the meantime, banks have lower franchise value and take on more credit risk.

2.6 Conclusions

In this paper, we establish that banks with high deposit market power take on less risk. In particular, they choose lower leverages, safer loan portfolios, and sustain fewer loan losses. We provide various identification schemes and robustness checks to rule out endogeneity concerns. Our results shed light on an important interaction between deposit-taking and risk-taking — when market power increases profits from deposit-taking, banks curb their risk-taking in order to avoid default, so they can stay in the market and exploit their deposit market power. We illustrate this mechanism through a tractable model of bank franchise value, and our findings suggest that deposit market power plays a disciplinary role in shaping bank risk-taking.

Chapter 3

Flight-To-Safety in a New Keynesian Model

3.1 Introduction

In recent years, variations in economic uncertainty have become an increasingly important source of aggregate fluctuations. In times of high uncertainty such as the Great Recession and the COVID-19 crisis, government debts (e.g., reserves and treasury bonds) provide nominal insurance against idiosyncratic risk. Following an abrupt rise in uncertainty, investors reallocate their resources from productive capital to safe government bonds for precautionary motives. Such "flight-to-safety" episodes feature sharp declines in the demand for capital, which leads to recessions in investment. Additionally, in an environment where short-term output is demand-determined, heightened uncertainty depresses effective demand and triggers recessions in consumption and output.

In this paper, we highlight a novel transmission mechanism of uncertainty shocks through portfolio reallocations. To this end, we build a tractable New Keynesian model with idiosyncratic risk and "flight-to-safety" behaviors. In our model, capital and government bonds are imperfect substitutes as they differ in their risk exposures. Capital is more productive but subject to idiosyncratic return risk, while government bonds are unproductive but nominally safe. As uncertainty about the return on capital increases, the

private sector hoards more government debts as consumption insurance, which we refer to as "flight-to-safety."

Importantly, the real value of *nominal* government bonds is directly linked to the price level. In the presence of nominal rigidity, the value of existing government debts adjusts slowly to shocks through changes in the price level. Consequently, movements in demand for safe bonds are disconnected from the bond price in the short run. Since changes in the bond price cannot accommodate uncertainty-induced fluctuations in household portfolios, uncertainty shocks instead result in *overshooting* of capital values. In the New Keynesian model where short-term output is demand-determined, a decline in the capital price lowers household wealth, which initiates a general decline in aggregate economic activities.

We further show that our model generates realistic business cycle co-movements following uncertainty shocks. Specifically, our model predicts recessions in investment, consumption, and output, and disinflation after uncertainty rises, as have been identified by previous papers (e.g., Bachmann, Elstner and Sims, 2013; Basu and Bundick, 2017; Carriero, Clark and Marcellino, 2018). Further, following a positive uncertainty shock, the economy in our model exhibits both heightened risk premium and low output, an important disconnect highlighted by Caballero and Simsek (2021).

The second focus of this paper is on stabilization policies. To stabilize the economy after uncertainty shocks, the government needs to either expand the supply of safe assets or suppress the demand for safe assets. On the supply side, traditional monetary policy that operates through interest rate changes can only move the value of nominal government bonds slowly through (dis)inflation when the quantity of bonds is controlled separately by the fiscal authority. In contrast, the government can rapidly move the supply of safe assets using fiscal policy.

On the demand side, it is sometimes believed the central bank can push households into holding riskier assets simply by adjusting the risk-free rate. While it is true in New Keynesian models without safe assets (e.g., Basu and Bundick, 2017), we show that the result breaks down when safe assets are in a positive net supply. In particular, the effect of interest rate policy will depend crucially on the fiscal responses it induces. Behind this result is a simple but yet underappreciated intuition. Households' demand for safe assets

depends on the level of uncertainty and returns on available assets. When interest rates drop, the interest payments on existing bonds fall simultaneously. Without supporting tax policies, interest rates cuts result in less bond issuance (decline in seigniorage income), which inflate the real return on bonds and offset the impact of interest rate policy on the real return on government bonds. We formalize this intuition by showing exactly how household portfolio decisions depend on (future) uncertainty and government policies.

To better understand the importance of the portfolio choice channel, we compare our model to an environment where government bonds are in zero net supply. Without having to fund interest payments on its debts, the government can freely vary the risk-free rate via monetary policy. Indeed, in this case, we recover the classical result that the central bank can stabilize the economy without any fiscal policy if the policy rate tracks the natural rate perfectly. Furthermore, even under the same monetary policy responses, the effects of uncertainty shocks are significantly amplified in the model with government bonds. The amplification result suggests that the overshooting mechanism has a major role in shaping macroeconomic dynamics following uncertainty shocks.

We then proceed to study how monetary-fiscal policy should be utilized to stabilize uncertainty-induced fluctuations in household portfolios. In response to uncertainty shocks, the fiscal authority can react by adjusting either lump-sum taxes or distortionary taxes.[1] While both types of policy can potentially stabilize the economy in the short run, they have distinct implications for welfare and longer-term economic outcomes. Importantly, lump-sum taxes are non-distortionary, and have the potential of ameliorating the impact of nominal rigidity without distorting long-run economic outcomes. Nevertheless, distortionary taxes have more profound impact on households' portfolio choices and can lead to different steady-state equilibria. Therefore, such taxes are more suitable for correcting incomplete markets frictions which cause long-run deviations from (constrained) efficient allocations. Indeed, by obtaining analytical solutions to the planner's problem, we show how coordinated monetary-fiscal policy that involves both fiscal tools can replicate

[1]This is sometimes labeled as "monetary stabilization" (e.g., in Bayer *et al.*, 2019) since it is typically assumed that taxes adjust passively to accommodate interest rate changes so the government budget constraint is satisfied. However, it can be confusing because at the heart of such policies is the distortionary effects of taxes on household portfolios.

constrained-efficient allocations.

Related Literature. First, our paper belongs to the recent literature on the transmission of uncertainty shocks in New Keynesian models.[2] Ilut and Schneider (2014) and Basu and Bundick (2017) study uncertainty-induced aggregate demand recessions in models where government bonds are in zero net supply. While these papers successfully capture the economic downturns resulting from high uncertainty, the household portfolio choice channel highlighted in our paper is missing. Christiano, Motto and Rostagno (2014) show that high uncertainty can negatively affect credit supply through a financial accelerator mechanism. Leduc and Liu (2016) investigate the effects of uncertainty shocks from the perspectives of search frictions and employment relationships. Fernández-Villaverde *et al.* (2015) study the impact of fiscal policy volatility in an environment with government bonds. However, since they study a representative-agent economy where Ricardian equivalence holds, the effect of the non-distortionary fiscal policy studied in our paper is absent. Schaab (2020) studies the transmission of aggregate (macro) uncertainty shocks in a New Keynesian model with idiosyncratic labor market risk. In contrast, our paper focuses on shocks to idiosyncratic (micro) uncertainty.

More closely related to our paper is Bayer *et al.* (2019), where they examine the interplay between idiosyncratic income risk and household portfolio decisions in a quantitative HANK model. Broadly speaking, both papers share the common theme that uncertainty leads to portfolio rebalancing and aggregate fluctuations, but the types of risk and the mechanisms generating imperfect substitutability between capital and government bonds are different. Bayer *et al.* (2019) follows the Aiyagari (1994) tradition and study idiosyncratic *labor income risk* faced by the households, whereas in this paper, we focus on idiosyncratic *investment risk* as in Angeletos (2007) and Bloom (2009). In Bayer *et al.* (2019), capital stock is illiquid compared to bonds, so households hold bonds for better *consumption smoothing*,[3] while in our paper, capital bears more idiosyncratic risk and households

[2] In addition to the New Keynesian models, the literature on uncertainty shocks has investigated the "wait-and-see" effect (Bloom, 2009; Bloom *et al.*, 2018) and various types of interactions between uncertainty and financial frictions (Gilchrist *et al.*, 2014; Alfaro *et al.*, 2024; Arellano *et al.*, 2019; Elenev *et al.*, 2021; Di Tella, 2017; Bianchi *et al.*, 2018).

[3] Recent papers that jointly study the liquidity service of government papers and monetary transmissions

hold bonds as an *insurance*.[4] In this regard, our paper offers a new mechanism that also contributes to the empirical patterns established in their paper. In addition, we closely examine the roles of different policy tools in stabilizing aggregate demand and characterize the optimal monetary-fiscal policy, which is complementary to the distributional results in Bayer *et al.* (2019). Finally, our model features more tractability and provides a more transparent display of different mechanisms.

Moreover, we echo the extensive HANK literature that emphasizes the role of fiscal policy when Ricardian equivalence breaks down under incomplete markets. For example, Kaplan, Moll and Violante (2018), Acharya and Dogra (2020), and Caramp and Silva (2023) have investigated fiscal-monetary interactions in New Keynesian models with technology and monetary shocks. Our paper contributes to this literature by highlighting the importance of fiscal policy in environments with uncertainty shocks and portfolio reallocations.

Our paper also links with the literature on safe asset shortage and macroeconomic dynamics (e.g., Caballero and Farhi, 2018; Acharya and Dogra, 2022). Distinct from the earlier studies, our mechanism does not rely on a binding zero lower bound on the nominal rate. We show that the scarcity of safe assets matters in the presence of nominal rigidity and uncertainty shocks, even when the economy is away from safety and liquidity traps.

Our analysis of optimal policy connects to the burgeoning literature on the optimal design of monetary-fiscal policy in models with nominal rigidity and incomplete markets (e.g., Acharya, Challe and Dogra, 2023; Bhandari *et al.*, 2021; Le Grand, Martin-Baillon and Ragot, 2021; Dávila and Schaab, 2022; McKay and Wolf, 2022). Notably, the existing literature mostly builds on one-asset models and ignores the portfolio choice between risky and safe assets,[5] whereas in this paper, we carefully study the implications of household portfolio adjustment. Our paper also focuses on different aspects of welfare calculation from the existing literature. Specifically, we draw our attention to the aggregate demand externality created by incomplete markets while abstracting away from wealth inequality

include Del Negro *et al.* (2017), Kiyotaki and Moore (2019) and Szőke (2019).

[4] In a similar vein, recent works by Di Tella (2020) and Brunnermeier, Merkel and Sannikov (2024) model government papers as a store of value in uncertain environments.

[5] A notable expectation is Bilbiie and Ragot (2021), who study optimal monetary policy when households solve a portfolio problem between money, bond and capital. Unlike in our paper, the portfolio problem is motivated by household liquidity shocks and infrequent participation in financial markets.

and distributional efficiency.

Our model also relates to the literature on money as a store of value against idiosyncratic risk. In this literature, money has functionalities similar to nominal government bonds, as in our paper. In particular, we share the same interest with Di Tella (2020) and Brunnermeier, Merkel and Sannikov (2024) in showing that the existence of nominally safe assets has important implications for monetary transmissions. In addition, we demonstrate how valuations of safe assets interact with nominal rigidity and how stabilization policies work differently with and without nominal government debts.

With regard to the methodology, we build on recent developments in continuous-time methods in macroeconomics and finance. Specifically, our formulation of household portfolio choice problem resembles those in Brunnermeier and Sannikov (2014, 2016), while our modeling of price adjustment frictions is along the same lines as Kaplan, Moll and Violante (2018).

Outline. Section 3.2 outlines the baseline model and our main numerical results. Section 3.3 discusses the transmission mechanisms of uncertainty shocks in our environment. Section 3.4 compares the baseline model with a model without safe government bonds. Section 3.5 studies the design of fiscal policy. Section 3.6 presents an extension with long-term government bonds. Section 3.7 concludes.

3.2 Model

In this section, we outline our baseline model. The model is based on the safe asset model of Brunnermeier, Merkel and Sannikov (2024) in which households solve a portfolio choice problem between idiosyncratically risky capital and safe nominal government bonds. The amount of idiosyncratic risk that agents face is time-varying. In times of high risk, households' demand for safe government bonds increases, which generates deflation pressures. We augment this model by introducing nominal rigidities in the form of price adjustment costs as in Rotemberg (1982). Nominal rigidities prevent the immediate revaluation of nominal safe assets so that deflationary pressures from flight to safety create a

demand shortage.

3.2.1 Setup

Overview. We study a continuous-time, infinite-horizon economy. The economy is populated by a continuum of households that own (risky) physical capital and (safe) government bonds. There exists another continuum of intermediate goods firms that rent capital from households to produce differentiated intermediate goods and sell them to a competitive sector of final goods firms. Final goods firms combine intermediate goods to final goods using a CES production technology.

The model features two key frictions: (1) incomplete markets limit idiosyncratic risk sharing by households, and (2) intermediate goods firms face nominal price adjustment frictions.

We use the final good as a numeraire. That is, if the price level is P_t, one dollar is worth $1/P_t$ in terms of final goods.

Households and Assets. There is a continuum of households indexed by $i \in [0,1]$. All households have logarithmic preferences over consumption streams with identical time preference rate ρ,

$$\mathbb{E}\left[\int_0^\infty e^{-\rho t} \log c_t^i \mathrm{d}t\right]. \tag{3.1}$$

Each household manages physical capital that produces a flow of capital services $u_t^i k_t^i \mathrm{d}t$ which the household rents out to intermediate goods firms at rental price p_t^R (per unit of capital services). Here, k_t^i is the quantity of capital managed by household i at time t and u_t^i is the utilization rate chosen by the household. In addition to providing capital services, capital holdings may be subject to taxation by the government and they entitle households to profit distributions from intermediate goods firms to be specified below. Capital of household i evolves according to

$$\mathrm{d}k_t^i = \underbrace{\left[\Phi(\iota_t^i) - \delta(u_t^i)\right]}_{:=g(u_t^i,\iota_t^i)} k_t^i \mathrm{d}t + \tilde{\sigma}_t k_t^i \mathrm{d}\tilde{Z}_t^i + \mathrm{d}\Delta_t^{K,i}, \tag{3.2}$$

where $\mathrm{d}\Delta_t^{K,i}$ represents agent i's market transactions in physical capital, $\iota_t^i k_t^i \mathrm{d}t$ are the agent's physical investment expenditures (in final output goods), $\Phi(\cdot)$ is an increasing and concave function that captures adjustment costs in capital accumulation, $\delta(\cdot)$ is an increasing and convex function that makes capital depreciation dependent on utilization u_t^i, and $\tilde{Z}^i$ is an agent-specific Brownian motion that is i.i.d. across households i. $\tilde{Z}^i$ introduces agent-specific idiosyncratic risk. $\tilde{\sigma}_t$ is an exogenous process that governs the magnitude of idiosyncratic risk faced by agents. We assume that $\tilde{\sigma}_t$ is driven by some (aggregate) Brownian motion Z that is independent of all the idiosyncratic $\tilde{Z}^i$ processes.

The first key friction in the model is that households are unable to share idiosyncratic risk due to market incompleteness. While they are allowed to trade physical capital and government bonds, they cannot write financial contracts contingent on individual $\tilde{Z}^i$ histories. As a consequence, all households have to bear the idiosyncratic risk inherent in their physical capital holdings.

We formulate the decision problem of household i as a standard consumption-portfolio choice problem that does not make explicit reference to the capital trading process $\mathrm{d}\Delta_t^{K,i}$ as a choice variable and instead works with the shares of net worth invested in capital and bonds, respectively.[6] Let n_t^i be the net worth of household i and let θ_t^i be the share of net worth invested in bonds. Then household i's net worth evolves according to

$$\mathrm{d}n_t^i = n_t^i \left[\theta_t^i \mathrm{d}R_t^B + (1-\theta_t^i)\mathrm{d}R_t^{K,i}(u_t^i, \iota_t^i)\right] - c_t^i \mathrm{d}t, \tag{3.3}$$

where $\mathrm{d}R_t^B$ and $\mathrm{d}R_t^{K,i}(\cdot,\cdot)$ are the infinitesimal return processes for bonds and capital, respectively. We describe these returns in the following.

Let q_t^K denote the market price of capital and let $q_t^B := \frac{B_t}{P_t}\frac{1}{K_t}$ the real value of the total bond stock in the economy per unit of aggregate capital. Here, $K_t := \int_0^1 k_t^i \mathrm{d}i$ is the capital stock, and B_t is the nominal face value of the outstanding stock of government bonds. Bonds make nominal interest payments to their holders at a floating rate i_t set by the gov-

[6] The trading process $\mathrm{d}\Delta_t^{K,i}$ can be backed out ex post from the solution to this portfolio problem.

ernment. We assume that B_t evolves locally deterministically,

$$\mathrm{d}B_t = \mu_t^B B_t \mathrm{d}t,$$

for reasons that we discuss below when specifying government policy. We postulate that q_t^B and q_t^K follow a generic Ito evolution

$$\mathrm{d}q_t^B = \mu_t^{q,B} q_t^B \mathrm{d}t + \sigma_t^{q,B} q_t^B \mathrm{d}Z_t, \qquad \mathrm{d}q_t^K = \mu_t^{q,K} q_t^K \mathrm{d}t + \sigma_t^{q,K} q_t^K \mathrm{d}Z_t$$

with drifts $\mu_t^{q,B}$, $\mu_t^{q,K}$ and (aggregate) volatility loadings $\sigma_t^{q,B}$, $\sigma_t^{q,K}$ that are determined in equilibrium. The return on bonds is simply the interest income minus inflation

$$\begin{aligned} \mathrm{d}R_t^B &= i_t \mathrm{d}t + \frac{\mathrm{d}\left(1/P_t\right)}{1/P_t} \\ &= \left(i_t - \mu_t^B + g_t + \mu_t^{q,B}\right) \mathrm{d}t + \sigma_t^{q,B} \mathrm{d}Z_t \end{aligned} \tag{3.4}$$

where the second equality uses the identity $1/P_t = q_t^B K_t / B_t$ by definition of q_t^B.[7] Importantly, the return on bonds is not subject to idiosyncratic risk.

The return on capital for household i is

$$\begin{aligned} \mathrm{d}R_t^{K,i}(u_t^i, \iota_t^i) &= \overbrace{\left(\frac{p_t^R u_t^i}{q_t^K} - \frac{\iota_t^i}{q_t^K} + \frac{\omega_t}{q_t^K} - \tau_t^K\right) \mathrm{d}t}^{\text{dividend yield}} + \frac{\overbrace{\mathrm{d}\left(q_t^K \left(k_t^i - \Delta_t^{K,i}\right)\right)}^{\text{capital gain}}}{q_t^K \left(k_t^i - \Delta_t^{K,i}\right)} \\ &= \left(\frac{p_t^R u_t^i - \iota_t^i}{q_t^K} + \frac{\omega_t}{q_t^K} - \tau_t^K + g(u_t^i, \iota_t^i) + \mu_t^{q,K}\right) \mathrm{d}t + \tilde{\sigma}_t \mathrm{d}\tilde{Z}_t^i + \sigma_t^{q,K} \mathrm{d}Z_t. \end{aligned} \tag{3.5}$$

The dividends per unit of capital consist of four parts: revenues from renting out capital to intermediate goods firms, $p_t^R u_t$, physical reinvestment in the capital stock, $-\iota_t$, profit transfers from intermediate goods firms, ω_t, and taxes levied by the government, $-\tau^K q_t$. The second term in the the first line corresponds to the capital gains, which are the result of both changes in the capital price q_t^K and changes in the quantity of capital before market

[7] We also use here $\mathrm{d}K_t = g_t K_t \mathrm{d}t$ with $g_t := \int_0^1 g(u_t^i, \iota_t^i) k_t^i \mathrm{d}i / K_t$, which follows readily from aggregating the individual capital evolutions (3.2).

transactions ($k_t^i - \Delta_t^{K,i}$) due to investment, depreciation, and idiosyncratic shocks.

In total, household i's problem is to choose consumption $\{c_t\}_{t=0}^{\infty}$, capital utilization $\{u_t\}_{t=0}^{\infty}$, physical investment $\{\iota_t\}_{t=0}^{\infty}$, and the bond portfolio share $\{\theta_t\}_{t=0}^{\infty}$ in order to maximize utility (3.1) subject to the net worth evolution (3.3), wherein the latter the return expressions are given by equations (3.4) and (3.5). When making decisions, the household takes initial net worth n_0^i and the processes $\{p_t^R, q_t^B, q_t^K, g_t, \omega_t, i_t, \tau_t^K, \mu_t^B\}$ as given.

Intermediate Goods Firms. There is a continuum of monopolistically competitive intermediate goods firms indexed by $j \in [0,1]$. Each intermediate goods firm operates a linear production technology

$$y_t^j = a\hat{k}_t^j$$

for a differentiated good of variety j. Here, a denotes the level of productivity and $\hat{k}_t^j$ are effective capital input services rented from households at (unit) rental price p_t^R.

Intermediate goods firms quote their output prices P_t^j in terms of the nominal unit. The second of the two key frictions in the model is that price adjustments are subject to adjustment costs as in Rotemberg (1982). Specifically, the nominal price P_t^j of firm j evolves according to

$$\mathrm{d}P_t^j = \pi_t^j P_t^j \mathrm{d}t$$

and the firm incurs a flow adjustment cost $\frac{\kappa}{2}\left(\pi_t^j\right)^2 Y_t \mathrm{d}t$ when choosing price inflation π_t^j, where $\kappa > 0$ is a parameter and Y_t is the aggregate output.

In total, the flow profit of firm j is given by

$$\varpi_t^j \mathrm{d}t := \left[\frac{P_t^j}{P_t} a\hat{k}_t^j - p_t^R \hat{k}_t^j - \frac{\kappa}{2}\left(\pi_t^j\right)^2 Y_t\right] \mathrm{d}t. \tag{3.6}$$

The firm chooses a path of price inflation π_t^j and capital inputs $\hat{k}_t^j$ to maximize the present value of flow profits

$$\mathbb{E}\left[\int_0^{\infty} \xi_t \varpi_t^j \mathrm{d}t\right]$$

subject to the demand for intermediate good variety j (equation (3.8) below). Future profits

are discounted using the stochastic discount factor $\xi_t = e^{-\rho t}\frac{1}{C_t}$ where $C_t = \int_0^1 c_t^i \mathrm{d}i$ is the aggregate household consumption.[8]

We assume that the both the profit flow ω_t^j of intermediate goods firms and the price adjustment costs $\frac{\kappa}{2}\left(\pi_t^j\right)^2 Y_t$ are rebated to the household proportionally to their capital holdings.[9] The transfer received by households per unit of capital is

$$\omega_t = \frac{\int_0^1 \left[\omega_t^j + \frac{\kappa}{2}\left(\pi_t^j\right)^2 Y_t\right] \mathrm{d}j}{K_t}. \tag{3.7}$$

We consider a symmetric equilibrium where the price paths are the same for all firms ($\pi_t^j = \pi_t$). In Appendix C.1, we present a detailed derivation of the New Keynesian Phillips Curve in this context.

Final Goods Firms. Final goods are produced by a competitive sector of firms using a CES technology

$$Y_t = \left[\int_0^1 \left(y_t^j\right)^{\frac{\varepsilon-1}{\varepsilon}} \mathrm{d}j\right]^{\frac{\varepsilon}{\varepsilon-1}},$$

where y_t^j is the input quantity of intermediate good variety j and ε are the elasticity of substitution across varieties. By standard CES cost minimization, final goods producers have downward-sloping demand curves

$$y_t^j = \left(\frac{P_t^j}{P_t}\right)^{-\varepsilon} Y_t \tag{3.8}$$

and the nominal price of the final good is given by

$$P_t = \left[\int_0^1 \left(P_t^j\right)^{1-\varepsilon} \mathrm{d}j\right]^{\frac{1}{1-\varepsilon}}.$$

[8] While different from any individual household's SDF, the use of this SDF maximizes the value of the profit share claims for any agent. This is the case because we distribute profits proportionally to capital holdings, which are idiosyncratically risky. See Brunnermeier *et al.* (2024) for an in-depth discussion of this weighted-average SDF.

[9] This is consistent with the redistribution strategy according to factor input shares as suggested by Kaplan, Moll and Violante (2018). Note We include price adjustment costs in the transfers for simplicity. At the expense of additional notation, we could also make price adjustment cost a resource cost without significantly altering any of our results.

Government. There is a government that issues floating-rate nominal government bonds and imposes taxes on capital. As stated previously, the total nominal quantity of outstanding bonds is denoted by B_t, its growth rate by μ_t^B, the nominal interest rate by i_t, and the proportional capital (value) tax rate by τ_t^K. The government's choices of the three policy variables, nominal interest i_t, the bond issuance rate μ_t^B, and the capital tax rate τ_t^K, must satisfy the flow budget constraint

$$i_t B_t = \mu_t^B B_t + P_t \tau_t^K \cdot q_t^K K_t. \tag{3.9}$$

That is, the total interest payments $i_t B_t$ have to funded by new bond issuance $\mu_t^B B_t$ or taxes $P_t \tau_t^K \cdot q_t^K K_t$.

The budget equation (3.9) makes apparent why we have assumed that bond growth $\mathrm{d}B_t/B_t$ is locally deterministic. In our framework, we have combined together all government liabilities in the single liability "bonds" B_t, so that no market transactions between different types of government liabilities (e.g., open market operations of exchanging bonds for reserves) can (discontinuously) change the quantity of outstanding bonds. Then, any $\mathrm{d}Z_t$-loading of $\mathrm{d}B_t/B_t$ would have to be absorbed by a $\mathrm{d}Z_t$-loading in tax revenues,[10] i.e., a shock-contingent tax/transfer scheme that continuously alternates between positive and negative transfer payments. Such contingent tax/transfer schemes are highly counterfactual in our view, which motivates us to restrict attention to locally deterministic bond growth.[11]

Henceforth, we denote by

$$\breve{s}_t := \frac{P_t \tau_t^K q_t^K K_t}{B_t} \tag{3.10}$$

the ratio of the primary surplus to outstanding government debt. With this notation, the

[10] Interest payments cannot absorb a $\mathrm{d}Z_t$-loading of $\mathrm{d}B_t/B_t$ as long as the government issues standard nominal debt, which must be made locally deterministic interest payments.

[11] It should be emphasized that our assumption does not rule out state-contingent changes in the capital tax *rate*. It merely rules out transfer schemes whose cash flows directly load on the Brownian innovations $\mathrm{d}Z_t$.

budget constraint (3.9) simplifies to

$$i_t = \mu_t^B + \check{s}_t. \tag{3.11}$$

In what follows, we assume that the government sets the nominal rate i_t and the surplus-debt ratio $\check{s}_t$ according to some policy rules

$$i_t = i\left(\mathbf{S}_t\right), \qquad \check{s}_t = \check{s}\left(\mathbf{S}_t\right) \tag{3.12}$$

and adjusts taxes τ_t^K and bond issuance μ_t^B to satisfy the budget constraint (3.11) and the definition equation of $\check{s}_t$.[12] Here, $\mathbf{S}_t$ is a vector of aggregate variables (e.g., $\pi_t, \tilde{\sigma}_t$) chosen by the government. In our language, we will loosely identify i_t with "monetary policy" and $\check{s}_t$ with "fiscal policy."

3.2.2 Equilibrium

Market Clearing. The goods market clears when the total output equals the sum of consumption and investment

$$\int_0^1 c_t^i \mathrm{d}i + \int_0^1 \iota_t^i k_t^i \mathrm{d}i = Y_t. \tag{3.13}$$

The bond market clearing condition states that bonds held by households must equal bonds supplied by the government

$$\int_0^1 \theta_t^i n_t^i \mathrm{d}i = \frac{B_t}{P_t}. \tag{3.14}$$

Equilibrium Definition. Natural state variables in our model are $\tilde{\sigma}_t$, B_t, K_t, and P_t. It is possible to reduce the dimensionality of the state space from four to two dimensions. First, because of the AK nature of the economy, the capital stock K_t only matters for the

[12] In general, the assumption of automatically adjusting taxes may lead to equilibrium multiplicity. However, the model always features at most one equilibrium in which the value of government debt is positive and stationary. Compare Brunnermeier, Merkel and Sannikov (2020) for a discussion of a flexible price version of our model. In the following, we always select this equilibrium. This choice is in full analogy to the standard equilibrium selection in models of money as a medium of exchange.

scale of the economy. We can eliminate it from the state space by considering descaled quantities. Second, the states B_t and P_t only matter through their impact on the real value of government bonds, B_t/P_t. Thus, we can equivalently use the normalized value of the bond stock q_t^B as our second state variable. Recall its definition

$$q_t^B := \frac{B_t}{P_t K_t}.$$

The dynamics of q_t^B follow by Ito's lemma from the dynamics of bond supply B_t, the price level P_t, and aggregate capital K_t:

$$\mu_t^{q,B} = \mu_t^B - \pi_t - g_t, \quad \sigma_t^{q,B} = 0. \tag{3.15}$$

Importantly, the value of nominal bonds is directly linked to the price level. In the presence of price stickiness, q_t^B is also locally deterministic ($\sigma_t^{q,B} = 0$), i.e., it becomes a slow-moving state instead of the instantaneously adjusting equilibrium price that it would be under flexible nominal prices.

Definition 1 (Markovian equilibrium) *An equilibrium consists of laws of motion for the state variables $\{\tilde{\sigma}_t, q_t^B\}$ and of equilibrium mappings*

$$\left\{q^K(\tilde{\sigma}_t, q_t^B), \vartheta(\tilde{\sigma}_t, q_t^B), u(\tilde{\sigma}_t, q_t^B), \iota(\tilde{\sigma}_t, q_t^B), \pi(\tilde{\sigma}_t, q_t^B), i(\tilde{\sigma}_t, q_t^B), \check{s}(\tilde{\sigma}_t, q_t^B)\right\}$$

that satisfy

- *household and firm optimality,*
- *the policy rule (3.12),*[13]
- *market clearing conditions (3.13) and (3.14),*
- *the consistency requirement (3.15).*

[13]The government budget constraint (3.11) and the definition of $\check{s}_t$ can then be used to back out the tax rate τ_t^K and the bond growth rate μ_t^B.

3.2.3 Solution Method

We solve the household problem using a recursive approach as in Brunnermeier, Merkel and Sannikov (2024) and intermediate goods firms' price setting problems using the stochastic maximum principle. Details are outlined in Appendix C.2. We collect and discuss key model equations below in Section 3.3 where we explain the model mechanisms. We proceed to solve for equilibrium mappings

$$\left\{q^K(\tilde{\sigma}_t, q_t^B), \vartheta(\tilde{\sigma}_t, q_t^B), u(\tilde{\sigma}_t, q_t^B), \iota(\tilde{\sigma}_t, q_t^B), \pi(\tilde{\sigma}_t, q_t^B), i(\tilde{\sigma}_t, q_t^B), \check{s}(\tilde{\sigma}_t, q_t^B)\right\}$$

numerically using an iterative method as in Brunnermeier and Sannikov (2016). Descriptions of the numerical algorithm can be found in Appendix C.3.

3.2.4 Quantitative Results

In this section, we present a calibration of our model and illustrate its main quantitative predictions.

Calibration. First, we calibrate the time discount rate ρ to match the household portfolio share of safe assets of 15% in the stochastic steady state, which is roughly consistent with the empirical evidence provided by Bayer *et al.* (2019).

We then assume the following functional forms for capital adjustment cost $\Phi(\cdot)$ and depreciation rate $\delta(\cdot)$. Following standard arguments, the investment function is concave, while the depreciation rate function is convex,

$$\Phi(\iota_t) = \frac{1}{\phi}\log(1+\phi\iota_t), \quad \delta(u_t) = \frac{\bar{\delta}}{2}u_t^2.$$

We set $\phi = 5$ as in Di Tella and Hall (2022). The intercept of the depreciation rate function $\bar{\delta}$ is chosen to target a depreciation rate of around 7% in the stochastic steady state (e.g., Kaplan, Moll and Violante, 2018). For the New Keynesian block, we follow Kaplan, Moll and Violante (2018) in setting $\varepsilon = 10$ and $\kappa = 100$ to match the slope of the Phillips Curve to 0.1.

We adopt the Heston (1993) model of stochastic volatility for the law of motion of uncertainty $\tilde{\sigma}_t$. That is,

$$\mathrm{d}\tilde{\sigma}_t^2 = b(\bar{\sigma}^2 - \tilde{\sigma}_t)\mathrm{d}t - \nu\tilde{\sigma}_t \mathrm{d}Z_t.$$

The calibration of the uncertainty process follows from Merkel (2020). Specifically, we choose the value of $\{b, \bar{\sigma}^2, \nu\}$ to match some of the important moments of $\{\tilde{\sigma}_t\}$ to those of the series of establishment-level TFP shocks reported by Bloom *et al.* (2018).

For expositional purposes, we first consider an economy with constant policy variables i and $\check{\mu}^B$.[14] We choose the fiscal policy to target a 1% primary surplus (% of GDP) in the stochastic steady state. The level of nominal rate i is chosen such that the steady-state inflation is zero. In Section 3.4, we present another parameterization where the nominal interest rate responds negatively to uncertainty shocks.

Table 3.1 summarizes the baseline calibration that will be used in the quantitative analysis.

Parameter	Description	Value	Target
Preference			
ρ	Discount Rate	0.07	$\vartheta^{SS} = 15\%$, Bayer *et al.* (2019)
Production			
a	Productivity	0.18	Standard
$\bar{\delta}$	Depreciation Rate Function	0.085	$\delta^{SS} \approx 7\%$
ϕ	Investment Adjustment Function	5	Di Tella and Hall (2022)
New Keynesian Block			
ε	Elasticity of Substitution	10	Kaplan *et al.* (2018)
κ	Menu Cost	100	Kaplan *et al.* (2018)
Uncertainty			
b	Speed of Adjustment	0.15	Bloom *et al.* (2018)
$\bar{\sigma}^2$	Mean	0.085	Bloom *et al.* (2018)
ν	Volatility	0.037	Bloom *et al.* (2018)
Monetary-Fiscal Policy			
i	Interest Rate	2.3%	$\pi^{SS} = 0$
$\check{s}$	Fiscal Policy	0.8%	1% Primary Surplus

Table 3.1. Model Parameterization

[14] Note that in the unique stationary monetary equilibrium (see footnote 12), the price level and inflation are determinate and the Taylor principle is not required for equilibrium selection.

Numerical Results. Consider an economy that is initially (at $t = 0$) in the stochastic steady state where $\tilde{\sigma}_0^2 = \bar{\sigma}^2$. We compute the impulse response functions (IRFs) to an uncertainty shock by comparing the results of the following two simulations

Simulation 1. At $t = 0$, the economy is hit by a positive uncertainty shock,[15] and no other shocks are realized hereafter.

Simulation 2. No shocks are realized forever, so the economy stays in the stochastic steady state.

The IRFs are defined as the difference between paths of relevant variables observed in these two simulations. Figure 3.1 visualizes such dynamics of the economy following a positive uncertainty shock. We briefly describe these dynamics here. An in-depth discussion of the mechanism is deferred to Section 3.3.

[15] We calibrate the size of the shock to generate a 3% recession in output.

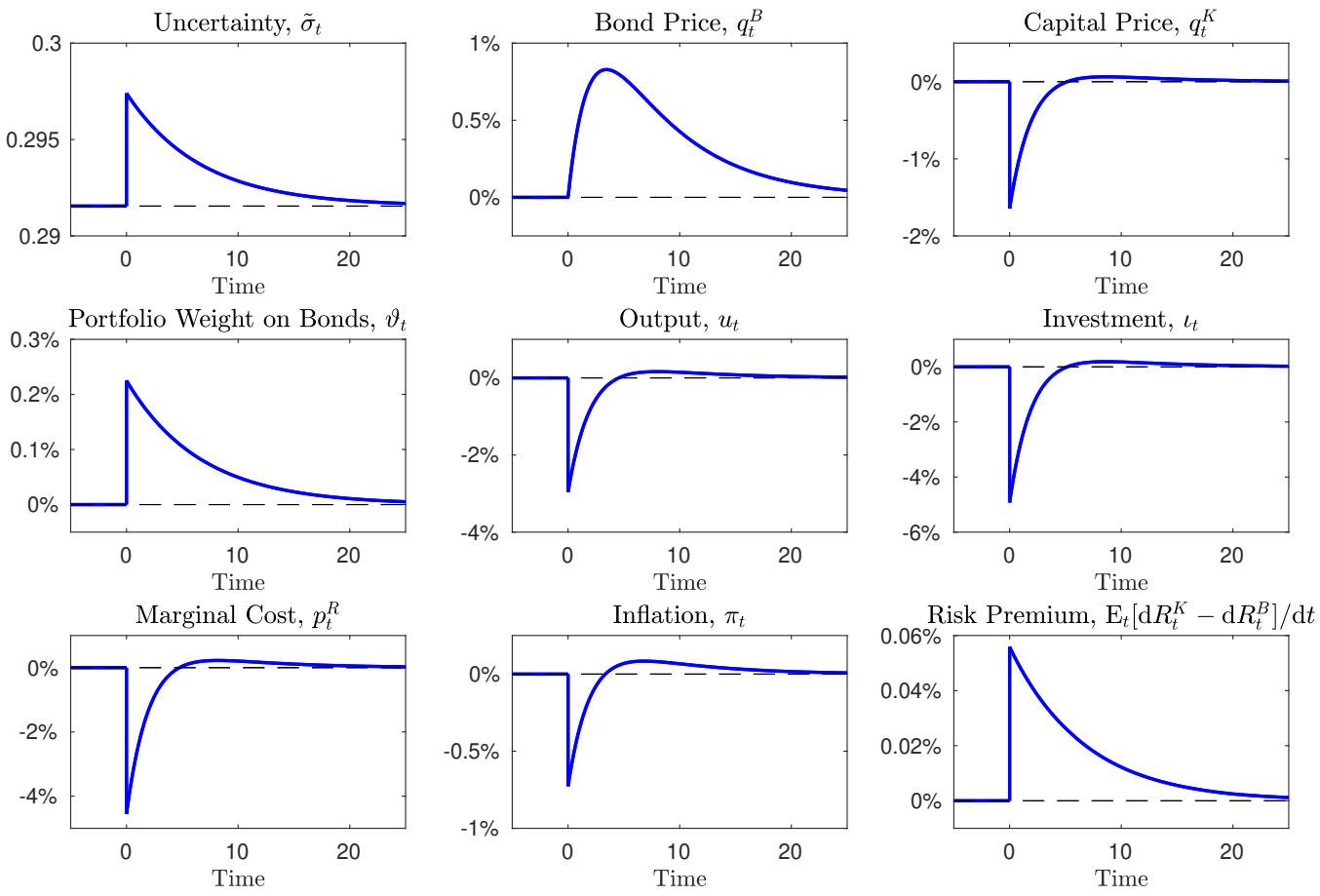


Figure 3.1. Impulse Response Functions (percentage differences)

We define the aggregate portfolio weight in bonds as the ratio of bond wealth to the total wealth of the economy,

$$\vartheta_t = \frac{B_t/P_t}{B_t/P_t + q_t^K K_t} = \frac{q_t^B}{q_t^B + q_t^K}. \tag{3.16}$$

As future uncertainty rises, the households increase their portfolio weight on bonds. When prices are sticky, the value of nominal bonds cannot adjust to clear the market, and the heightened demand for bonds leads to overshooting in the price of capital. As plotted in panels 2 and 3, the capital price q_t^K drops sharply when the shock hits and then slowly converges to the new steady state level. In the meantime, the bond price q_t^B is sticky and rises gradually over time.

The drop in the price of capital, in turn, depresses effective demand. Both investment and aggregate output fall. The recession in aggregate demand reduces the marginal cost facing intermediary goods producers and increases their markups. Since the current price level is too high, the firms optimally set lower prices in the future, resulting in a period of disinflation. Finally, households demand a higher risk premium as the return on capital becomes more uncertain.

In summary, our model implies that uncertainty leads to recessions in consumption, investment, and output, disinflation, and portfolio rebalancing towards safe bonds. It is worth noting that our model predicts that the return on capital increases while the real economy is in a downturn following positive uncertainty shocks. Hence, our model can potentially account for the recent disconnect between the return on capital and the real economy (e.g., Caballero and Simsek, 2021).[16]

3.3 Mechanism

3.3.1 Solving the Household Problem

As detailed in Appendix C.2, our setup leads to an analytical solution to the household problem.

Proposition 7 *The first-order conditions for household i are*

$$c_t^i : \qquad c_t^i = \rho n_t^i \tag{3.17}$$

$$\iota_t^i : \qquad \Phi'(\iota_t^i) = 1/q_t^K \tag{3.18}$$

$$u_t^i : \qquad \delta'(u_t^i) = p_t^R/q_t^K \tag{3.19}$$

$$\theta_t^i : \qquad \mathbb{E}_t\left[\mathrm{d}R_t^K - \mathrm{d}R_t^B\right]/\mathrm{d}t = (1-\theta_t^i)\left[(\sigma_t^{q,K})^2 + \tilde{\sigma}_t^2\right] \tag{3.20}$$

The first-order conditions have intuitive economic interpretations. With the logarithmic utility, the households always consume a constant fraction ρ of their net worth. The

[16] Our current calibration does not fully match the magnitude of increases in risk premia following uncertainty shocks. To quantitatively capture this adjustment, the model needs a larger risk aversion. Nevertheless, we maintain the assumption of log utility in this paper for the sake of tractability.

investment rate is positively associated with the price of capital, which is a standard Tobin's q relationship. The utilization rate is increasing in the rental price of capital p_t^R, which represents the marginal revenue from production, and decreasing in the price of capital q_t^K, which represents the opportunity cost of depreciating more capital. Capital earns a risk premium on both aggregate risk and idiosyncratic risk, where the premium depends on the households' risk exposure $(1-\theta_t^i)$, the amount of aggregate risk $\sigma_t^{q,K}$, and the amount of idiosyncratic risk $\tilde{\sigma}_t$.

The first-order conditions (3.18) – (3.20) also imply that the household's decisions on investment ι_t, utilization u_t, and portfolio weight θ_t are independent of their own net worth or capital stock. Therefore, the households in this economy are *homogeneous up to scale*, as they all choose the same investment and utilization rates and hold the same portfolio regardless of their net worth.[17] While agents are heterogeneous with regard to their net worth n_t^i, the net worth distribution does not affect macro aggregates. It is in this sense that our analysis abstracts from distributional aspects that have been the focus of much of the HANK literature.

Note that the total net worth of the households consists of the total (real) value of government bonds and capital,

$$\int_0^1 n_t^i \mathrm{d}i = (q_t^B + q_t^K)K_t.$$

It is then useful to write the goods market clearing condition (3.13) as

$$\rho(q_t^B + q_t^K)K_t + \iota_t K_t = a u_t K_t. \tag{3.21}$$

Since all households choose the same portfolio $\theta_t^i = \theta_t$, the bond market clearing condition (3.14) can be simplified to

$$\theta_t = \frac{B_t/P_t}{B_t/P_t + q_t^K K_t} = \frac{q_t^B}{q_t^B + q_t^K}. \tag{3.22}$$

Comparing equations (3.16) and (3.22), we see that the individual portfolio weight must

[17] Henceforth, we omit the i superscript since all decision variables are identical across households.

coincide with the aggregate portfolio weight, $\theta_t = \vartheta_t$.

3.3.2 Understanding Household Portfolio Decisions

To understand how household portfolio decisions respond to fluctuations in economic uncertainty, we derive a more intuitive condition that characterizes the dynamics of ϑ_t. Since the portfolio weight is uniform across households and thus not driven by any idiosyncratic shocks, we postulate that

$$\frac{\mathrm{d}\vartheta_t}{\vartheta_t} = \mu_t^{\vartheta}\mathrm{d}t + \sigma_t^{\vartheta}\mathrm{d}Z_t.$$

Plugging the expressions for asset returns (3.4), (3.5) and market clearing conditions (3.21), (3.22) into the household portfolio FOC (3.20), we obtain a closed form solution for μ_t^{ϑ}.

Proposition 8 (Bond Valuation Equation) *The law of motion of ϑ_t satisfies*

$$\mu_t^{\vartheta} = \rho - (1-\vartheta_t)^2\,\tilde{\sigma}_t^2 - \check{s}_t. \tag{3.23}$$

In integral form,

$$\vartheta_t = \mathbb{E}_t\left\{\int_t^{\infty} e^{-\rho(s-t)}\vartheta_s\left[(1-\vartheta_s)^2\tilde{\sigma}_s^2 + \check{s}_s\right]\mathrm{d}s\right\}. \tag{3.24}$$

This result clarifies that households' portfolio choice depends on only two processes, the path of future uncertainty $\{\tilde{\sigma}_s\}_{s\geq t}$ and the path of future surplus-debt ratios $\{\check{s}_s\}_{s\geq t}$. Households demand more government bonds when they are valuable as insurance (higher $\tilde{\sigma}$) or when they are subsidized by government policy (higher $\check{s}_t$).[18]

Importantly, household portfolio choice does *not* directly depend on output or capital utilization (u_t), inflation (π_t), the nominal interest rate (i_t), and any parameters governing the price-setting behavior of firms (ε, κ). These variables and parameters only affect household portfolio choice between capital and bonds if (fiscal) policy adjusts $\check{s}$ in response to them. This leads to the following separation result.

[18] A higher surplus-debt ratio effectively subsidizes bonds relative to capital holdings because it implies that the government taxes capital at a larger rate to make payouts to bondholders.

Proposition 9 (Separation of Portfolio Choice) *Suppose that the fiscal policy rule chooses $\check{s}$ as a function of $(\tilde{\sigma}_t, \vartheta_t)$ only.*[19] *Then*

$$\vartheta_t = \vartheta(\tilde{\sigma}_t)$$

is a function of the exogenous uncertainty state $\tilde{\sigma}_t$ only, and this function does not depend on the model parameters ε and κ.

In particular, portfolio choice is unaffected by inflation π_t, capital utilization u_t, nominal interest rates i_t, and the degree of price stickiness.

This proposition has two important corollaries. First, monetary policy is *portfolio-neutral*: the nominal interest rate path i_t set by the monetary authority does not distort the portfolio choice between bonds and capital unless it induces changes in the fiscal policy instrument $\check{s}_t$. Second, regardless of how sluggish nominal prices adjust, portfolio choice between capital and bonds is always "fast" in the sense that portfolios adjust precisely under flexible prices. This second corollary plays an important role in the overshooting result discussed below.

Interest Rate Policy and Fiscal Policy. It is sometimes believed that interest rate policy can distort the households' demand for safe assets by changing the risk-free rate. We show that this is not necessarily the case when bonds are in a positive net supply. In our baseline model, the government only affects household portfolios through (capital) taxes in this economy. The reason is that the bond return (3.4) depends on the difference $i_t - \mu_t^B$ of nominal interest payments and bond issuance, which equals the surplus-debt ratio $\check{s}_t$ by the government budget constraint (3.11) and is thus directly proportional to taxes.[20] Intuitively, changes in seigniorage income through bond issuance (μ_t^B) dilute the claim of existing bondholders in a way that exactly offsets changes in interest rates (i_t) unless they are associated with changes in the distribution of primary surpluses to bondholders (i.e., changes in $\check{s}_t$).

To control household portfolio decisions, the government thus needs to adjust distor-

[19] This includes, for example, simple policies such as a constant capital tax rate τ_t^K.

[20] The return on capital (3.5) also depends on government policy, but naturally only on the capital tax rate τ_t^K.

tionary taxes. More specifically, the government can encourage investments in bonds by taxing capital and subsidizing bondholders through interest payments.

It should be emphasized that this strong result (i.e., interest rate policy alone is completely ineffective) is a special feature of our baseline model that is, for example, relaxed by the introduction of long-term bonds (Section 3.6). However, we would like to stress that fiscal policy is crucial in an environment with nominally safe assets, which is in sharp contrast to models without safe assets where fiscal policy only plays a minor role (see, for example, Section 3.4 and Basu and Bundick, 2017). We also highlight the possibility that the seigniorage income of the government dampens the transmission of monetary policy and that the response of fiscal policy becomes crucial when markets are incomplete.

3.3.3 The Transmission of Uncertainty Shocks

To understand how uncertainty affects output, we can rewrite the market clearing condition (3.21) as

$$u_t = \frac{1}{a}\left[\underbrace{\rho(q_t^K + q_t^B)}_{\substack{\text{consumption}\\ \text{demand}}} + \underbrace{\iota_t}_{\substack{\text{investment}\\ \text{demand}}}\right]. \tag{3.25}$$

The demand for final goods can be decomposed as demand for consumption and investment. The consumption demand is tied to the households' net worth through wealth effects. Net worth depends on the value of both bonds and capital. The investment demand ι_t instead depends on q_t^K through the Tobin's q relationship (3.18). To determine the short-run output u_t, it is thus important to understand the behavior of the *levels of asset valuations*, q_t^K and q_t^B.

The solution of the household portfolio problem (equation (3.24)) determines *relative asset valuations*. Households invest more in nominal bonds as future uncertainty increases. Formally, the nominal wealth share ϑ_t rises. Because portfolio choice is separated from output determination by Proposition 9, we can treat ϑ_t in the following as an exogenous process and discuss how the components of aggregate demand depend on it.

Recall that

$$\vartheta_t = \frac{q_t^B}{q_t^B + q_t^K} = \frac{1}{1 + q_t^K / q_t^B}.$$

An increase in ϑ_t mechanically implies a drop in the price of capital relative to the value of bonds. However, the absolute movements in q_t^K and q_t^B hinge on the presence of price stickiness.

Equilibrium under Flexible Prices. When prices are flexible, intermediate goods firms' problem collapses to a static profit-maximization problem at each time, and firms engage in constant markup pricing (see Appendix C.4 for details). Price setting merely determines the capital rental price,

$$p_t^{R,flex} = a\frac{\varepsilon - 1}{\varepsilon}, \tag{3.26}$$

while the nominal price level P_t is free to adjust in order to clear the goods market, i.e., make equation (3.25) hold. In that equation, P_t enters through the scaled bond value $q_t^B = B_t/(P_t K_t)$, which it is inversely proportional to.

Together with equations (3.19), (3.22), and (3.26), we can solve the goods market clearing equation (3.25) for prices q_t^K and q_t^B analytically. For tractability, we keep using the following functional forms: $\Phi(\iota) = \log(1 + \phi\iota)/\phi$ and $\delta(u) = (\bar{\delta}/2)u^2$, which then imply that under flexible prices,

$$q_t^{K,flex} = \left[\frac{a^2}{\rho\bar{\delta}}\frac{\varepsilon - 1}{\varepsilon}\right]^{1/2}(1 - \vartheta_t)^{1/2}, \tag{3.27}$$

$$q_t^{B,flex} = \left[\frac{a^2}{\rho\bar{\delta}}\frac{\varepsilon - 1}{\varepsilon}\right]^{1/2}\frac{\vartheta_t}{(1 - \vartheta_t)^{1/2}}. \tag{3.28}$$

As uncertainty increases ($\vartheta_t \uparrow$), government bonds gain in value ($q_t^B \uparrow$) while capital loses ($q_t^K \downarrow$). Since $q_t^B \propto 1/P_t$, the increase in q_t^B implies a drop in the price level P_t.

Economically, an increase in ϑ_t induced by heightened uncertainty means that agents desire more bond savings and less capital savings. As a result, both the capital price q_t^K

and the physical investment rate ι_t fall, implying lower consumption demand due to capital wealth and investment demand on the right-hand side of equation (3.25). For fixed utilization u_t and bond values q_t^B, aggregate demand thus falls short of supply.

However, unlike capital, bond holdings cannot be used as an aggregate savings device. As households collectively demand more nominal bonds and fewer goods, the price level falls, and the real value of bonds q_t^B appreciates. A wealth effect from increased bond wealth generates additional consumption demand that eliminates the shortfall in aggregate demand without any reduction in supply.[21]

Equilibrium under Sticky Prices: Impact Effect. When the price level P_t is sticky, it can no longer drop immediately in response to an uncertainty shock. There is no (immediate) deflationary revaluation of nominal wealth that raises consumption demand under flexible prices. Instead, supply must adjust to the shortfall in demand to clear the goods market. In this model, this adjustment happens through a reduction in capital utilization u_t.

In fact, in our continuous-time model, the state variable q_t^B for (scaled) bond wealth is perfectly rigid over short time periods and thus cannot adjust at all on shock impact.[22] As a consequence, when higher uncertainty raises ϑ_t, both total wealth $q_t^K + q_t^B = q_t^B/\vartheta_t$ and capital valuations $q_t^K = (1-\vartheta_t)/\vartheta_t \cdot q_t^B$ fall. The former implies a reduction in consumption demand, the latter a reduction in investment demand through Tobin's q relationship (3.18). Importantly, both components of aggregate demand in equation (3.25) are fully predetermined by the (separate) portfolio choice ϑ_t and the (rigid) state variable q_t^B. The only free variable to adjust on impact is u_t, and a recession is inevitable.

In fact, the investment demand and the capital price always fall by more than under flexible prices. The reason is that when q_t^B is unable to adjust, a higher portfolio weight ϑ_t can only be achieved through a more substantial drop in the capital price q_t^K. That is, since the value of government bonds cannot adjust quickly to match fluctuations in the demand for bonds, uncertainty shocks depress the demand for capital even further.

Suppose the economy is in a steady state before an uncertainty shock hits. Immediately

[21] In fact, in this model, aggregate supply even expands under flexible prices because the lower capital price q_t^K reduces the opportunity cost of higher capital utilization u_t.

[22] Formally, this is apparent in $\sigma_t^{q,B} = 0$ in equation (3.15).

after uncertainty increases, the price of bonds is stuck at the pre-shock level q_{t-}^B, which is smaller than the post-shock flexible price value $q_t^{B,flex}$. At the onset of the shock, the price of capital is determined by the new portfolio weight ϑ_t, so

$$q_t^K \;=\; q_{t-}^B \frac{1-\vartheta_t}{\vartheta_t} \;<\; q_t^{B,flex} \frac{1-\vartheta_t}{\vartheta_t} \;=\; q_t^{K,flex}. \tag{3.29}$$

Thus, the price of capital *overshoots* relative to the flexible price response following uncertainty shocks when nominal prices are sticky.

This result is reminiscent of the classic overshooting model by Dornbusch (1976), which shows that stickiness in domestic prices results in overshooting in exchange rates, whereas in our model, the effective stickiness in bond valuations leads to overshooting in the price of capital.

Equilibrium under Sticky Prices: Adjustment Dynamics. After the shock, the price level P_t slowly decreases over time to bring it closer to its natural (flexible price) level, leading to a period of disinflation. Adjustment dynamics are guided by the Phillips curve resulting from intermediate goods firms' forward-looking price-setting behavior and by the state equation (3.15). Under the simplifying assumption that agents do not expect any additional future shocks going forward, these two equations can be written as[23]

$$\mathrm{d}\pi_t = \left[\rho\pi_t - \frac{\varepsilon}{\kappa}\left(p_t^R - p^{R,flex}\right)\right]\mathrm{d}t \tag{3.30}$$

$$\mathrm{d}q_t^B = \left(i_t - \pi_t - \check{s}_t - g_t\right)\mathrm{d}t \tag{3.31}$$

where p_t^R and g_t are functions of utilization u_t, and the latter itself is fully determined by the demand equation (3.25) and the current bond value q_t^B.

The Phillips curve (3.30) is a forward-looking equation that encodes the standard price setting logic in New Keynesian models: firms' price setting is trading off a desire to minimize deviations of marginal unit costs p_t^R from their flexible price value $p^{R,flex}$ to achieve the statically optimal markup (second term in equation (3.30)) and a desire to smooth in-

[23] The fully stochastic Phillips curve that guides the actual model dynamics can be found in Appendix C.1. The equations stated here facilitate interpretation as they are significantly simpler.

flation in order to minimize price adjustment costs (first term in equation (3.30)). After an increase in uncertainty, a lack of demand for capital inputs drives the capital rental price p_t^R below its flexible price value so that

$$-\frac{\varepsilon}{\kappa}\left(p_t^R - p^{R,flex}\right) > 0$$

and equation (3.30) implies gradually increasing inflation. As this is a (forward-looking) backward equation, the gradual increase in inflation is achieved by an immediate reduction of π_t into deflationary territory.

Low and potentially negative π_t increases the rate of appreciation of the state variable q_t^B in equation (3.31), so that q_t^B gradually approaches its natural level $q_t^{B,flex}$ over time. As q_t^B becomes closer to $q_t^{B,flex}$, the marginal cost gap $p_t^R - p^{R,flex}$ in the Phillips curve (3.30) starts to shrink, thereby dampening further adjustments in inflation.[24]

It is in the state equation (3.31) that nominal interest rates i_t enter. By raising the nominal rate, the government expands nominal bonds at a faster rate μ_t^B (for given $\check{s}_t$) so that the price level has to adjust by less in order to expand the real quantity of safe assets q_t^B. Importantly, interest rate policy only acts on a state evolution (forward equation), not on some forward-looking choice condition (backward equation). As a consequence, interest rate policy can affect the speed of adjustment dynamics but not prevent the initial reduction in aggregate demand on shock impact.

3.3.4 Relations to the Existing Literature

Monetary Models with Idiosyncratic Risk. Recent works by Di Tella (2020) and Brunnermeier, Merkel and Sannikov (2020, 2024) have emphasized the role of nominal assets (e.g., money and government bonds) as insurance against idiosyncratic risk. Our paper shares the same spirit that uncertainty shocks affect the precautionary savings of households, which leads to portfolio rebalancing between safe assets and risky assets ("flight-to-safety"). Further, our paper extends this literature by introducing nominal rigidity and

[24] Whether q_t^B asymptotically reaches $q_t^{B,flex}$ depends on the long-run behavior of nominal rates as the Phillips curve is only consistent with a zero long-run output gap if inflation settles down at zero.

highlighting the interaction between sticky prices and portfolio decisions.

Safe Asset Shortage at the Zero Lower Bound (ZLB). Recently, a number of works (e.g., Caballero and Farhi, 2018; Acharya and Dogra, 2022) have examined the implications of safe asset scarcity. However, in this class of models, government policy affects the safety demand only through the nominal interest rate, and safe asset supply only matters for equilibrium outcomes when the nominal rate is constrained by the ZLB. In contrast, we show that when safe assets take the form of nominal government bonds whose value is slow to adjust due to nominal rigidity, it is important to consider the entire government budget constraint. In particular, safe asset supply can have a direct impact on macroeconomic dynamics even if the nominal rate is positive, and it is crucial to consider the response of fiscal policy to portfolio reallocations.

Government Bonds as a Liquid Asset. A recent strand of the New Keynesian literature focuses on the liquidity service of government debts. A notable example is Bayer *et al.* (2019), where households are subject to idiosyncratic income risk as in Aiyagari (1994). In their model, the capital stock is subject to transaction costs, whereas bonds can be easily liquidated.[25] When uncertainty increases, the households hold more government bonds to facilitate future consumption smoothing. In this paper, we adopt an alternative framework and motivate the agents' portfolio choice problem with idiosyncratic investment risk (e.g., Angeletos, 2007; Bloom, 2009). The households instead face a risk-return trade-off between capital and bonds. When uncertainty rises, households shy away from risk due to precautionary savings motives.

Despite having different foundations for household portfolio decisions, the overshooting mechanism emphasized here also applies to models where assets differ in their degrees of liquidity. In fact, the interaction between nominal rigidity and the valuation of nominal government bonds is ubiquitous in models with multiple assets. However, while the existing literature has quantitatively established that uncertainty shocks can trigger aggregate demand recessions, the role of nominal government bonds has not received adequate

[25] Del Negro *et al.* (2017) provides a different modeling approach where government bonds ease the financial frictions facing entrepreneurs.

attention. In this regard, our paper further clarifies the transmission mechanisms behind previous quantitative results.

3.4 Comparison to Models without a Safe Asset

Previous literature has studied the impact of uncertainty shocks in New Keynesian models where government bonds are in zero net supply (e.g., Basu and Bundick, 2017). While abstracting away from portfolio reallocations following uncertainty shocks, the authors still find similar business cycle co-movements following an uncertainty shock. In this section, we contrast models without safe bonds to our baseline model and further highlight the importance of portfolio adjustment in shaping macroeconomic dynamics following uncertainty shocks.

The model without a safe asset corresponds to a special case of our model where the supply of bonds is zero ($B_t = 0$). In this case, the households are forced to choose a portfolio entirely in capital ($\vartheta_t = 0$).

The Source of Fluctuations. When $B_t = 0$, the short-term output is given by

$$u_t = \frac{1}{a}\Bigg[\underbrace{\rho q_t^K}_{\substack{\text{consumption}\\ \text{demand}}} + \underbrace{\iota_t}_{\substack{\text{investment}\\ \text{demand}}}\Bigg]. \tag{3.32}$$

Since household portfolios stay constant over time, the interaction between portfolio rebalancing and price stickiness is shut off. Instead, the recessions in consumption, investment, and output stem from inadequate responses to monetary policy. To further clarify the transmission mechanism of uncertainty shocks in this model, it is useful to revisit the household portfolio choice condition (3.20), which now becomes

$$\mathbb{E}_t\left[\mathrm{d}R_t^K\right]/\mathrm{d}t - r_t^f = (\sigma_t^{q,K})^2 + \tilde{\sigma}_t^2. \tag{3.33}$$

When uncertainty increases, the households demand a higher risk premium on capital.

In this case, the risk-free rate is given by the Fisher equation

$$r_t^f = i_t - \pi_t$$

and therefore directly controlled by the monetary authority through the policy rate. If monetary policy fails to lower the risk-free rate aggressively enough, the heightened risk premium requires a higher return on capital, which leads to a drop in capital price q_t^K. From equation (3.32), we see that a drop in q_t^K translates to recessions in consumption, investment, and output when prices are sticky.

Interest Rate Policy. Furthermore, Basu and Bundick (2017) show that first best allocations can be implemented in their environment if the nominal interest rate pegs the natural rate perfectly, in which case investment and output increase after uncertainty rises. Here, we prove a similar result but within our model. Plugging the return on capital (3.5) into equation (3.33), we see that

$$\frac{u_t a - \iota_t}{q_t^K} + g_t + \left[\mu_t^{q,K} - (\sigma_t^{q,K})^2\right] = r_t^f + \tau_t^K + \tilde{\sigma}_t^2. \tag{3.34}$$

In equilibrium, all variables on the left-hand side depend on q_t^K. So by changing the real rate r_t^f, the monetary policy directly influences the required return on capital and, therefore, the price of capital q_t^K. Formally, interest rate policy alone is adequate in stabilizing the economy when government bonds are in zero net supply if the nominal rate is perfectly aligned with the natural rate.

Proposition 10 *If bonds are in zero net supply, the flexible price equilibrium with zero inflation can be implemented with the following policy*

$$i_t = i_t^n, \quad \tau_t^K = 0.$$

The natural interest rate i_t^n is defined as

$$i_t^n = \rho + g_t^n - \tilde{\sigma}_t^2,$$

where g_t^n is the steady state growth rate of the aggregate capital stock (see Appendix C.4).

In contrast, when government bonds are in positive net supply, equation (3.29) shows that interest rates only affect the initial recession in q_t^K if they affect household portfolios. However, from the bond evaluation equation (3.23), we see that the household portfolio and the risk premium on capital depend only on the level of uncertainty $\tilde{\sigma}_t$ and $\check{s}_t$, the surplus-debt ratio, which is only affected by the tax rate τ_t^K (and the relative price ϑ_t). When the tax rate is unresponsive to shocks, the effects of interest rate changes are offset by movements in bond growth. As has been summarized in Proposition 9, interest rate policy can only affect the portfolio of the households if it induces responses in fiscal policy (distortionary taxes).

Amplification. More importantly, even under the same monetary policy, the effects of uncertainty shocks are significantly amplified in the presence of nominal bonds. To test this prediction quantitatively, we numerically solve the model with $B_t = 0$ and compare the implied impulse response functions with the baseline model with $B_t > 0$. We specify a Taylor rule for the model without safe bonds

$$i_t = i^* + \varphi(\pi_t - \pi^*).$$

To ensure that monetary policy responses do not drive the results of the comparison, we feed the same paths of $\{i_t\}$ into the baseline model when computing the impulse response functions.[26] Further, the government's interest payments become zero when $B_t = 0$. To maintain comparability, we also impose $\check{s}_t = 0$ on the baseline model in this exercise.

Figure 3.2 compares the impulse response functions of the two models following the same uncertainty shocks and nominal rate responses. As shown in the figure, the model with nominal bonds generates deeper recessions in capital price and output, as well as greater deflationary pressure. We then conclude that the interaction between nominal rigidity and household portfolio adjustment constitutes a powerful amplification mechanism.

[26]Technically, we construct a mapping of uncertainty to the nominal rate $i_t = i(\tilde{\sigma}_t)$ and replace equation (3.12) with this mapping.

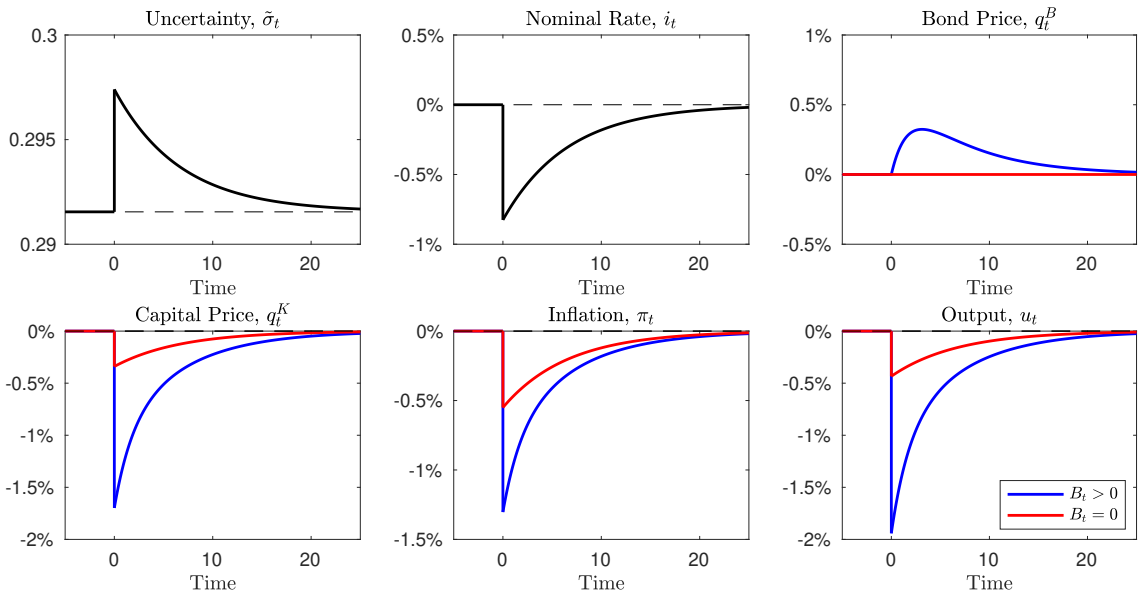


Figure 3.2. Impulse Response Function Comparison

3.5 Fiscal Policy

In previous sections, we have demonstrated how nominal rigidity leads to amplified recessions in the presence of nominal government bonds and how interest rate policy alone is inadequate for price stabilization. In this section, we examine how appropriately designed monetary and fiscal policy can stabilize an economy with uncertainty shocks and even implement constrained efficient allocations.

3.5.1 Non-distortionary Fiscal Policy

First, we show how fiscal policy can be utilized to stabilize uncertainty-induced fluctuations. Distortionary fiscal policy (e.g., taxes on capital) has very powerful effects on our economy as it changes both the short-term dynamics and the steady state. This section instead focuses on non-distortionary fiscal policies. Discussions on the design of distortionary taxes will be deferred to Section 3.5.2.

Lump-sum Taxes. Assume that in addition to the capital tax, each household also has to pay $\tau_t K_t \mathrm{d}t$ units of final goods as taxes over the time interval $[t, t + \mathrm{d}t]$. Since the mass of households is one, the aggregate flow of real lump-sum taxes is also $\tau_t K_t \mathrm{d}t$. The govern-

ment can also make transfers to the households by selecting a $\tau_t < 0$. Further, we assume that the market for aggregate risk is complete.

Assumption 8 *The households can write contracts on aggregate variables.*

In this case, the households trade claims on future lump-sum taxes with each other. Importantly, the amount of capital tax paid by an individual household depends on its capital stock, which is subject to an idiosyncratic risk. Therefore, unlike the lump-sun tax, the capital tax is not tradable.

The government is long in the tax claims while the households are collectively short. Let $q_t^\tau K_t$ be the value of all tax claims at time t and $\mathrm{d}q_t^\tau = \mu_t^{q,\tau} q_t^\tau \mathrm{d}t$.[27] The return on the tax claims is

$$\mathrm{d}R_t^\tau = \frac{\tau_t}{q_t^\tau}\mathrm{d}t + \frac{\mathrm{d}(q_t^\tau K_t)}{q_t^\tau K_t} = \left(\frac{\tau_t}{q_t^\tau} + g_t + \mu_t^{q,\tau}\right)\mathrm{d}t.$$

In equilibrium, the price of tax claims q_t^τ is pinned down by a no-arbitrage condition between bonds and tax claims and is ultimately a function of *future* tax rates,

$$q_t^\tau = q^\tau(\{\tau_s\}_{s=t}^\infty).$$

Essentially, the government expands the set of safe assets by introducing a tradable lump-sum tax. The total supply of idiosyncratic-risk-free assets to the household sector is now $q_t^G K_t = (q_t^B - q_t^\tau)K_t$. The dynamics of the economy are the same as before but with a new safe asset (i.e., with bonds $q_t^B K_t$ replaced by total government liabilities $q_t^G K_t$).[28] Instead of choosing a portfolio between capital and bonds, the households now allocate their portfolio between capital and all government liabilities. Importantly, the price of all safe assets q_t^G is no longer sticky, and the government can potentially stabilize the economy by choosing future tax rates $\{\tau_s\}_{s=t}^\infty$ such that q_t^G is at its flexible-price level.

Proposition 11 *Suppose that the rate of distortionary tax is a function of $(\tilde{\sigma}_t, \vartheta_t)$ only. For any such tax schemes, the associated zero-inflation flexible price equilibrium can be implemented if the*

[27] We consider a case where the future path of lump-sum taxes $\{\tau_t\}$ is deterministic, so the value of tax claims does not bear any aggregate risk.

[28] See Appendix C.6 for a formal discussion.

nominal rate i_t and lump-sum taxes $\{\tau_s\}_{s=t}^{\infty}$ satisfy

$$i_t = g_t^n, \quad q_t^{B,flex} = q_t^B - q^\tau(\{\tau_s\}_{s=t}^{\infty}).$$

The price of tax claims $q^\tau(\{\tau_s\}_{s=t}^{\infty})$ is increasing in future tax rates. Its functional form, together with the price of safe assets under flexible prices $q_t^{B,flex}$ and the formula for the steady-state capital growth rate g_t^n, is derived in Appendices C.4 and C.6.

As discussed in Section 3.3, the steady-state price of safe assets increases after a positive uncertainty shock. Without lump-sum taxes, the appreciation of safe bonds is achieved over time through disinflation. With lump-sum taxes and a complete market for aggregate risk, the government can rapidly boost the total supply of safe assets by committing to lower taxes (or higher transfers) in the future.

3.5.2 Optimal Capital Tax

Welfare and Constrained Efficiency. To study optimal monetary-fiscal policy in this economy, we first derive the value function of the households. The consumption of an individual household can be written as

$$c_t = \underbrace{(au_t - \iota_t)K_t}_{\text{aggregate consumption}} \times \underbrace{\frac{n_t}{N_t}}_{\text{wealth share}}, \tag{3.35}$$

where $N_t = (q_t^B + q_t^K)K_t$ is the total net worth of the economy. Since the households are homogeneous, the wealth share of any individual household is only subject to the idiosyncratic risk in its capital accumulation process. Specifically,

$$\frac{\mathrm{d}(n_t/N_t)}{n_t/N_t} = \frac{\mathrm{d}(k_t/K_t)}{k_t/K_t} = (1-\vartheta_t)\tilde{\sigma}_t \mathrm{d}\tilde{Z}_t.$$

Then, the household value function can be obtained by taking logs on both sides of the equation (3.35) and integrating them over time.

Proposition 12 *The households' value function can be written as*

$$
\begin{aligned}
V_0 &= \mathbb{E}_0\left[\int_0^\infty e^{-\rho t}\log c_t \mathrm{d}t\right] \\
&= \underbrace{\mathbb{E}_0\left[\int_0^\infty e^{-\rho t}\log(au_t-\iota_t)\mathrm{d}t\right]}_{\text{"marginal productivity"}} + \underbrace{\mathbb{E}_0\left[\frac{1}{\rho}\int_0^\infty e^{-\rho t}\left[g(u_t,\iota_t)-\frac{(1-\vartheta_t)^2\tilde{\sigma}_t^2}{2}\right]\mathrm{d}t\right]}_{\text{growth-risk trade-off}} + \textit{constant}.
\end{aligned}
$$

The household's welfare depends first on a "marginal productivity" term which determines the fraction of aggregate capital stock that is transformed to consumption goods. The household also faces a growth-risk trade-off. While holding a portfolio more concentrated in safe assets reduces the household's exposure to idiosyncratic risk, it also lowers the equilibrium price of capital and investment (see equation (3.27)).

The constrained-optimal allocation is defined as the solution to the following problem where a planner maximizes the household value function subject to the market clearing constraints and Tobin's q equation

$$
\begin{aligned}
\max_{u_t,\iota_t,\vartheta_t} V_0 \quad \text{s.t.} \quad & au_t-\iota_t=\rho(q_t^B+q_t^K), \quad \vartheta_t=\frac{q_t^B}{q_t^K+q_t^B}, \\
& \Phi'(\iota_t)=1/q_t^K.
\end{aligned} \tag{3.36}
$$

It is assumed that the government cannot directly distort the households' investment decisions, so Tobin's q equation appears as a constraint. It is apparent that the planner's problem collapses into a static problem at each time.

As is common in models with incomplete markets, the competitive equilibrium in our model features *pecuniary externality*. Specifically, the households fail to fully internalize the impacts of their decisions on aggregate prices such as q_t^K. Denote the solution to the planner's problem by $\iota_t^o, u_t^o, \vartheta_t^o$. With the parameter values in Table 3.1, the competitive equilibrium yields in steady state

$$
\iota_t > \iota_t^o, \qquad u_t > u_t^o, \qquad \vartheta_t < \vartheta_t^o.
$$

That is, the competitive equilibrium exhibits insufficient risk sharing and excessive invest-

ment and production and is therefore constrained-inefficient.

Replicating the Optimal Portfolio Weight. In this section, we show that appropriately designed fiscal policy can replicate the constrained-efficient portfolio weight ϑ_t^o. The procedure takes three steps. First, solve for ϑ_t^o from the first-order conditions of the planner's problem. Then, obtain its drift $(\mu_t^\vartheta)^o$ by applying Ito's Lemma. Third, plug $(\mu_t^\vartheta)^o$ into the bond evaluation equation (3.23) to get the appropriate surplus-debt ratio $\check{s}_t$ and tax rate on capital.

Figure 3.3 plots ϑ_t^o and the optimal τ_t^K as a function of uncertainty $\tilde{\sigma}_t$. The constrained-efficient portfolio puts more weight on bonds when uncertainty is high due to stronger precautionary motives of the households. Meanwhile, the optimal tax rate is also increasing with uncertainty. When uncertainty is low, the planner subsidizes capital to encourage risk-taking, while when uncertainty is high, the planner taxes capital to achieve better insurance against idiosyncratic risk.

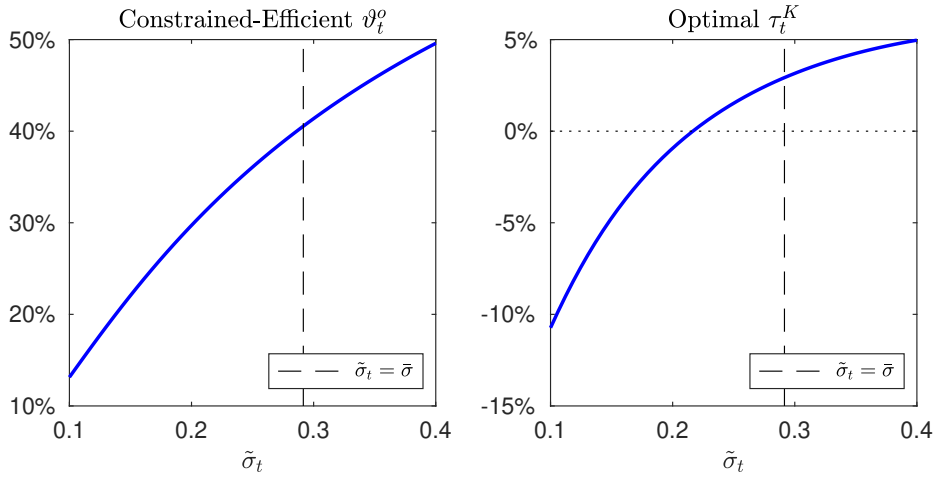


Figure 3.3. Optimal capital tax under parameterization in Table 3.1

Apart from the pecuniary externality in optimal choice, the economy also sustains welfare loss from monopolistic competition among the intermediary goods firms. To tackle the market power of intermediary goods producers, the government needs additional tools, where the New Keynesian literature typically assumes a subsidy on the intermediary goods producers (Woodford, 2003; Galí, 2008). The same type of output subsidy also

works in our model. We relegate the details to Appendix C.5.

To restore constrained efficiency, the government can take the following two steps. First, it can eliminate the distortions associated with nominal rigidity using a lump-sun tax as described in Proposition 11. Second, it can choose distortionary taxes (and subsidies on intermediary goods firms) optimally so the flexible-price equilibrium is constrained-efficient.

3.6 Long-term Bonds

So far, we have assumed that the government issues nominal bonds with infinitesimally short duration. As infinitesimally short-term nominal bonds are essentially the same thing as money, this setting requires the nominal price of bonds to be always 1. As a consequence, when the price level is sticky, then so must the real value of government bonds – and thus safe assets – in the economy.

In this section, we generalize our model to allow for long-duration government bonds. Then the tight link between the price level and the market value of safe assets breaks down, yet our conclusions are not radically altered:

First, we show that even when the government issues long-term debt, the determinants of portfolio choice and the nominal wealth share ϑ_t remain essentially unchanged. As a consequence, nominal interest rate policy is still unable to affect portfolio choice directly (as opposed to indirectly through its fiscal consequences). Conditional on the safe asset value q_t^B, aggregate demand remains determined independently of nominal variables.

Second, with long-term bonds, there is a relative price between bonds (safe assets) and money that can adjust instantaneously, even under sticky prices. The adjustment is tightly linked to the path of future policy rates by a condition that largely resembles the expectations hypothesis. This enlarges the power of monetary policy to stabilize aggregate demand on shock impact, as it can now move the safe asset value q_t^B instantaneously by adjusting the path of future policy rates. However, with the single interest rate policy instrument, monetary policy is generally unable to simultaneously close the gap between safe asset demand and supply on the impact of an uncertainty shock and keep the nominal

rate close to the natural rate so as not to introduce future distortions in price setting.

The setup of our generalized model is as before, except that we replace the assumptions on government bonds: instead of floating-rate bonds, the government issues bonds with a geometric maturity structure with duration $1/\lambda$ where $\lambda > 0$ is a model parameter. Specifically, each bond has a face value b_t that decays over time at rate λ, and the bond makes continuous payments $1/P_t \cdot \lambda b_t \mathrm{d}t$ of final goods to its holder.[29] We continue to assume that monetary policy controls the nominal short rate i_t.[30] In the limit $\lambda \to \infty$, this setup collapses to our baseline model.

We relegate a more detailed description of the generalized model as well as all model derivation steps to Appendix C.7. Here, we only present the main conclusions.

As before, let B_t be the face value of the total stock of outstanding government bonds and μ_t^B its growth rate. Let furthermore P_t^B denote the nominal bond price so that $q_t^B K_t = P_t^B B_t / P_t$ is the real value of the bond stock. The government's flow budget constraint in this setting can be written as

$$\underbrace{\lambda \left(\frac{1}{P_t^B} - 1 \right)}_{=: \bar{i}_t} - \mu_t^B = \check{s}_t,$$

where as before, $\check{s}_t = \frac{\tau_t^K q_t^K}{q_t^B}$ is the surplus-to-debt ratio. The only difference to our baseline model is that nominal net payouts to bondholders are not equal to i_t, but to a variable $\bar{i}_t$ that turns out to be a type of smoothed version of future interest rates i_t.

As in our baseline model, only the difference $\bar{i}_t - \mu_t^B$ enters the return on bonds and, hence, it is again only the fiscal policy variable $\check{s}_t$ that affects portfolio choice between bonds and capital. In fact, Propositions 8 and 9 about the determination of the bond wealth share ϑ_t and the separation of portfolio choice from nominal variables, including the policy rate i_t, remain valid here.[31]

The important change is that while the nominal price level P_t is sticky, the nominal bond price P_t^B is not. As a consequence, the (scaled) safe asset value $q_t^B = P_t^B \frac{B_t}{P_t K_t}$ is no

[29] Assuming a settlement in goods indexed to P_t instead of money avoids the need to also introduce money into the model, but is otherwise without loss of generality.

[30] The nominal short rate equals the nominal interest rate on a hypothetical zero-net-supply bond with infinitesimal duration.

[31] As a corollary, the natural (flexible price) allocation is also unaffected by the bond duration parameter λ.

longer a purely backward-looking state variable. Instead, only its second factor, $\bar{q}_t^B := \frac{B_t}{P_t K_t}$, is a state. Its evolution can be written as

$$\frac{\mathrm{d}\bar{q}_t^B}{\bar{q}_t^B} = \left(\bar{i}_t - \check{s}_t - \pi_t - g_t\right) \mathrm{d}t \tag{3.37}$$

in full analogy to equation (3.31), except that the policy instrument i_t is here replaced with $\bar{i}_t$.

Finally, the nominal bond price P_t^B can be written in terms of $\bar{i}_t$. The actual safe asset value q_t^B is then related to the state variable $\bar{q}_t^B$ by the identity

$$q_t^B = \frac{\lambda}{\lambda + \bar{i}_t} \bar{q}_t^B. \tag{3.38}$$

The link between the state variable $\bar{q}_t^B$ and the safe asset value q_t^B is thus solely determined by $\bar{i}_t$. The shorter the debt duration (larger λ), the larger movements in $\bar{i}_t$ are required to move q_t^B away from $\bar{q}_t^B$ in order to stabilize aggregate demand.[32]

In sum, all model equations are the same as in our baseline model, except that i_t is everywhere replaced with $\bar{i}_t$ and q_t^B now is the product of a backward-looking state term $\bar{q}_t^B$ and a "jump" term that only depends on $\bar{i}_t$. We show in the appendix that $\bar{i}_t$, in turn, is related solely to the path of future policy rates $\{i_s\}_{s \geq t}$. Without aggregate risk in policy rates, this relationship can be represented as

$$\bar{i}_t = \int_t^\infty \left(\lambda + \bar{i}_s\right) e^{-\int_t^s \left(\lambda + \bar{i}_{s'}\right) \mathrm{d}s'} i_s \mathrm{d}s,$$

i.e., $\bar{i}_t$ is essentially a weighted average of future nominal short rates. The same intuition remains valid when interest rates are stochastic, although the formal relationship is then more complex. We can thus work directly with $\bar{i}_t$ instead of i_t as a monetary policy instrument.[33]

[32] While not the focus of this paper, the equation also shows that the impact of a lower bound on nominal interest rates for aggregate demand stabilization is more severe, the shorter is the duration of government debt: for larger λ, monetary policy needs to engineer a smaller (more negative) weighted-average interest rate $\bar{i}_t$ to offset a shortfall in aggregate demand.

[33] There are technical restrictions on which paths for $\bar{i}$ are attainable. However, one can show that any bounded path that satisfies $\inf_{t \geq 0} \bar{i}_t > \lambda$ is always feasible.

As discussed in Sections 3.3 and 3.5, the inability of monetary policy to stabilize aggregate demand on the impact of an uncertainty shock in our baseline model is due to the fact that there $q_t^B = \bar{q}_t^B$ is a state that does not react to monetary policy. Here, monetary policy $\bar{i}_t$ can affect q_t^B directly through equation (3.38). Nevertheless, this is insufficient to implement the flexible price allocation (or any other desired path of q^B). The reason is that with the single instrument $\bar{i}_t$, policy cannot simultaneously implement the flexible-price safe asset value q_t^B through equation (3.38) to close the output gap in the short run and set the nominal rate to the natural rate to make the state evolution (3.37) consistent with zero inflation in the long run. This is because the implementation of each policy objective constrains the full path of future policy rates, but the requirements to achieve both objectives simultaneously are usually incompatible, except by coincidence.

To illustrate this point clearly, we consider a very simple example: suppose we start the economy in a steady state with constant $\tilde{\sigma}$ and consider an unanticipated shock that permanently raises $\tilde{\sigma}$ at $t = 0$. For unchanged fiscal policy $\check{s}$,[34] the permanent shock leads to a (one-time) permanent increase in ϑ and the flexible-price level of q^B. For simplicity, restrict attention to a simple monetary policy that changes the nominal rate i only once to a new level and keeps it there forever (then automatically $\bar{i} = i$).[35] Monetary policy could to do one of the following:

(1) Set $i = i^n$ equal to the new (constant) natural rate. This policy ensures that q_t^B converges to the flexible price steady-state value, and there is no distortion from sticky prices in the long run. Given this policy, equation (3.38) then implies that the safe asset value on shock impact jumps to

$$q_0^B = \frac{\lambda}{\lambda + i^n} \bar{q}_0^B.$$

This happens to be equal to the new flexible price steady-state level of q^B for only a single specific value of the parameter λ.

[34] An identical conclusion would hold for a one-time change in $\check{s}$ to a new constant value to implement the optimal new steady state policy

[35] The limited room for monetary policy in this example is *not* due to this additional assumption. Allowing $\{i_t\}$ to follow an arbitrary path would not affect the conclusion.

(2) Set i to produce a jump in q^B at $t = 0$ that moves q_0^B immediately to the new flexible price steady state $q^{B,flex}$. This implies that at the time the shock hits, there is no output gap. By equation equation (3.38), the required interest rate is

$$i = \lambda \left(\bar{q}_0^B / q^{B,flex} - 1 \right).$$

This required rate happens to be equal to the natural rate i^n for only a single specific value of λ. Otherwise, this policy introduces a drift into the state variable $\bar{q}_t^B$ so that both $\bar{q}^B$ and q^B move over time. Thus q^B starts to deviate from its flexible price level in future periods and an output gap opens up then.

Except for one specific bond duration parameter λ, the policy instruments i required for (1) and (2) thus differ. Unless λ happens to be just right, the policy cannot simultaneously generate zero output gaps and zero inflation.[36]

3.7 Conclusions

In this paper, we present a New-Keynesian model with idiosyncratic risk and nominal government bonds. We highlight a new transmission mechanism of uncertainty shocks through household portfolios. As uncertainty builds up, households rebalance their portfolios towards government bonds, which leads to overshooting capital prices when prices are sticky. The drop in the price of capital further depresses aggregate demand and results in declines in economic activities. Monetary policy alone has a limited impact on household portfolios without coordinated fiscal policy. Finally, we show that the government can stabilize the economy with non-distortionary taxes and restore constrained efficiency with distortionary taxes.

[36] Moreover, that "coincidence level" of debt maturity depends on the size of the shock. Generally, it is thus not possible to set λ ex-ante such that (1) and (2) coincide ex-post.

Appendix A

Appendix to Chapter 1

A.1 Supplementary Figures

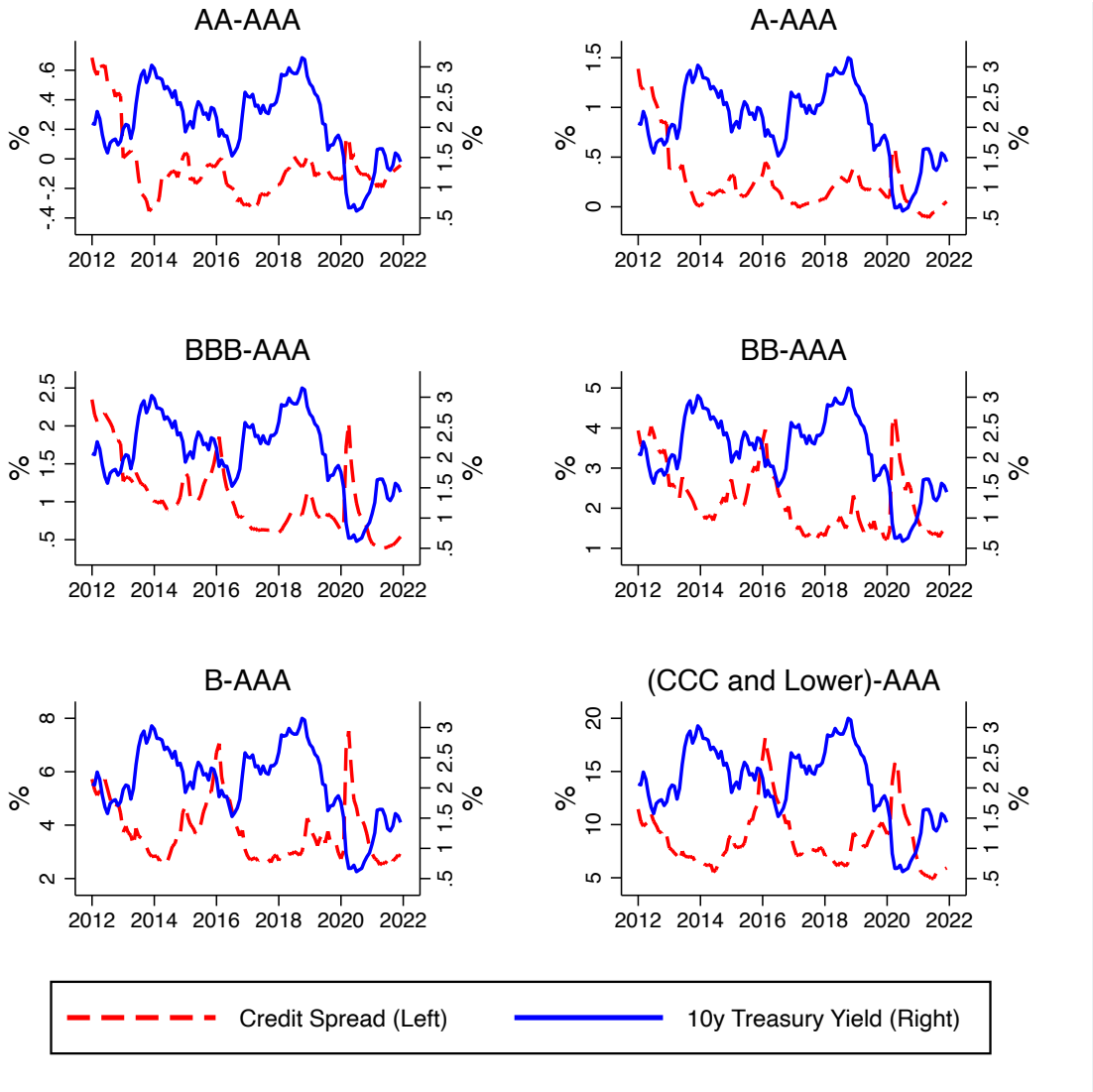


Figure A.1. **The 10-year Treasury Yield and Bond Credit Spreads (2010-2019).** *This figure plots the 10-year Treasury yield and the spreads of corporate bond indices relative to the index of AAA bonds. The 10-year Treasury yield is shown as the solid blue line and corresponds to the y-axis on the right-hand side. The credit spreads are shown as dashed red lines and correspond to the y-axis on the left-hand side.*

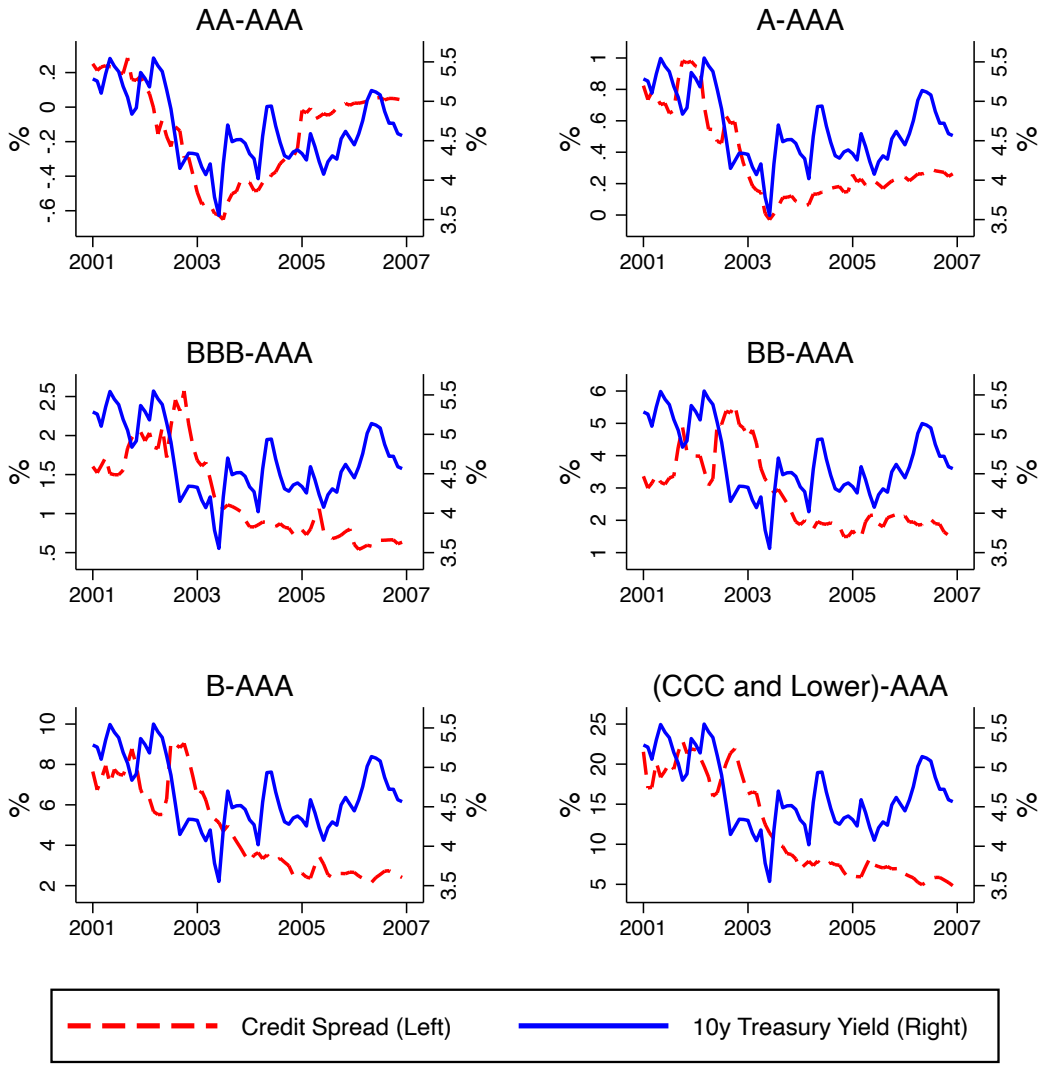


Figure A.2. **The 10-year Treasury Yield and Bond Credit Spreads (2001-2007).** *This figure plots the 10-year Treasury yield and the spreads of corporate bond indices relative to the index of AAA bonds. The 10-year Treasury yield is shown as the solid blue line and corresponds to the y-axis on the right-hand side. The credit spreads are shown as dashed red lines and correspond to the y-axis on the left-hand side.*

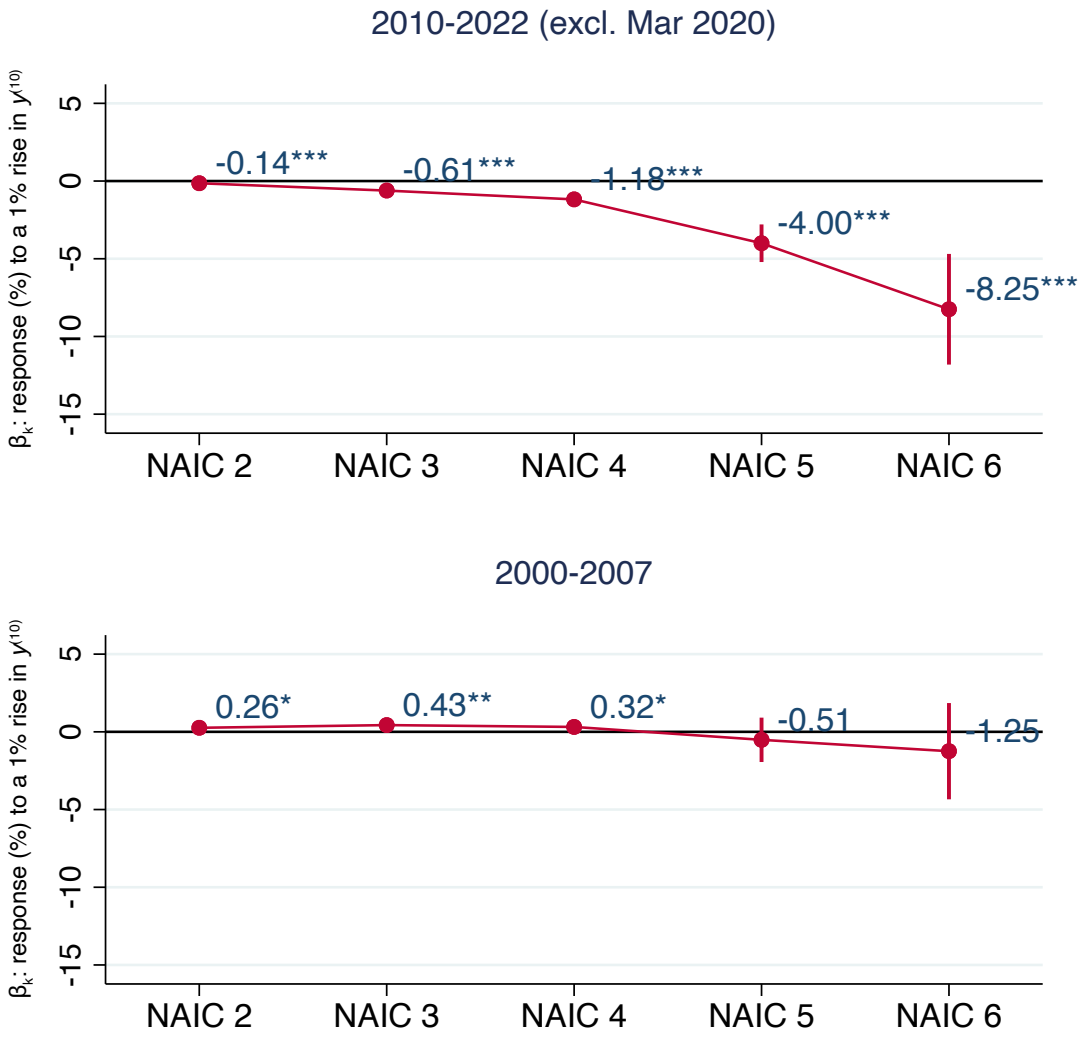


Figure A.3. **Credit Spread Responses (Controlling for CDS Spreads).**

This figure plots the coefficients β_k estimated from regression (1.2), controlling for the trading volume, outstanding amount, maturity, duration, credit ratings, coupon amount, and coupon frequency of each bond, and the recent default rate and average CDS spreads of each NAIC category. Both corporate bond yields and the Treasury yield are in percentage points. The top panel shows results for the post-crisis sample, while the bottom panel shows results for the pre-crisis sample. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

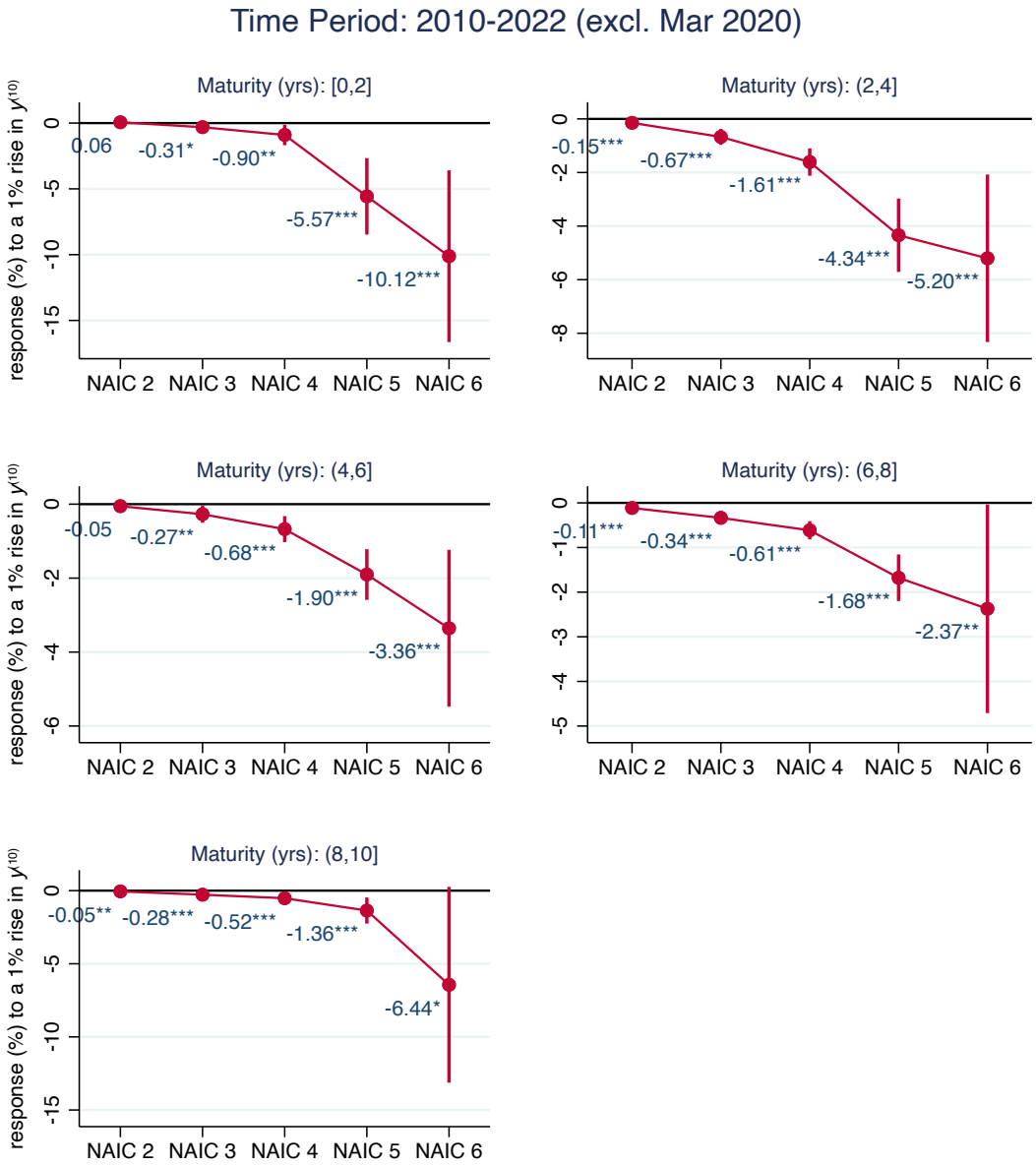


Figure A.4. **Credit Spread Responses in Different Maturity Groups (post-2008).** *This figure plots the coefficients β_k estimated from regression (1.2), controlling for the trading volume, outstanding amount, maturity, duration, credit ratings, coupon amount, and coupon frequency of each bond, and the recent default rate and average CDS spreads of each NAIC category. Both corporate bond yields and the Treasury yield are in percentage points. The different panels estimate coefficients for bonds in different maturity segments. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels.* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

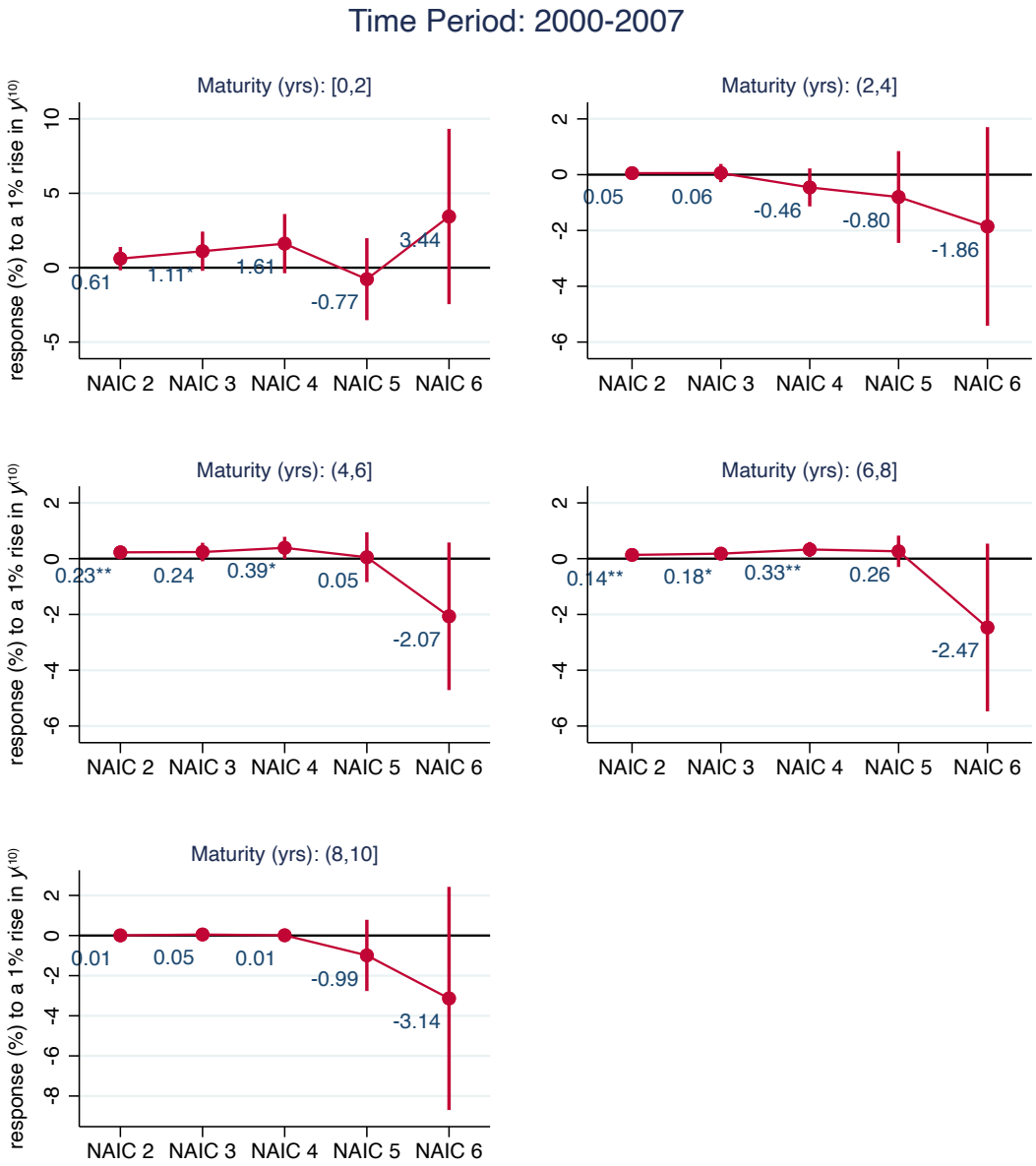


Figure A.5. **Credit Spread Responses in Different Maturity Groups (pre-2008).** *This figure plots the coefficients β_k estimated from regression (1.2), controlling for the trading volume, outstanding amount, maturity, duration, credit ratings, coupon amount, and coupon frequency of each bond, and the recent default rate and average CDS spreads of each NAIC category. Both corporate bond yields and the Treasury yield are in percentage points. The different panels estimate coefficients for bonds in different maturity segments. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels.* $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

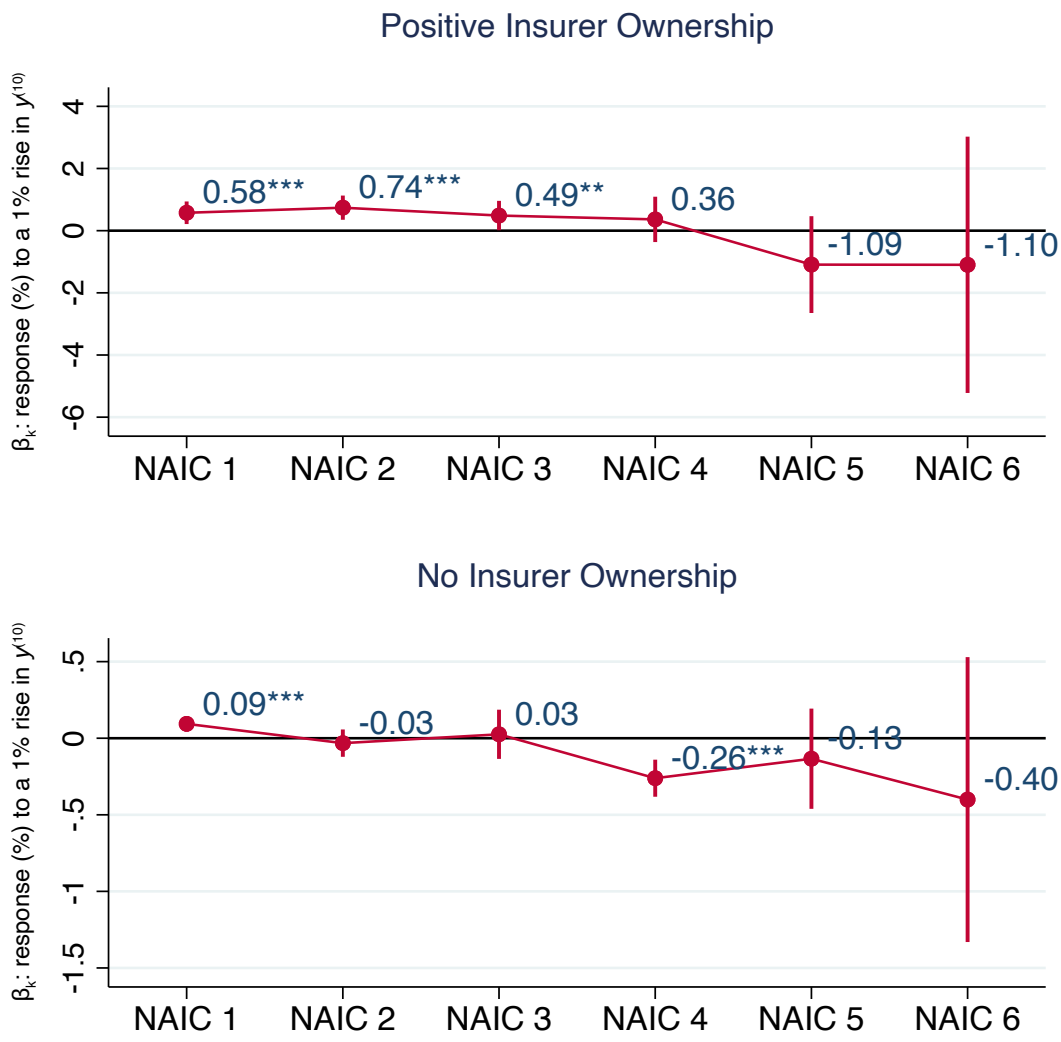
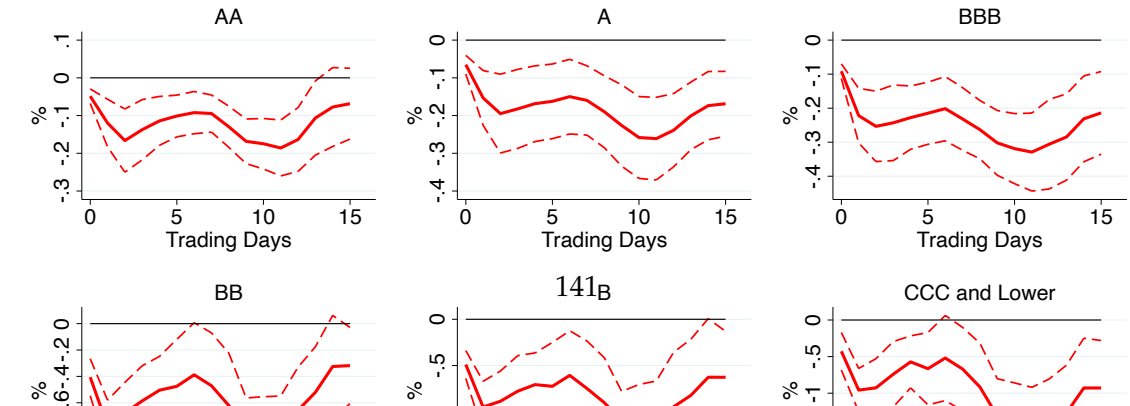


Figure A.6. **Pass-through by Life Insurance Ownership (pre-2008).**

This figure plots the coefficients β_k estimated from regression (1.5) for the period of 2000-2007, controlling for the trading volume, outstanding amount, maturity, duration, credit ratings, coupon amount, and coupon frequency of each bond, and the recent default rate of each NAIC category. Both corporate bond yields and the Treasury yield are in percentage points. The top panel shows estimates for β_k^1, while the bottom panel shows estimates for β_k^0. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.



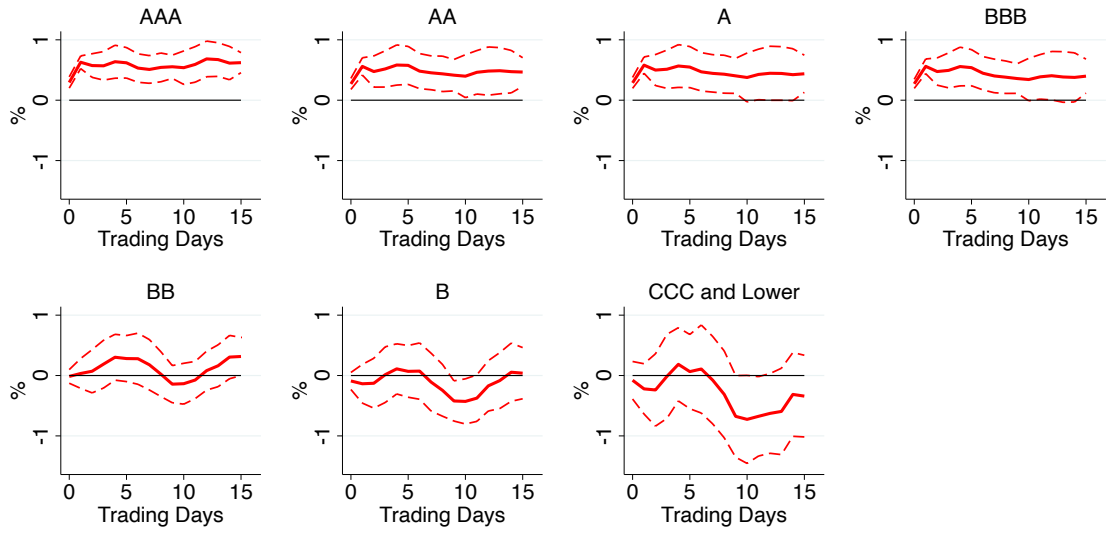


Figure A.8. **Impulse Responses of Yield Indices (2010-2022).**

This figure plots the cumulative responses of yield indices to a 1% increase in the 10-year Treasury yield and 90% confidence intervals based on Newey-West standard errors with a maximum lag of 30 trading days.

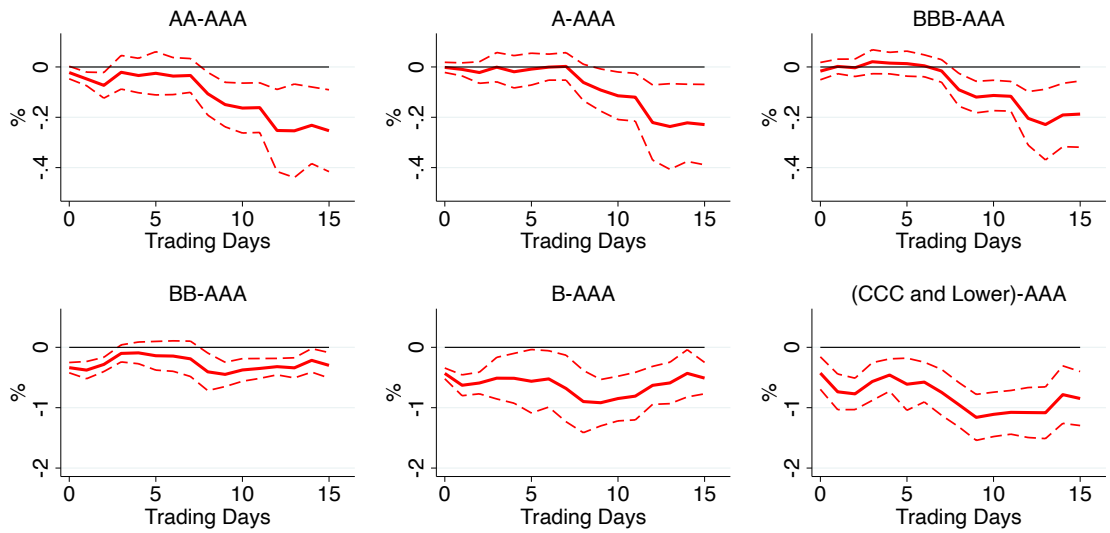


Figure A.9. **Impulse Responses of Credit Spreads (2010-2022).**

This figure plots the cumulative responses of credit spreads to a 1% increase in the 10-year Treasury yield and 90% confidence intervals based on Newey-West standard errors with a maximum lag of 30 trading days. ***I now include changes in the 1-month Treasury yield and average CDS spreads around 2-day FOMC windows as controls.*** *In particular, the regression specification is*

$$\begin{aligned} Spread^{k}_{t+h} - Spread^{k}_{t-1} = \alpha_h &+ \beta_h \left(\Delta y^{(10)}_t \Big|_{FOMC} \right) \\ &+ \gamma_h \left(\Delta y^{(1m)}_t \Big|_{FOMC} \right) \\ &+ \delta_h \left(\Delta \left(CDS\ Spread \right)^{AAA}_t \Big|_{FOMC} \right) \\ &+ \zeta_h \left(\Delta \left(CDS\ Spread \right)^{Rating\ k}_t \Big|_{FOMC} \right) + \varepsilon_{t,h}. \end{aligned}$$

Here $\left(\Delta y^{(1m)}_t \Big|_{FOMC} \right)$ *are the changes in the 1-month Treasury yield around 2-day FOMC windows.* $\left(\Delta \left(CDS\ Spread \right)^{AAA}_t \Big|_{FOMC} \right)$ *are the changes in the average CDS spread of AAA bonds around 2-day FOMC windows.* $\left(\Delta \left(CDS\ Spread \right)^{Rating\ k}_t \Big|_{FOMC} \right)$ *are the changes in the average CDS spread of rating k bonds around 2-day FOMC windows.*

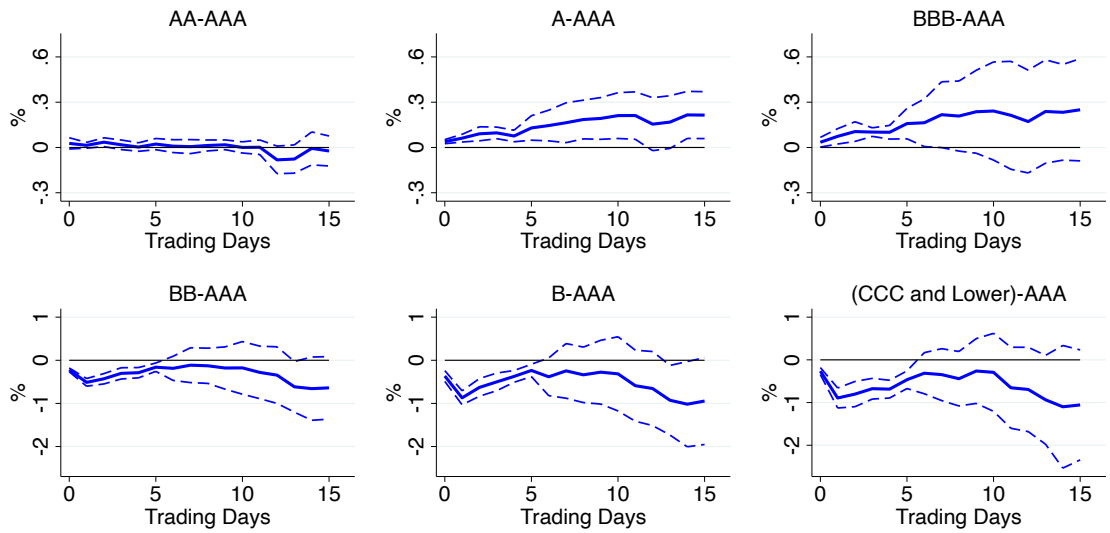


Figure A.10. **Impulse Responses of Credit Spreads (1997-2007).**

This figure plots the cumulative responses of credit spreads to a 1% increase in the 10-year Treasury yield and 90% confidence intervals based on Newey-West standard errors with a maximum lag of 30 trading days. ***I now include changes in the 1-month Treasury yield and average CDS spreads around 2-day FOMC windows as controls.*** *In particular, the regression specification is*

$$\begin{aligned} Spread^{k}_{t+h} - Spread^{k}_{t-1} = \alpha_h &+ \beta_h \left(\Delta y^{(10)}_t \Big|_{FOMC} \right) \\ &+ \gamma_h \left(\Delta y^{(1m)}_t \Big|_{FOMC} \right) \\ &+ \delta_h \left(\Delta \left(CDS\ Spread \right)^{AAA}_t \Big|_{FOMC} \right) \\ &+ \zeta_h \left(\Delta \left(CDS\ Spread \right)^{Rating\ k}_t \Big|_{FOMC} \right) + \varepsilon_{t,h}. \end{aligned}$$

Here $\left(\Delta y^{(1m)}_t \Big|_{FOMC} \right)$ *are the changes in the 1-month Treasury yield around 2-day FOMC windows.* $\left(\Delta \left(CDS\ Spread \right)^{AAA}_t \Big|_{FOMC} \right)$ *are the changes in the average CDS spread of AAA bonds around 2-day FOMC windows.* $\left(\Delta \left(CDS\ Spread \right)^{Rating\ k}_t \Big|_{FOMC} \right)$ *are the changes in the average CDS spread of rating k bonds around 2-day FOMC windows.*

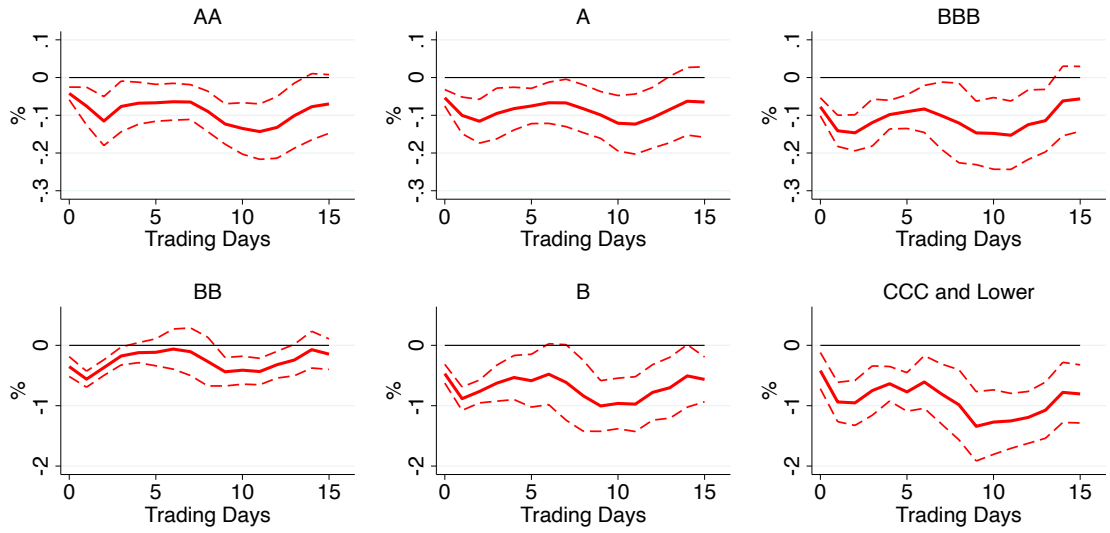


Figure A.11. **Impulse Responses of Spreads Relative to Treasuries (2010-2022).** *This figure plots the cumulative responses of credit spreads relative to Treasury securities to a 1% increase in the 10-year Treasury yield and 90% confidence intervals based on Newey-West standard errors with a maximum lag of 30 trading days.* ***I now include changes in the 1-month Treasury yield and average CDS spreads around 2-day FOMC windows as controls.*** *In particular, the regression specification is*

$$\begin{aligned} Spread^{k}_{t+h} - Spread^{k}_{t-1} = \alpha_h &+ \beta_h \left(\Delta y^{(10)}_t \Big|_{FOMC} \right) \\ &+ \gamma_h \left(\Delta y^{(1m)}_t \Big|_{FOMC} \right) \\ &+ \zeta_h \left(\Delta \left(CDS\ Spread \right)^{Rating\ k}_t \Big|_{FOMC} \right) + \varepsilon_{t,h}. \end{aligned}$$

Here $\left(\Delta y^{(1m)}_t \Big|_{FOMC} \right)$ *are the changes in the 1-month Treasury yield around 2-day FOMC windows.* $\left(\Delta \left(CDS\ Spread \right)^{Rating\ k}_t \Big|_{FOMC} \right)$ *are the changes in the average CDS spread of rating k bonds around 2-day FOMC windows.*

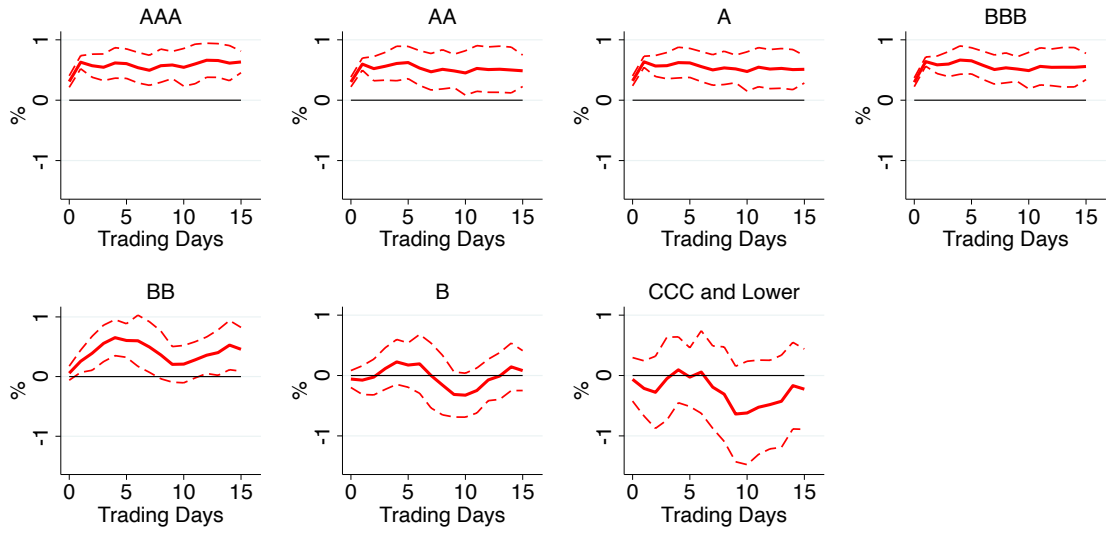


Figure A.12. **Impulse Responses of Yield Indices (2010-2022).**

This figure plots the cumulative responses of yield indices to a 1% increase in the 10-year Treasury yield and 90% confidence intervals based on Newey-West standard errors with a maximum lag of 30 trading days. ***I now include changes in the 1-month Treasury yield, and average CDS spreads around 2-day FOMC windows as controls.*** *In particular, the regression specification is*

$$\begin{aligned} Yield^{k}_{t+h} - Yield^{k}_{t-1} = \alpha_h &+ \beta_h \left(\Delta y^{(10)}_t \Big|_{FOMC} \right) \\ &+ \gamma_h \left(\Delta y^{(1m)}_t \Big|_{FOMC} \right) \\ &+ \zeta_h \left(\Delta \left(CDS\ Spread \right)^{Rating\ k}_t \Big|_{FOMC} \right) + \varepsilon_{t,h}. \end{aligned}$$

Here $\left(\Delta y^{(1m)}_t \Big|_{FOMC} \right)$ *are the changes in the 1-month Treasury yield around 2-day FOMC windows.* $\left(\Delta \left(CDS\ Spread \right)^{Rating\ k}_t \Big|_{FOMC} \right)$ *are the changes in the average CDS spread of rating k bonds around 2-day FOMC windows.*

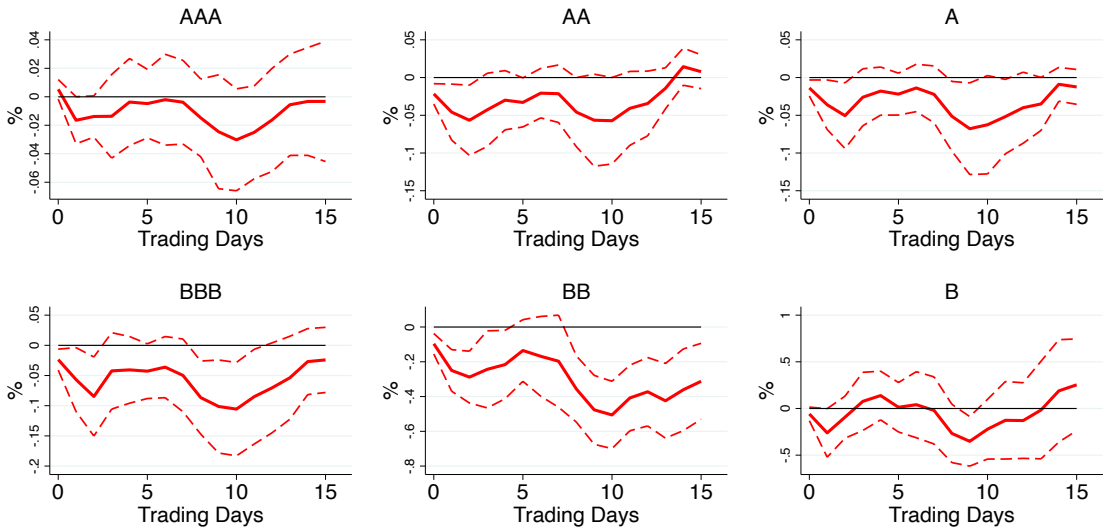


Figure A.13. **Impulse Responses of CDS Spreads (2010-2022).**

This figure plots the cumulative responses of the average CDS spreads of bonds in different risk categories to a 1% increase in the 10-year Treasury yield and 90% confidence intervals based on Newey-West standard errors with a maximum lag of 30 trading days.

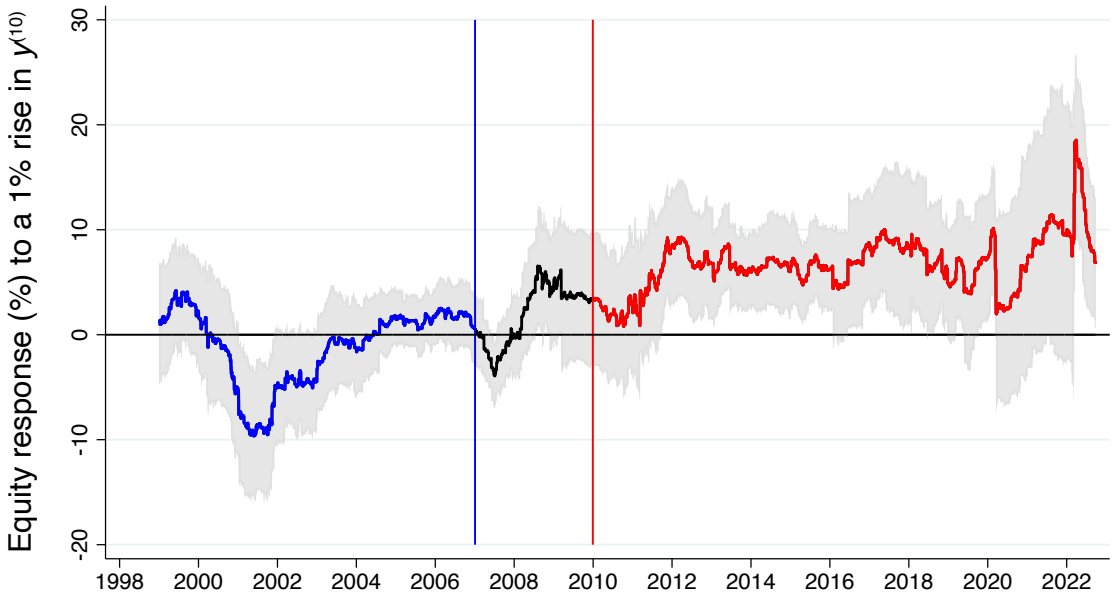


Figure A.14. **Life Insurers' Interest Rate Risk Exposure Over Time.**

This figure plots the two-year rolling estimates of β from regression (1.4), controlling for the market return and changes in the one-month Treasury yield. The blue segment indicates the pre-Crisis sample, and the red segment indicates the post-Crisis sample. The stock returns are winsorized at 2.5% and 97.5% thresholds. The shaded area indicates 95% confidence intervals using robust standard errors.

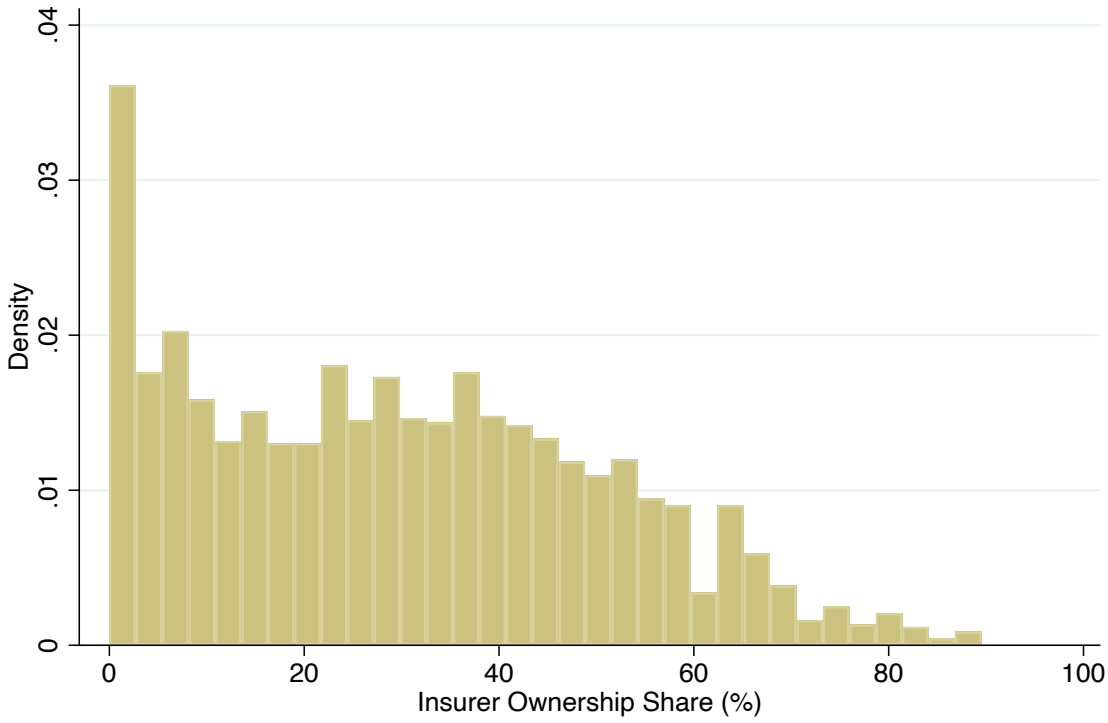


Figure A.15. **Insurer Ownership in the Cross-section of Firms.**

This histogram shows the average bond ownership by insurers (φ_j^{Ins}) in the cross-section of Compustat firms at the beginning of 2010.

A.2 Supplementary Tables

	Bandwidth				
	1yr	2yrs	4yrs	6yrs	8yrs
γ_2	-0.416***	-0.452***	-0.423***	-0.403***	-0.395***
	[-4.903]	[-4.745]	[-4.131]	[-4.485]	[-4.237]
γ_{3-6}	-0.402	-0.813**	-0.712**	-0.962***	-1.392***
	[-0.935]	[-3.229]	[-2.574]	[-4.449]	[-5.173]
Time FE	✓	✓	✓	✓	✓
R^2	.696	.664	.667	.632	.581
First-stage F	112.7	111.2	92.1	55	60.8
# Identifying Bonds	2011	3774	4894	5823	7340

Table B.1. **Robustness: Bandwidth Choice.**

This table shows the coefficients estimated from regression (1.6) in the post-Crisis sample for different choices of bandwidth. The controls are the same as in Table 1.5. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	2000-2007	2010-2019
γ_2	0.197	-0.465***
	[0.805]	[-4.862]
γ_{3-6}	0.473	-0.824***
	[0.786]	[-3.383]
Time FE	✓	✓
R^2	.599	.67
First-stage F	310	1950.4
# Identifying Bonds	1092	2802

Table B.2. **Robustness: Excluding New Bonds.**

This table shows the coefficients estimated from regression (1.6) excluding bonds issued less than 3 months ago. The controls are the same as in Table 1.5. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	2000-2007	2010-2019
γ_2	0.131	-0.450***
	[0.599]	[-4.713]
γ_{3-6}	0.442	-0.895***
	[0.786]	[-3.375]
Time FE	✓	✓
R^2	.591	.659
First-stage F	3.6	122
# Identifying Bonds	1209	3617

Table B.3. **Robustness: Long Maturity at Issuance.**

This table shows the coefficients estimated from regression (1.6), including only bonds whose maturities are longer than 10 years when issued. The controls are the same as in Table 1.5. The t-statistics shown in brackets are based on standard errors clustered at the issuer and year-month levels. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

	$\mathbf{1}\{\varphi_{it}^{\text{Ins}} > 0\}$	$\mathbb{E}_t[\varphi_{it}^{\text{Ins}} \mid \varphi_{it}^{\text{Ins}} > 0]$	max $\varphi_{it}^{\text{Ins}}$	Market Cap ($ bn)
NAIC 1	84.6%	32.5%	100%	1990.6
NAIC 2	98.5%	39.2%	98.6%	1102.6
NAIC 3	94.3%	16.0%	95.9%	255.8
NAIC 4	84.6%	6.0%	50.1%	260.5
NAIC 5	66.3%	3.9%	60.4%	81.6
NAIC 6	52.4%	3.7%	10.1%	6.2
NAIC 1-2	90.9%	35.7%	100%	3093.2
NAIC 3-6	85.1%	10.3%	95.9%	604.1

Table B.4. **Life Insurance Ownership (end of 2010).**

This table summarizes life insurers' bond ownership at the end of 2010. The first column shows the fraction of bonds with positive insurer holdings. The second column shows the average life insurance ownership share in bonds with life insurance ownership. The third column shows the maximum life insurer share for each category. The last column shows the total market cap of each category.

	Dependent Variable		
	Bond Yields (%)	3-month Net Purchases (%)	3-month Issuance (%)
β_{3-6}	-1.064***	1.002***	0.633***
	[-7.096]	[8.340]	[2.999]
Maturity-Time FE	✓		
Bond FE	✓		
Time FE		✓	✓
NAIC FE		✓	✓
Controls	✓	✓	✓
R^2	.753	.893	.65

Table B.5. **Untargeted Responses: The Empirical Estimates.**

This table shows the coefficients estimated from variations of regressions (1.2), (1.7), and (1.8) where $y_t^{(10)}$ interacts only with $\mathbf{1}_{\{NAIC\ 3\text{-}6\}}$. The controls are the same as in the corresponding regressions in the main context. The t-statistics shown in brackets are based on clustered standard errors. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$.

A.3 Analytical Model: Derivation

A.3.1 A Sufficient Condition for Duration Mismatch

Now we show that a set of sufficient conditions for Assumption 3 is that (1) $\tau^T < \tau^L$ and (2) the annuity demand L is sufficiently large.

First, differentiating equation (1.21),

$$\frac{\partial \widehat{A}}{\partial \widehat{y}} = \frac{L\phi^L}{(\widehat{y} + (1/\tau^L))^2} - \frac{T\phi^T}{(\widehat{y} + (1/\tau^T))^2}.$$

A set of sufficient conditions for $\partial \widehat{A}/\partial \widehat{y} > 0, \forall \widehat{y} \geq 0$ is that

$$\tau^T < \tau^L \tag{D.1}$$

$$T\phi^T < L\phi^L \tag{D.2}$$

Condition (D.2) can be written as

$$\begin{aligned}
\frac{w^{I,0}A}{P^T}\phi^T &< L\phi^L \\
w^{I,0}A(y+\lambda^T) &< L\phi^L \\
w^{I,0} &< \frac{L\phi^L}{A(y+\lambda^T)} \\
1+\frac{L\phi^L}{A(y+\lambda^L)}-\sum_{n=1}^{N} w^{I,n} &< \frac{L\phi^L}{A(y+\lambda^T)} \\
1+\frac{L\phi^L(\lambda^T-\lambda^L)}{A(y+\lambda^T)(y+\lambda^L)} &< \sum_{n=1}^{N} w^{I,n}
\end{aligned} \tag{D.3}$$

Consider the case with $\gamma^n = 0$. Before the yield shock, the first-order condition implies

$$\frac{\phi^n}{P^n} - \nu^n\delta = y \quad \Longrightarrow \quad P^n = \frac{\phi^n}{y+\nu^n\delta}.$$

Then the market clearing conditions imply

$$\begin{aligned}
w^{I,n} &= \frac{P^n\left[B^n(P^n) - D^{P,n}(P^n)\right]}{A} \\
&= \frac{\phi^n}{(y+\nu^n\delta)A}\left[B^n\left(\frac{\phi^n}{y+\nu^n\delta}\right) - D^{P,n}\left(\frac{\phi^n}{y+\nu^n\delta}\right)\right].
\end{aligned}$$

Thus, condition (D.3) holds for $\gamma^n = 0$ if

$$\begin{aligned}
\sum_{n=1}^{N}\phi^n\left[B^n\left(\frac{\phi^n}{y+\nu^n\delta}\right) - D^{P,n}\left(\frac{\phi^n}{y+\nu^n\delta}\right)\right] &> (y+\nu^n\delta)A\left[1+\frac{L\phi^L(\lambda^T-\lambda^L)}{(y+\lambda^T)(y+\lambda^L)}\right] \\
N(y+\nu^n\delta)^{\frac{\theta-1}{\theta}} - \sum_{n=1}^{N}\alpha^n\left(\frac{\phi^n}{y+\nu^n\delta}\right)^{-\beta} &> (y+\nu^n\delta)A\left[1+\frac{L\phi^L(\lambda^T-\lambda^L)}{(y+\lambda^T)(y+\lambda^L)}\right].
\end{aligned} \tag{D.4}$$

The condition (D.4) holds when N and ϕ^n are large enough.

In Section A.3.2, I will show that the portfolio weight $w^{I,n}$ decreases in γ^n. Since $w_t^{I,n}$ is a continuous function in γ^n, there exists some positive constant condition $\overline{\gamma} > 0$ such that (D.3) holds for $\gamma^n \in (0, \overline{\gamma})$. To summarize, we have now found a set of conditions under

which $\partial \widehat{A}/\partial \widehat{y} > 0$ holds:

$$\gamma^n \in (0, \overline{\gamma}), (D.1), \text{ and, } (D.4).$$

A.3.2 Proof

Proof of Proposition 1. The market clearing condition (1.18) can be written as

$$w_t^{I,n} A_t^I = \underbrace{P_t^n \left(B^n(P_t^n) - D^{P,n}(P_t^n) \right)}_{\uparrow \text{ in } P_t^n}$$

Under Assumption 4, the right-hand side is increasing in P_t^n. The equation implies that P_t^n is a function of $w_t^{I,n}$ and A_t^I. Denote $P_t^n = P^n(w_t^{I,n}, A_t^I)$. It is easy to show that

$$\frac{\partial P_t^n}{\partial w_t^{I,n}} > 0, \quad \frac{\partial P_t^n}{\partial A_t^I} > 0.$$

In the simplified model, the return rate on Treasuries is simply $\mu_t^T = y_t^T$. Consider the insurer's first-order condition

$$\mu_t^{r,n} - y_t^T = \gamma^n w_t^{I,n} \tag{D.5}$$

$$\frac{\phi^n}{P^n(w_t^{I,n}, A_t^I)} - \nu^n \delta - y_t^T = \gamma^n w_t^{I,n}. \tag{D.6}$$

Differentiating (D.6) yields

$$\frac{\partial w_t^{I,n}}{\partial y_t^T} = -\left[\gamma^n + \frac{\phi^n}{(P_t^n)^2} \frac{\partial P_t^n}{\partial w_t^{I,n}} \right]^{-1} \left[1 + \frac{\phi^n}{(P_t^n)^2} \frac{\partial P_t^n}{\partial A_t^I} \frac{\partial A_t^I}{\partial \mu_t^T} \right]. \tag{D.7}$$

Under Assumption 3, $\partial A_t^I / \partial y_t^T > 0$, so $\partial w_t^{I,n} / \partial y_t^T < 0$. That is, the portfolio weight $w_t^{I,n}$ increases when the Treasury yield μ_t^T decreases. From (D.5), we see that the credit spreads must also increase. Equation (D.7) also tells us the magnitude of the effect (i.e., $\left| \frac{\partial w_t^{I,n}}{\partial y_t^T} \right|$) is increasing in the severity of duration mismatch (i.e., $\left| \frac{\partial A_t^I}{\partial y_t^T} \right|$).

We can also show that the portfolio weight $w_t^{I,n}$ decreases in the holding cost γ^n by

differentiating (D.6),

$$\frac{\partial w_t^{I,n}}{\partial \gamma^n} = -\left[\gamma^n + \frac{\phi^n}{(P_t^n)^2}\frac{\partial P_t^n}{\partial w_t^{I,n}}\right]^{-1} w_t^{I,n} < 0.$$

A.4 Quantitative Model: Numerical Solution Method

Consider the insurer's net worth dynamics

$$\begin{aligned}\frac{\mathrm{d}A_t^I}{A_t^I} &= \left[w_t^{I,0}\mu_t^{r,T} + \sum_{n=1}^N w_t^{I,n}\mu_t^{r,n} - w_t^{I,L}\mu_t^{r,L} - \sum_{n=1}^N \frac{1}{2}(\zeta^n w_t^{I,n})^2 + \psi_t\right]\mathrm{d}t + \sum_{n=1}^N w_t^{I,n}\sigma_t^{r,n}(\mathrm{d}J_t - \delta \mathrm{d}t) \\ &= \left[w_t^{I,0}\mu_t^{r,T} + \sum_{n=1}^N w_t^{I,n}(\mu_t^{r,n} - \delta\sigma_t^{r,n}) - w_t^{I,L}\mu_t^{r,L} - \sum_{n=1}^N \frac{1}{2}(\zeta^n w_t^{I,n})^2 + \psi_t\right]\mathrm{d}t + \sum_{n=1}^N w_t^{I,n}\sigma_t^{r,n}\mathrm{d}J_t \\ &:= \mu_t^{A,I}\mathrm{d}t + \sigma_t^{A,I}\mathrm{d}J_t.\end{aligned}$$

Suppose $P_t^n = P^n(y_t^T, A_t^I)$. By Ito's Lemma,

$$\begin{aligned}\mathrm{d}r_t^n &= \frac{\phi^n - \lambda^n P_t^n}{P_t^n}\mathrm{d}t + \frac{\mathrm{d}P_t^n}{P_t^n} - \nu^n \mathrm{d}J_t \\ &= \underbrace{\frac{1}{P_t^n}\left[(\phi^n - \lambda^n P_t^n) + \frac{\partial P_t^n}{\partial y_t^T}\alpha_y\left(y_t^T - \overline{y}^T\right) + \frac{\partial P_t^n}{\partial A_t^I}A_t^I\mu_t^{A,I}\right]}_{:=\mu_t^{r,n} - \delta\sigma_t^{r,n}}\mathrm{d}t + \underbrace{\left[1 - \frac{P^n(y_t^T, A_t^I - \sigma_t^{A,I})}{P^n(y_t^T, A_t^I)} - \nu^n\right]}_{:=\sigma_t^{r,n}}\mathrm{d}J_t\end{aligned}$$

Plugging $\mu_t^{r,n}$ into $\mu_t^{A,I}$, we can solve for $\mu_t^{A,I}$ as

$$\begin{aligned}\mu_t^{A,I} = &\left[1 - \sum_n w_t^{I,n}\frac{A_t^I}{P_t^n}\frac{\partial P_t^n}{\partial A_t^I}\right]^{-1} \cdot \\ &\left\{w_t^{I,0}\mu_t^{r,T} - w_t^{I,L}\mu_t^{r,L} + \sum_n w_t^{I,n}\frac{1}{P_t^n}\left[\phi^n - \lambda^n P_t^n + \frac{\partial P_t^n}{\partial y_t^T}\alpha_y\left(y_t^T - \overline{y}^T\right)\right] - \sum_n \frac{1}{2}(\zeta^n w_t^{I,n})^2 + \psi_t\right\}.\end{aligned}$$

To obtain a solvable partial differential equation, we now add the time dimension and postulate $P_t^n = P^n(t, y_t^T, A_t^I)$. By Ito's Lemma,

$$\mathrm{d}r_t^n = \frac{\phi^n - \lambda^n P_t^n}{P_t^n}\mathrm{d}t + \frac{\mathrm{d}P_t^n}{P_t^n} - \nu^n \mathrm{d}J_t$$

$$= \underbrace{\frac{1}{P_t^n}\left[(\phi^n - \lambda^n P_t^n) + \frac{\partial P_t^n}{\partial t} + \frac{\partial P_t^n}{\partial y_t^T}\alpha_y\left(y_t^T - \overline{y}^T\right) + \frac{\partial P_t^n}{\partial A_t^I}A_t^I\mu_t^{A,I}\right]}_{:=\mu_t^{r,n}-\delta\sigma_t^{r,n}} \mathrm{d}t$$
$$+ \underbrace{\left[1 - \frac{P^n(y_t^T, A_t^I - \sigma_t^{A,I})}{P^n(y_t^T, A_t^I)} - \nu^n\right]}_{:=\sigma_t^{r,n}} \mathrm{d}J_t.$$

The first-order condition of the portfolio choice problem is

$$\mu_t^{r,n} - \mu_t^{r,T} = a\delta\sigma_t^{A,I}\sigma_t^{r,n} + (\zeta^n)^2 w_t^{I,n}.$$

Plugging in the expression for $\mu_t^{r,n}$ and μ_t^T, we get

$$\frac{1}{P_t^n}\left[(\phi^n - \lambda^n P_t^n) + \frac{\partial P_t^n}{\partial t} + \frac{\partial P_t^n}{\partial y_t^T}\alpha_y\left(y_t^T - \overline{y}^T\right) + \frac{\partial P_t^n}{\partial A_t^I}A_t^I\mu_t^{A,I}\right]$$
$$- \left[\frac{(\phi^T - \lambda^T P_t^T)}{P_t^T} - \frac{1}{y_t^T + \lambda^T}\alpha_y\left(y_t^T - \overline{y}^T\right)\right] + \delta\sigma_t^{r,n} = a\delta\sigma_t^{A,I}\sigma_t^{r,n} + (\zeta^n)^2 w_t^{I,n}.$$

Therefore, we get the following system of partial differential equations:

$$\begin{aligned}\frac{\partial P_t^n}{\partial t} =& -\alpha_y\left(y_t^T - \overline{y}^T\right)\frac{\partial P_t^n}{\partial y_t^T} - \left(A_t^I\mu_t^{A,I}\right)\frac{\partial P_t^n}{\partial A_t^I} \\ &+ \left[y_t^T - \frac{1}{y_t^T + \lambda^T}\alpha_y\left(y_t^T - \overline{y}^T\right) + \lambda^n + (a\sigma_t^{A,I} - 1)\delta\sigma_t^{r,n} + (\zeta^n)^2 w_t^{I,n}\right]P_t^n - \phi^n,\end{aligned} \tag{E.1}$$

where

$$B_t^n = \left(1/\phi^n\right)^{\frac{1}{\theta}}\left(P_t^n\right)^{\frac{1-\theta}{\theta}}, \qquad D_t^n = \alpha^n (P_t^n)^{-\beta}, \qquad w_t^{I,n} = P_t^n(B_t^n - D_t^n)/A_t^I$$

$$\mu_t^{A,I} = \left[1 - \sum_n w_t^{I,n}\frac{A_t^I}{P_t^n}\frac{\partial P_t^n}{\partial A_t^I}\right]^{-1} \cdot$$
$$\left\{w_t^{I,0}\mu_t^{r,T} - w_t^{I,L}\mu_t^{r,L} + \sum_n w_t^{I,n}\frac{1}{P_t^n}\left[\phi^n - \lambda^n P_t^n + \frac{\partial P_t^n}{\partial y_t^T}\alpha_y\left(y_t^T - \overline{y}^T\right)\right] - \sum_n \frac{1}{2}(\zeta^n w_t^{I,n})^2 + \psi_t\right\}$$

$$\sigma_t^{r,n} = 1 - \frac{P^n(y_t^T, A_t^I - \sigma_t^{A,I})}{P^n(y_t^T, A_t^I)} - \nu^n$$

Finally, $\sigma_t^{A,I}$ is obtained by solving the following system of equations

$$\begin{aligned}\sigma_t^{A,I} &= \sum_{n=1}^{N} w_t^{I,n}\sigma_t^{r,n} \\ &= \sum_{n=1}^{N} w_t^{I,n}\left[1 - \frac{P^n(y_t^T, A_t^I - \sigma_t^{A,I})}{P^n(y_t^T, A_t^I)} - \nu^n\right] \\ &= \sum_{n=1}^{N} w_t^{I,n}(1-\nu^n) - \sum_{n=1}^{N} w_t^{I,n}\frac{P^n(y_t^T, A_t^I - \sigma_t^{A,I})}{P^n(y_t^T, A_t^I)},\end{aligned}$$

which can be simplified to

$$\sigma_t^{A,I} - \sum_{n=1}^{N} w_t^{I,n}(1-\nu^n) + \sum_{n=1}^{N} w_t^{I,n}\frac{P^n(y_t^T, A_t^I - \sigma_t^{A,I})}{P^n(y_t^T, A_t^I)} = 0.$$

I solve the PDE system (E.1) using a finite difference method. I start with a guess for $P^n(0, y_t^T, A_t^I)$ and iterate backward through time until the system converges.

Appendix B

Appendix to Chapter 2

B.1 Supplementary Results

Table B.1 demonstrates the relationship between banks' local deposit market share and their deposit market power. The result suggests that deposit market power strongly and positively predicts county-level bank market share. Intuitively, large banks are more likely to have market power in the local deposit market.

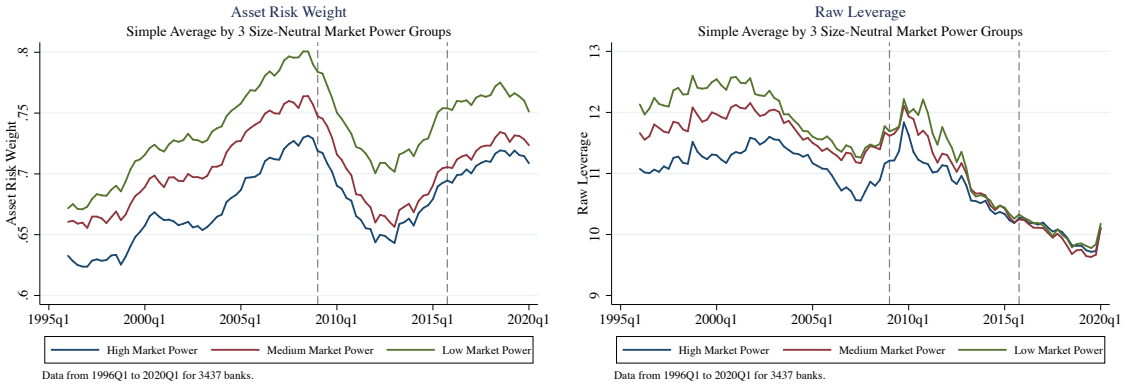
Table B.1. Deposit Market Share and Interest-Expense Beta

	Dep Var: Log Avg. Deposit Mkt Share at Bank-Year Level	
	(1) Branch-Wgt	(2) Deposit-Wgt
IntExp-FFR Beta	-1.003**	-1.085**
	[-3.125]	[-3.281]
Log Assets	0.178**	0.183**
	[9.454]	[10.41]
Year FE	✓	✓
Within R^2	.035	.034
# Banks	3437	3437
Observations	50308	50308

Note: We use the Summary of Deposits data to compute market share at the bank-county-year level and then aggregate to bank-year level using the number of branches (column 1) or amount of deposits (column 2) as weights. We then regress the log of average bank-level market share on interest expense beta and log assets, with year fixed effects, to ensure cross-sectional comparison. *t*-statistics based on standard errors clustered at bank and year level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Figure A.1 plots the time series of bank asset risk weight and raw leverage. The gaps between high-market-power banks and low-market-power banks narrowed significantly during the zero lower bound period, especially for raw leverage.

Figure A.1. Market Power and Asset Risk Weight (Left) / Leverage (Right)



Note: We sort banks into three size-neutral groups by interest expense beta. For each group-year, we compute the average asset risk weight (left) and raw leverage (right). Data covers 3437 banks in the main sample from 1996Q1 to 2020Q1.

B.2 More Robustness Results

In this appendix, we show that our results are robust to two alternative measures of deposit market power.

First, Table B.2 replicates the main regression results (Table 2.2) using the deposit market Herfindahl Index (HHI) as the measure of deposit market power. Following Drechsler, Savov and Schnabl (2017) and Li, Loutskina and Strahan (2023), we first construct a county-level deposit market HHI using the FDIC Summary of Deposits data, which we then aggregate to the bank level using the number of branches as weights, as shown in Equations (E.1-E.2). A higher bank HHI means that a bank has more branches in counties with concentrated deposit markets.

$$\text{CountyHHI}_{c,t} = \sum_{b} \left(\frac{\text{Deposits}_{b,c,t}}{\sum_b \text{Deposits}_{b,c,t}} \right)^2 \tag{E.1}$$

$$\text{BankHHI}_{b,t} = \frac{\sum_c \#\text{Branch}_{b,c,t} \times \text{CountyHHI}_{c,t}}{\sum_c \#\text{Branch}_{b,c,t}} \tag{E.2}$$

Table B.2. Main Risk Regression with Bank HHI as Market Power Measure

	Dependent Variable: Risk Metrics		
	(1) Log Risk-Wgt Lev.	(2) Risk Weight	(3) Log Lev.
BankHHI	-0.0278**	-0.0118**	-0.00987*
	[-5.348]	[-5.991]	[-2.584]
Log Assets	-0.000715	0.00121	-0.000688
	[-0.0773]	[0.317]	[-0.0993]
Deposit/Liability	-0.436**	-0.0222	-0.385**
	[-6.668]	[-0.825]	[-8.536]
Log(# Branches)	0.0568**	0.0119*	0.0355**
	[4.830]	[2.487]	[4.050]
Log(County PC Income)	0.00753	0.00493	0.0102
	[0.245]	[0.408]	[0.437]
County Bus. Cycle Beta	0.0438**	0.0340**	-0.00245
	[2.853]	[5.344]	[-0.209]
Multi State	-0.00291	0.00277	-0.00470
	[-0.282]	[0.612]	[-0.606]
Deposit Fee Income	-0.0738**	-0.0607**	0.0144
	[-4.082]	[-8.846]	[1.006]
Other Non-Interest Income	-0.00852	0.000574	-0.00807+
	[-1.311]	[0.201]	[-1.775]
Year-Quarter FE	✓	✓	✓
Within R^2	.095	.08	.06
# Banks	3437	3437	3437
Observations	195225	195225	195225

Note: Regression based on Equation (2.4), with bank-level deposit HHI (Equation E.2) as measure of market power. HHI is cross-sectionally standardized for each quarter. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Second, other studies have also used the level of deposit spread as a proxy for deposit market power (e.g., Balloch and Koby, 2022). Table B.3 replicates the main results using the deposit spread as a measure of market power. We define deposit spread for a bank-quarter as the difference between the 4-quarter average Federal Funds Rate and the 4-quarter average of the bank's deposit expense rate, where the deposit expense rate is a bank's interest expense on deposits divided by total deposits. Banks with higher deposit market power will charge higher deposit spreads.

Table B.4 further shows that the results based on bank HHI are robust to controlling for

mortgage HHI, which proxies for a bank's loan market power.

Table B.3. Main Risk Regression with Deposit Spread as Market Power Measure

	Dependent Variable: Risk Metrics		
	(1) Log Risk-Wgt Lev.	(2) Risk Weight	(3) Log Lev.
Deposit Spread	-0.114**	-0.0458**	-0.0445**
	[-10.92]	[-11.82]	[-6.419]
Log Assets	-0.00392	-0.0000614	-0.00196
	[-0.418]	[-0.0161]	[-0.281]
Deposit/Liability	-0.307**	0.0298	-0.334**
	[-4.807]	[1.144]	[-7.351]
Log(# Branches)	0.0645**	0.0151**	0.0384**
	[5.367]	[3.161]	[4.306]
Log(County PC Income)	0.108**	0.0465**	0.0480*
	[3.719]	[4.193]	[2.135]
County Bus. Cycle Beta	0.0578**	0.0398**	0.00286
	[3.867]	[6.445]	[0.244]
Multi State	-0.0148	-0.00210	-0.00919
	[-1.461]	[-0.477]	[-1.189]
Deposit Fee Income	-0.00178	-0.0319**	0.0430**
	[-0.0940]	[-4.540]	[2.955]
Other Non-Interest Income	-0.00283	0.00286	-0.00584
	[-0.452]	[1.045]	[-1.288]
Year-Quarter FE	✓	✓	✓
Within R^2	.122	.108	.067
# Banks	3437	3437	3437
Observations	194149	194149	194149

Note: Regression based on Equation (2.4), with deposit spread (federal funds rate minus bank deposit expense rate) as a measure of market power. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

Table B.4. Additional Robustness for Loan Market Power

	Dependent Variable: Risk Metrics		
	(1) Log(RWA/T1 Cap)	(2) Risk Weight	(3) Log(Asset/T1 Cap)
BankHHI	-0.0305**	-0.0149**	-0.00840*
	[-5.485]	[-6.788]	[-2.068]
Log Assets	0.00277	0.00192	0.000829
	[0.266]	[0.457]	[0.109]
Deposit/Liability	-0.402**	-0.00239	-0.379**
	[-5.977]	[-0.0869]	[-8.162]
Log(# Branches)	0.0487**	0.0104*	0.0313**
	[3.727]	[2.018]	[3.247]
Log(County PC Income)	0.00745	0.00730	0.00414
	[0.234]	[0.582]	[0.170]
County Bus. Cycle Beta	0.0462**	0.0354**	-0.00227
	[2.844]	[5.195]	[-0.184]
Multi State	0.00205	0.00280	-0.000569
	[0.204]	[0.628]	[-0.0733]
Deposit Fee Income	-0.0921**	-0.0612**	-0.00307
	[-4.725]	[-8.334]	[-0.198]
Other Non-Interest Income	-0.00555	0.00196	-0.00788+
	[-0.877]	[0.724]	[-1.665]
Mortgage HHI (STD)	0.0120**	0.0110**	-0.00432
	[2.648]	[6.998]	[-1.232]
Year-Quarter FE	✓	✓	✓
Within R^2	.093	.084	.058
# Banks	3197	3197	3197
Observations	171501	171501	171501

Note: Regression based on Equation (2.4), with bank-level deposit HHI (Equation E.2) as a measure of market power, and with additional control of mortgage HHI as a measure for loan market power. Both HHI measures are cross-sectionally standardized for each quarter. t-statistics based on standard errors clustered at the bank and year-quarter level in brackets, $^{+}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$.

B.3 Proofs

In this appendix, we present proofs of Propositions 2-4, while the proofs of Propositions 5 and 6 are straightforward and already given in the main text. We start from the first-order

conditions (2.13) and (2.14),

$$(r + \theta_j - r_j^d)\eta_j(1 - s_j) = 1,$$
$$p'(\theta_j)(r + \theta_j - r_j) + p(\theta_j) = 0.$$

Proofs of Propositions 2 and 4. Differentiating the first-order conditions with respect to η_j, we get,

$$\frac{\partial r_j^d}{\partial \eta_j} = \frac{\frac{r+\theta_j - r_j^d}{\eta_j}\left(\frac{p''(\theta_j)}{p'(\theta_j)}(r + \theta_j - r_j^d) + 2\right)\left(1 + \eta_j(x_j - r_j^d)s_j\right)}{\left(1 + (r + \theta_j - r_j^d)\eta_j\right)\left(\frac{p''(\theta_j)}{p'(\theta_j)}(r + \theta_j - r_j^d) + 1\right) + (r + \theta_j - r_j^d)\eta_j},$$
$$\frac{\partial \theta_j}{\partial \eta_j} = \frac{\frac{r+\theta_j - r_j^d}{\eta_j}\left(1 + \eta_j(x_j - r_j^d)s_j\right)}{\left(1 + (r + \theta_j - r_j^d)\eta_j\right)\left(\frac{p''(\theta_j)}{p'(\theta_j)}(r + \theta_j - r_j^d) + 1\right) + (r + \theta_j - r_j^d)\eta_j}.$$

Under Assumption 6, $x_j > r_j^d$, so

$$\frac{\partial r_j^d}{\partial \eta_j} > 0, \quad \frac{\partial \theta_j}{\partial \eta_j} > 0.$$

Proof of Proposition 3. Differentiating the first-order conditions with respect to r, we get

$$\frac{\partial r_j^d}{\partial r} = \frac{\frac{p''(\theta_j)}{p'(\theta_j)}(r + \theta_j - r_j^d) + 1}{\left(1 + (r + \theta_j - r_j^d)\eta_j s_j\right)\left(\frac{p''(\theta_j)}{p'(\theta_j)}(r + \theta_j - r_j^d) + 1\right) + (r + \theta_j - r_j^d)\eta_j s_j}.$$

Plugging in (2.13) and simplifying,

$$\frac{\partial r_j^d}{\partial r} = \frac{\frac{p''(\theta_j)}{p'(\theta_j)}(1 - s_j) + \eta_j(1 - s_j^2)}{\frac{p''(\theta_j)}{p'(\theta_j)} + \eta_j(1 - s_j^2)}.$$

Under Assumption 5, the expression above becomes

$$\frac{\partial r_j^d}{\partial r} = \frac{\kappa(1 - s_j) + \eta_j(1 - s_j)^2}{\kappa + \eta_j(1 - s_j^2)}.$$

Differentiating once more with respect to η_j,

$$\frac{\partial^2 r_j^d}{\partial \eta_j \partial r} = \frac{\kappa s_j(1-s_j^2) + \left[2\eta_j(\eta_j+\kappa_j)(1-s_j)^2 + \kappa^2 + \kappa\eta_j(1-s_j^2)\right](-\frac{\partial s_j}{\partial \eta_j})}{\left[\kappa + \eta_j(1-s_j^2)\right]^2}.$$

Under Assumption 6, $\partial s_j/\partial \eta_j < 0$, so

$$\frac{\partial^2 r_j^d}{\partial \eta_j \partial r} > 0.$$

Appendix C

Appendix to Chapter 3

C.1 The New-Keynesian Phillips Curve

Proposition 13 (The New-Keynesian Phillips Curve) *In a symmetric equilibrium where all firms set the same price and produce the same amount of output ($y_t^j = Y_t, P_t^j = P_t, \pi_t^j = \pi_t$), the inflation rate satisfies*

$$\mathrm{d}\Pi_t = \left[\Pi_t\left(r_t - g_t + \sigma_t^{\Pi}\varsigma_t\right) - \frac{\varepsilon}{\kappa}(p_t^R - p^{R,flex})u_t\right]\mathrm{d}t + \Pi_t\sigma_t^{\Pi}\mathrm{d}Z_t. \tag{E.1}$$

where $r_t := i_t - \pi_t$, $\Pi_t := \pi_t\frac{Y_t}{K_t}$, $\varsigma_t = (1-\vartheta)\sigma_t^{q,K}$ and $p^{R,flex} = a\frac{\varepsilon-1}{\varepsilon}$.

Proof. The intermediary goods firms' problem implies the following Hamiltonian:

$$H_t = \frac{\xi_t}{\xi_0}\left[\left(\frac{P_t^j}{P_t} - \frac{p_t^R}{a}\right)\left(\frac{P_t^j}{P_t}\right)^{-\varepsilon} - \frac{\kappa}{2}\left(\pi_t^j\right)^2\right]Y_t + \lambda_t\pi_t^j P_t^j.$$

The optimality condition is

$$\frac{\xi_t}{\xi_0}\kappa\pi_t^j Y_t = \lambda_t P_t^j \quad \Longrightarrow \quad \pi_t^j = \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{\lambda_t P_t^j}{Y_t}.$$

The co-state equation is (with $P_t^j = P_t$ imposed)

$$\begin{aligned}\mathrm{d}\lambda_t &= -\frac{\partial H}{\partial P_t^j}\mathrm{d}t + \lambda_t \sigma_t^\lambda \mathrm{d}Z_t \\ &= -\left[\frac{\xi_t}{\xi_0}\frac{Y_t}{P_t}\frac{\varepsilon}{a}(p_t^R - p^{R,flex}) + \lambda_t \pi_t\right]\mathrm{d}t + \lambda_t \sigma_t^\lambda \mathrm{d}Z_t.\end{aligned}$$

Define

$$\Pi_t = a u_t \pi_t = \pi_t \frac{Y_t}{K_t} = \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{\lambda_t P_t}{K_t}.$$

By Ito's Lemma,

$$\begin{aligned}\mathrm{d}\Pi_t &= \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{P_t}{K_t}\mathrm{d}\lambda_t + \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{\lambda_t}{K_t}\mathrm{d}P_t + \frac{1}{\kappa}\xi_0\frac{\lambda_t P_t}{K_t}\mathrm{d}\frac{1}{\xi_t} + \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\lambda_t P_t \mathrm{d}\frac{1}{K_t} + \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{\lambda_t P_t}{K_t}(\sigma_t^\lambda \varsigma_t)\mathrm{d}t \\ &= \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{P_t}{K_t}\left[-\left(\frac{\xi_t}{\xi_0}\frac{Y_t}{P_t}\frac{\varepsilon}{a}(p_t^R - p^{R,flex}) + \lambda_t \pi_t\right)\mathrm{d}t + \lambda_t \sigma_t^\lambda \mathrm{d}Z_t\right] + \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{\lambda_t P_t}{K_t}\pi_t \mathrm{d}t \\ &\qquad + \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{\lambda_t P_t}{K_t}\frac{\mathrm{d}(1/\xi_t)}{1/\xi_t} + \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{\lambda_t P_t}{K_t}\frac{\mathrm{d}(1/K_t)}{1/K_t} + \frac{1}{\kappa}\frac{\xi_0}{\xi_t}\frac{\lambda_t P_t(i)}{K_t}(\sigma_t^\lambda \varsigma_t)\mathrm{d}t \\ &= -\frac{\varepsilon}{\kappa a}(p_t^R - p^{R,flex})\frac{Y_t}{K_t}\mathrm{d}t + \Pi_t(r_t + \varsigma_t^2)\mathrm{d}t - \Pi_t g_t \mathrm{d}t + \Pi_t(\sigma_t^\lambda \varsigma_t)\mathrm{d}t + \Pi_t(\varsigma_t + \sigma_t^\lambda)\mathrm{d}Z_t \\ &= \left[\Pi_t(r_t - g_t) + \Pi_t(\varsigma_t^2 + \sigma_t^\lambda \varsigma_t) - \frac{\varepsilon}{\kappa a}(p_t^R - p^{R,flex})\frac{Y_t}{K_t}\right]\mathrm{d}t + \Pi_t(\varsigma_t + \sigma_t^\lambda)\mathrm{d}Z_t\end{aligned}$$

Note that we used

$$\begin{aligned}\frac{\mathrm{d}\xi_t}{\xi_t} = -r_t \mathrm{d}t - \varsigma_t \mathrm{d}Z_t \quad &\Longrightarrow \quad \frac{\mathrm{d}(1/\xi_t)}{1/\xi_t} = (r_t + \varsigma_t^2)\mathrm{d}t + \varsigma_t \mathrm{d}Z_t \\ \frac{\mathrm{d}K_t}{K_t} = g_t \mathrm{d}t \quad &\Longrightarrow \quad \frac{\mathrm{d}(1/K_t)}{1/K_t} = -g_t \mathrm{d}t\end{aligned}$$

where r_t is the risk-free rate, ς_t is the price of aggregate risk,[1] and $g_t = \Phi(\iota_t) - \delta(u_t)$ is the growth rate of capital. Define

$$\sigma_t^\Pi = \varsigma_t + \sigma_t^\lambda.$$

[1]For derivations of the dynamics of SDF, see Brunnermeier and Sannikov (2016) for example.

Now we end up with an equation (E.1). Further, notice that under log utility,

$$\varsigma_t = (1 - \vartheta_t)\sigma_t^{q,K}.$$

C.2 Model Solution

We solve the model using a recursive approach. Let $V_t(n_t)$ be the households' value function. For expository purposes, we dropped the aggregate states and instead let the value function be dependent on time t. The households' problem yields the following Hamilton-Jacobi-Bellman (HJB) equation

$$\rho V_t(n_t) = \max_{c_t, \mu_t, \iota_t \theta_t} \left\{ \log c_t + \frac{\partial V_t(n_t)}{\partial n_t} n_t \mu_t^n + \frac{1}{2} \frac{\partial^2 V_t(n_t)}{\partial n_t^2} n_t^2 \left[(\sigma_t^n)^2 + (\tilde{\sigma}_t^n)^2 \right] \right\} + \frac{\mathrm{d}\mathbb{E}_t \left[V_t(n_t) \right]}{\mathrm{d}t},$$

where μ_t^n and $\sigma_t^n, \tilde{\sigma}_t^n$ are the drift and volatility of $\mathrm{d}n_t/n_t$, respectively,

$$\begin{aligned}
\mu_t^n &= \theta_t(\mathrm{d}R_t^B/\mathrm{d}t) + (1 - \theta_t)\mathbb{E}_t \left[\mathrm{d}R_t^K \right] / \mathrm{d}t - \frac{c_t}{n_t}, \\
\sigma_t^n &= (1 - \theta_t)\sigma_t^{q,K}, \\
\tilde{\sigma}_t^n &= (1 - \theta_t)\tilde{\sigma}_t.
\end{aligned}$$

The assumption of logarithmic preferences yields the convenient property of scale invariance. Following Brunnermeier and Sannikov (2016) and Di Tella and Hall (2022), we guess and verify that the households' value function takes the form

$$V_t(n_t) = A_t + \frac{\log n_t}{\rho}, \tag{E.2}$$

where A_t denotes investment opportunities of the households and is potentially a function of the aggregate states $\{q_t^B, \tilde{\sigma}_t\}$. We denote

$$\mathrm{d}A_t = \mu_t^A \mathrm{d}t + \sigma_t^A \mathrm{d}Z_t.$$

Plugging the guess into the HJB equation,

$$\rho A_t + \log n_t = \max_{c_t, u_t, \iota_t \theta_t} \left\{ \log c_t + \frac{\mu_t^n}{\rho} - \frac{1}{2} \frac{(\sigma_t^n)^2 + (\tilde{\sigma}_t^n)^2}{\rho} \right\} + \mu_t^A. \tag{E.3}$$

Taking the first-order conditions, we see that $c_t = \rho n_t$ and that the choice of u_t, ι_t, θ_t does not depend on n_t. Further, since in equilibrium, all households choose the same portfolio θ_t and consumption rate $c_t/n_t = \rho$, we see that μ_t^n and σ_t^n are also independent of the individual state n_t. Hence, $\log n_t$ can be canceled out on both sides of (E.3). In addition, A_t must satisfy

$$\mu_t^A = \rho A_t - \max_{c_t, u_t, \iota_t \theta_t} \left\{ \log \rho + \frac{\mu_t^n}{\rho} - \frac{1}{2} \frac{(\sigma_t^n)^2 + (\tilde{\sigma}_t^n)^2}{\rho} \right\}. \tag{E.4}$$

The transversality condition requires that $\lim_{T \to \infty} e^{-\rho T} \mathbb{E}[A_T] = 0$, which ensures that the linear backward stochastic differential equation (BSDE) (E.4) has a unique solution. Therefore, we conclude that (E.2) is indeed the household value function.

C.3 The Numerical Algorithm

Here we outline the numerical algorithm used to solve the model in Section 3.2.4. First, from the market clearing equation (3.21),

$$\rho(q_t^B + q_t^K) = u_t a - \iota_t \quad \Longrightarrow \quad \frac{u_t a - \iota_t}{q_t^K} = \frac{\rho}{1 - \vartheta_t} \quad \Longrightarrow \quad q_t^K = (1 - \vartheta_t) \frac{1 + \phi a u_t}{1 - \vartheta_t + \phi \rho}. \tag{E.5}$$

Using (3.19), we can then express p_t^R as

$$p_t^R = \frac{1 - \vartheta_t}{1 - \vartheta_t + \phi \rho} (1 + \phi a u_t) \delta'(u_t). \tag{E.6}$$

We can rewrite the bond evaluation equation (3.23), the consistency requirement (3.15),

and the Phillips curve (E.1) as

$$\mu_t^{\vartheta} = \rho - (1-\vartheta_t)^2\tilde{\sigma}_t^2 - \check{s}_t \tag{E.7}$$

$$\mu_t^{q,B} = \mu_t^B - \pi_t - \Phi(\iota_t) + \delta(u_t) \tag{E.8}$$

$$\mu_t^{\Pi} = \left[i_t - \pi_t - \Phi(\iota_t) + \delta(u_t) + \sigma_t^{\Pi}\varsigma_t\right] - \frac{\varepsilon}{\kappa}\left[\frac{1-\vartheta_t}{1-\vartheta_t+\phi\rho}(1+\phi a u_t)\delta'(u_t) - p^{R,flex}\right]\frac{u_t}{\Pi_t} \tag{E.9}$$

where

$$u_t = \frac{1}{a}\left(\rho(q_t^K + q_t^B) + \frac{1}{\phi}(q_t^K - 1)\right) = \frac{1}{a}\left[\left(\rho + \frac{1}{\phi}\right)\frac{q_t^B}{\vartheta_t} - \frac{1}{\phi}(1+q_t^B)\right]$$

$$\varsigma_t = (1-\vartheta_t)\sigma_t^{q,K}$$

$$\sigma_t^{q,K} = -\frac{\vartheta'(\tilde{\sigma}_t)\nu(\tilde{\sigma}_t)}{\vartheta_t(1-\vartheta_t)}$$

Postulate that

$$\vartheta_t = \vartheta(t, q_t^B, \tilde{\sigma}_t), \quad \Pi_t = \Pi(t, q_t^B, \tilde{\sigma}_t).$$

For generality, the dynamics of $\tilde{\sigma}_t$ is denoted by

$$\mathrm{d}\tilde{\sigma}_t = \mu(\tilde{\sigma}_t)\mathrm{d}t + \nu(\tilde{\sigma}_t)\mathrm{d}Z_t.$$

Then, by Ito's lemma,

$$\vartheta\mu^{\vartheta} = \partial_t\vartheta + (\partial_q\vartheta)q^B\mu^{q,B} + (\partial_\sigma\vartheta)\mu(\tilde{\sigma}) + \frac{1}{2}(\partial_{\sigma\sigma}\vartheta)(\nu(\tilde{\sigma}))^2,$$

$$\Pi\mu^{\Pi} = \partial_t\Pi + (\partial_q\Pi)q^B\mu^{q,B} + (\partial_\sigma\Pi)\mu(\tilde{\sigma}) + \frac{1}{2}(\partial_{\sigma\sigma}\Pi)(\nu(\tilde{\sigma}))^2$$

$$\Pi\sigma^{\Pi} = (\partial_\sigma\Pi)\nu(\tilde{\sigma})$$

Plugging the expressions above into (E.7) - (E.9), we get

$$\partial_t\vartheta = \vartheta\left[\rho - (1-\vartheta)^2\tilde{\sigma}^2 - \check{s}\right]$$

$$
\begin{aligned}
&- (\partial_q \vartheta) q^B \left[\mu^B - \frac{\Pi}{au} - \Phi(\iota) + \delta(u) \right] - (\partial_\sigma \vartheta) \mu(\tilde{\sigma}) - \frac{1}{2} (\partial_{\sigma\sigma} \vartheta) (\nu(\tilde{\sigma}))^2 \\
\partial_t \Pi = \Pi &\left[i - \frac{\Pi}{au} - \Phi(\iota) + \delta(u) + \sigma^\Pi \varsigma \right] \\
&- \frac{\varepsilon}{\kappa} \left[\frac{1-\vartheta}{1-\vartheta+\phi\rho} (1 + \phi a u) \delta'(u) - a \frac{\varepsilon - 1}{\varepsilon} \right] u \\
&- (\partial_q \Pi) q^B \left[\mu^B - \frac{\Pi}{au} - \Phi(\iota) + \delta(u) \right] - (\partial_\sigma \pi) \mu(\tilde{\sigma}) - \frac{1}{2} (\partial_{\sigma\sigma} \pi) (\nu(\tilde{\sigma}))^2
\end{aligned}
$$

where

$$
\begin{aligned}
\iota &= \frac{1}{\phi} \left(q^B \frac{1-\vartheta}{\vartheta} - 1 \right) & \sigma^\Pi &= (\partial_\sigma \Pi) \frac{\nu(\tilde{\sigma})}{\Pi} \\
u &= \frac{1}{a} \left[\left(\rho + \frac{1}{\phi} \right) \frac{q^B}{\vartheta} - \frac{1}{\phi} (1 + q^B) \right] & i &= i(q^B, \tilde{\sigma}) \\
\sigma^{q,K} &= - \frac{(\partial_\sigma \vartheta) \nu(\tilde{\sigma})}{\vartheta(1-\vartheta)} & \check{s} &= \check{s}(q^B, \tilde{\sigma}) \\
\varsigma &= (1-\vartheta) \sigma^{q,K}
\end{aligned}
$$

To solve this system of PDE, we start with guesses for terminal conditions $\vartheta(T, q^B, \tilde{\sigma}), \pi(T, q^B, \tilde{\sigma})$ and iterate backward in time using a finite difference method.

C.4 Flexible Price Equilibrium

Portfolio Choice. Assume that the excess debt growth is a function of $(\tilde{\sigma}_t, \vartheta_t)$, $\check{s}_t = \check{s}(\tilde{\sigma}_t, \vartheta_t)$. We postulate that $\vartheta_t = \vartheta(\tilde{\sigma}_t)$. By Ito's Lemma,

$$
\mu_t^\vartheta = \vartheta'(\tilde{\sigma}_t) \frac{\mu(\sigma_t)}{\vartheta_t} + \frac{1}{2} \vartheta''(\tilde{\sigma}_t) \frac{[\nu(\sigma_t)]^2}{\vartheta_t}, \qquad \sigma_t^\vartheta = \vartheta'(\tilde{\sigma}_t) \frac{\nu(\tilde{\sigma}_t)}{\vartheta_t}.
$$

Then, ϑ_t can be solved from the bond evaluation equation

$$
\begin{aligned}
\mu_t^\vartheta &= \rho - (1 - \vartheta(\tilde{\sigma}_t))^2 \tilde{\sigma}_t^2 - \check{s}(\tilde{\sigma}_t, \vartheta(\tilde{\sigma}_t)) \\
\vartheta'(\tilde{\sigma}_t) \frac{\mu(\sigma_t)}{\vartheta_t} + \frac{1}{2} \vartheta''(\tilde{\sigma}_t) \frac{[\nu(\sigma_t)]^2}{\vartheta_t} &= \rho - (1 - \vartheta(\tilde{\sigma}_t))^2 \tilde{\sigma}_t^2 - \check{s}(\tilde{\sigma}_t, \vartheta(\tilde{\sigma}_t))
\end{aligned}
$$

which reduces to a one-dimensional ordinary differential equation.

Production and Investment. When prices are flexible, the intermediary goods firms' problem collapses to a static profit-maximization problem each time

$$\max_{P_t^j} \quad \left(\frac{P_t^j}{P_t} - \frac{p_t^R}{a}\right) y_t^j \qquad \text{s.t.} \qquad y_t^j = \left(\frac{P_t^j}{P_t}\right)^{-\varepsilon} Y_t.$$

The firms set their prices at

$$\frac{P_t^j}{P_t} = \frac{1}{a}\frac{\varepsilon}{\varepsilon - 1} p_t^R.$$

In a symmetric equilibrium all firms charge the same price ($P_t^j = P_t$), so

$$p_t^{R,flex} = a\frac{\varepsilon - 1}{\varepsilon}. \tag{E.10}$$

First, from equation (E.6) and (E.10), we see that equilibrium utilization is a function of the portfolio weight ϑ_t,

$$a\frac{\varepsilon - 1}{\varepsilon} = \frac{1 - \vartheta_t}{1 - \vartheta_t + \phi\rho}(1 + \phi a u_t)\delta'(u_t) \tag{E.11}$$

As we did in equation (E.5), we can express q_t^K, q_t^B, ι_t in terms of ϑ,[2]

$$\begin{aligned} q_t^K &= (1 - \vartheta_t)\frac{1 + \phi a u_t}{1 - \vartheta_t + \phi\rho}, \\ q_t^B &= \frac{\vartheta_t}{1 - \vartheta_t} q_t^K = \vartheta_t \frac{1 + \phi a u_t}{1 - \vartheta_t + \phi\rho}, \\ \iota_t &= a u_t - \rho(q_t^K + q_t^B) = \frac{a u_t (1 - \vartheta_t) - \rho}{1 - \vartheta_t + \phi\rho}. \end{aligned} \tag{E.12}$$

The steady-state capital growth rate can be backed out from equations (E.11) and (E.12)

$$g_t^n = \Phi(\iota_t) - \delta(u_t).$$

[2]When $\Phi(\iota) = \log(1 + \phi\iota)/\phi$ and $\delta(u) = (\bar{\delta}/2)u^2$, the flexible price values of q_t^K and q_t^B are given by equations (3.27) and (3.28).

The Model without a Safe Asset. The flexible price allocation of the model is similar. Specifically, since $\vartheta_t = 0$, equations (E.11) and (E.12) becomes

$$a\frac{\varepsilon-1}{\varepsilon} = \frac{1}{1+\phi\rho}(1+\phi a u_t)\delta'(u_t), \quad \iota_t = \frac{a u_t - \rho}{1+\phi\rho}.$$

The steady-state capital growth rate is still $g_t^n = \Phi(\iota_t) - \delta(u_t)$.

C.5 Optimal Policy Implementation

Suppose that the government imposes a subsidy τ_t^f on intermediary goods firms.[3] In this case, the rental price of capital under flexible prices (3.26) is modified to

$$p^{R,flex} = (1+\tau_t^f)a\frac{\varepsilon-1}{\varepsilon}.$$

Together with (E.6), we see that utilization under flexible prices is determined by

$$(1+\tau_t^f)a\frac{\varepsilon-1}{\varepsilon} = \frac{1-\vartheta_t}{1-\vartheta_t+\phi\rho}(1+\phi a u_t)\delta'(u_t).$$

We then get the optimal τ_t^f by plugging in the efficient level of portfolio weight ϑ_t^o and utilization rate u_t^o from the planner's problem (3.36).

In addition, the first-order conditions of the planner's problem are

$$\begin{aligned}
\delta'(u_t) &= \frac{a}{1+\phi a u_t}\left[\rho\phi + (1-\vartheta_t) + \frac{1}{\rho}(1-\vartheta_t+\phi\rho)(1-\vartheta_t)^2\tilde{\sigma}_t^2\right], \\
\Phi'(\iota_t) &= \frac{1-\vartheta_t+\phi\rho}{1+\kappa a u_t}\left[1 + \frac{1}{\rho}(1-\vartheta_t+\phi\rho)(1-\vartheta_t)\tilde{\sigma}_t^2\right].
\end{aligned}$$

Simplifying the first-order conditions, we see that the optimal ϑ_t^o satisfies the following cubic equation,

$$\vartheta_t^3 - (3+\phi\rho)\vartheta_t^2 + \left(3 + 2\rho\phi + \frac{\rho}{\tilde{\sigma}_t^2}\right)\vartheta_t - (1+\phi\rho) = 0.$$

[3]For simplicity, we assume that the subsidy is funded by lump-sum taxes on the firms, so it is a pure decision wedge and does not interact with household portfolio choice.

Applying Ito's Lemma gives us the dynamics of ϑ_t^o,

$$\sigma_t^\vartheta = \frac{2\rho\nu(\tilde{\sigma}_t)}{\tilde{\sigma}_t^3\left[3\vartheta_t^2 - 2(3+\phi\rho)\vartheta_t + (3+2\rho\phi+\frac{\rho}{\tilde{\sigma}_t^2})\right]},$$
$$\mu_t^\vartheta = \frac{\frac{2\rho}{\tilde{\sigma}^3}\mu(\tilde{\sigma}) - \frac{3\rho}{\tilde{\sigma}^4}[\nu(\tilde{\sigma})]^2 + \frac{2\rho}{\tilde{\sigma}^3}\sigma_t^\vartheta\nu(\tilde{\sigma}) - (\sigma_t^\vartheta)^2\left[3\vartheta_t^2 - (3+\phi\rho)\vartheta_t\right]}{3\vartheta_t^2 - 2(3+\phi\rho)\vartheta_t + (3+2\rho\phi+\frac{\rho}{\tilde{\sigma}_t^2})}.$$

Recall the bond evaluation equation

$$\mu_t^\vartheta = \rho - (1-\vartheta_t)^2\tilde{\sigma}_t^2 - \check{s}_t.$$

It is then obvious that the optimal tax rate should be

$$\check{s}_t = \rho - (1-\vartheta_t)^2\tilde{\sigma}_t^2 - \mu_t^\vartheta,$$
$$\implies \quad \tau_t^K = \frac{\vartheta_t}{1-\vartheta_t}\left[\rho - (1-\vartheta_t)^2\tilde{\sigma}_t^2 - \mu_t^\vartheta\right].$$

C.6 Proofs

Proof of Proposition 7. First, since the households are homogeneous and the intermediary goods firms are symmetric, the transfers from firms (3.7) are simply

$$\omega_t = au_t - p_t^R u_t.$$

Hence, the return on capital (3.5) is

$$\mathrm{d}R_t^{K,i}(u_t^i, \iota_t^i) = \left(\frac{au_t^i - \iota_t^i}{q_t^K} - \tau_t^K + g(u_t^i, \iota_t^i) + \mu_t^{q,K}\right)\mathrm{d}t + \tilde{\sigma}_t\mathrm{d}\tilde{Z}_t^i + \sigma_t^{q,K}\mathrm{d}Z_t.$$

Then we can easily obtain the first-order conditions from the HJB laid out in Appendix C.2 (i.e., equation (E.3)).

Proof of Proposition 8. Plugging the expressions for $\mathrm{d}R_t^B$ and $\mathrm{d}R_t^K$ into the first-order condition (3.20), we get

$$\begin{aligned}
&\frac{au_t - \iota_t}{q_t^K} - \tau_t^K + g_t + \mu_t^{q,K} - \left(i_t - \mu_t^B + g_t - \mu_t^{q,B}\right) = (1-\vartheta_t)\left[\tilde{\sigma}_t^2 + (\sigma_t^{q,K})^2\right] \\
&\frac{au_t - \iota_t}{q_t^K} - (1-\vartheta_t)\tilde{\sigma}_t^2 - (i_t - \mu_t^B + \tau_t^K) = \mu_t^{q,B} - \mu_t^{q,K} + (1-\vartheta_t)(\sigma_t^{q,K})^2. \qquad \text{(E.13)}
\end{aligned}$$

Applying Ito's Lemma to the asset market clearing condition $\vartheta_t = \frac{q_t^B}{q_t^K + q_t^B}$ yields

$$\begin{aligned}
\sigma_t^{q,B} - \sigma_t^{q,K} &= \frac{\sigma_t^\vartheta}{1-\vartheta_t}, \\
\mu_t^{q,B} - \mu_t^{q,K} &= \frac{1}{1-\vartheta_t}\left[\mu_t^\vartheta + \sigma_t^\vartheta\left(\sigma_t^{q,B} - \sigma_t^\vartheta\right)\right].
\end{aligned}$$

Since $\sigma_t^{q,B} = 0$,

$$\mu_t^{q,B} - \mu_t^{q,K} + (1-\vartheta_t)(\sigma_t^{q,K})^2 = \frac{1}{1-\vartheta_t}\mu_t^\vartheta.$$

Further, notice that the goods market clearing condition implies that

$$au_t - \iota_t = \rho(q_t^B + q_t^K) \quad \Longrightarrow \quad \frac{au_t - \iota_t}{q_t^K} = \frac{\rho}{1-\vartheta_t}.$$

Finally, the government budget constraint (3.9) requires that

$$i_t - \mu_t^B + \tau_t^K = \frac{1}{1-\vartheta_t}\check{s}_t.$$

Plugging all terms into (E.13) results in the bond evaluation equation (3.23). Applying Ito's Lemma to $(e^{-\rho t}\vartheta_t)$ and integrating forward gives us the integral form (3.24).

Proof of Proposition 9. ϑ_t is given by the bond evaluation equation

$$\vartheta_t = \mathbb{E}_t\left\{\int_t^\infty e^{-\rho(s-t)}\vartheta_s\left[(1-\vartheta_s)^2\tilde{\sigma}_s^2 + \check{s}(\tilde{\sigma}_t, \vartheta_t)\right]\mathrm{d}s\right\}.$$

It is obvious that the solution to this equation only depends on $\tilde{\sigma}_t$.

Proof of Proposition 10. Consider equation (3.34),

$$\frac{u_t a - \iota_t}{q_t^K} + g_t + \left[\mu_t^{q,K} - (\sigma_t^{q,K})^2\right] = r_t^f + \tau_t^K + \tilde{\sigma}_t^2.$$

We want an equilibrium with $\pi_t = \mu_t^{q,K} = \mu_t^{q,B} = \tau_t^K = 0$ and $r_t^f = i_t$, so

$$i_t = \frac{u_t a - \iota_t}{q_t^K} + g_t - \tilde{\sigma}_t^2.$$

By market clearing, $(u_t a - \iota)/q_t^K = \rho$. Then the capital growth rate coincides with its steady-state level if the interest rate is set at

$$i_t^n = \rho + g_t^n - \tilde{\sigma}_t^2.$$

By standard arguments, we need other equilibrium selection techniques to ensure that this is the unique equilibrium (e.g., the Taylor Principle).

Proof of Proposition 11. With lump-sum taxes, the government budget constraint is

$$i_t B_t = \mu_t^B B_t + P_t \tau_t K_t + P_t \tau_t^K \cdot q_t^K K_t \quad \Longrightarrow \quad i_t = \mu_t^B + \frac{1}{q_t^B}\tau_t + \frac{q_t^K}{q_t^B}\tau_t^K.$$

The consistency condition (3.15) becomes

$$\mu_t^{q,B} = \mu_t^B - \pi_t - g_t = i_t - \frac{\tau_t}{q_t^B} - \frac{q_t^K}{q_t^B}\tau_t^K - \pi_t - g_t. \tag{E.14}$$

The return on bonds is now

$$\mathrm{d}R_t^B = i_t \mathrm{d}t + \frac{\mathrm{d}(q_t^B K_t / B_t)}{q_t^B K_t / B_t} = \left(\frac{1}{q_t^B}\tau_t + \frac{q_t^K}{q_t^B}\tau_t^K + g_t + \mu_t^{q,B}\right)\mathrm{d}t.$$

No arbitrage between government bonds and tax claims requires

$$\frac{\tau_t}{q_t^\tau} + \mu_t^{q,\tau} = \frac{\tau_t}{q_t^B} + \frac{q_t^K}{q_t^B}\tau_t^K + \mu_t^{q,B} \tag{E.15}$$

The total supply of idiosyncratic-risk-free assets to the household sector is $q_t^G K_t = (q_t^B - q_t^\tau)K_t$. The portfolio of all safe assets that is long in the bond stock and short in the total tax liabilities has the return

$$\mathrm{d}R_t^G = \frac{q_t^B}{q_t^G}\mathrm{d}R_t^B - \frac{q_t^\tau}{q_t^G}\mathrm{d}R_t^\tau = \left(\frac{q_t^K}{q_t^G}\tau_t^K + g_t + \mu_t^{q,G}\right)\mathrm{d}t. \tag{E.16}$$

In addition, the law of motion of q_t^G is given by

$$\mu_t^{q,G} = \frac{q_t^B}{q_t^G}\mu_t^{q,B} - \frac{q_t^\tau}{q_t^G}\mu_t^{q,\tau} = \left(i_t - \frac{q_t^K}{q_t^G}\tau_t^K\right) - \pi_t - g_t. \tag{E.17}$$

Comparing (E.16) with (3.4) and (3.9), we see that the return $\mathrm{d}R_t^G$ is the same as the return on bonds $\mathrm{d}R_t^B$ in the model without lump-sum taxes. Similarly, the law of motion of q_t^G (E.17) is the same as (3.15), the law of motion of q_t^B in the baseline model. In equilibrium, market clearing dictates that the households collectively hold all safe assets (long in government bonds and short in tax claims). It is then obvious that the economy with lump-sum taxes has the same dynamics as before, with the price of bonds q_t^B replaced by the price of all safe assets q_t^G.

Using equations (E.14) and (E.15), we see that in the model with lump-sum taxes, q_t^τ satisfies the following ODE

$$\frac{\mathrm{d}q_t^\tau}{q_t^\tau} = \left(i_t - \pi_t - g_t - \frac{\tau_t}{q_t^\tau}\right)\mathrm{d}t. \tag{E.18}$$

We consider a zero-inflation equilibrium with $\pi_t = 0$. Suppose that in the flexible price equilibrium, the nominal rate tracks the economic growth rate $i_t = g_t^n$. In the equilibrium, the ODE (E.18) then becomes

$$\frac{\mathrm{d}q_t^\tau}{\mathrm{d}t} = -\tau_t,$$

which is a forward equation with solutions of the following form

$$q_t^\tau = \int_t^\infty \tau_s \mathrm{d}s + D.$$

where D is a constant. For simplicity, we assume that there exist no bubbles in the valuation of tax claims, so $D = 0$.

For a given value of q_t^B, the government can then choose $\{\tau_s\}_{s=t}^{\infty}$ to ensure that the total value of government liability is the same as the bond price under flexible prices,

$$q_t^G = q_t^B - q_t^\tau = q_t^{B,flex}.$$

As we have argued in Proposition 9, the household portfolio problem is unaffected by price-setting frictions, so q_t^K will be at its flexible price level whenever q_t^G is.

Proof of Proposition 12. The welfare decomposition follows directly from the consumption decomposition in the main text. For the second integral, we use the mathematical result below.

For an Ito process X_t where $\mathrm{d}X_t/X_t = \mu_t^X \mathrm{d}t + \sigma_t^X \mathrm{d}Z_t + \tilde{\sigma}_t^X \mathrm{d}\tilde{Z}_t$, the dynamics of $\log X_t$ is given by

$$\mathrm{d}\log X_t = \left[\mu_t^X - \frac{1}{2}(\sigma_t^X)^2 - \frac{1}{2}(\tilde{\sigma}_t^X)^2\right]\mathrm{d}t + \sigma_t^X \mathrm{d}Z_t + \tilde{\sigma}_t^X \mathrm{d}\tilde{Z}_t.$$

Hence,

$$\log X_t = \log X_0 + \int_0^t \left[\mu_s^X - \frac{1}{2}(\sigma_s^X)^2 - \frac{1}{2}(\tilde{\sigma}_s^X)^2\right]\mathrm{d}s + \underbrace{\int_0^t \sigma_s^X \mathrm{d}Z_s + \int_0^t \tilde{\sigma}_s^X \mathrm{d}\tilde{Z}_s}_{\text{mean zero}}.$$

Using integration by parts, one can show that

$$\mathbb{E}_0\left[\int_0^\infty e^{-\rho t}\log X_t \mathrm{d}t\right] = \frac{1}{\rho}\log X_0 + \frac{1}{\rho}\mathbb{E}_0\left[\int_0^\infty e^{-\rho t}\left(\mu_t^X - \frac{1}{2}(\sigma_t^X)^2 - \frac{1}{2}(\tilde{\sigma}_t^X)^2\right)\mathrm{d}t\right].$$

C.7 Additional Details on Model Extension with Long-term Bonds

We start by deriving the return on bonds $\mathrm{d}R_t^B$ in the model with long-term bonds that replace equation (3.4) from the baseline model.

Suppose the nominal bond price P_t^B satisfies

$$\frac{\mathrm{d}P_t^B}{P_t^B} = \mu_t^{P,B}\mathrm{d}t + \sigma_t^{P,B}\mathrm{d}Z_t.$$

Then the return on bonds is (in general, permitting flexible prices)

$$\begin{aligned}\mathrm{d}R_t^B &= \frac{\mathrm{d}\left(\frac{P_t^B}{P_t}\right) + \lambda\left(\frac{1}{P_t} - \frac{P_t^B}{P_t}\right)\mathrm{d}t}{\frac{P_t^B}{P_t}} \\ &= \left(\mu_t^{P,B} - \pi_t - \sigma_t^P\left(\sigma_t^{P,B} - \sigma_t^P\right)\right)\mathrm{d}t + \left(\sigma_t^{P,B} - \sigma_t^P\right)\mathrm{d}Z_t + \underbrace{\lambda\left(\frac{1}{P_t^B} - 1\right)}_{=\bar{\imath}_t}\mathrm{d}t. \qquad \text{(E.19)}\end{aligned}$$

As before, we define $q_t^B := \frac{P_t^B B_t}{P_t K_t}$, so that $\frac{P_t^B}{P_t} = \frac{q_t^B K_t}{B_t}$ and thus

$$\mu_t^{P,B} - \pi_t - \sigma_t^P\left(\sigma_t^{P,B} - \sigma_t^P\right) = \mu_t^{q,B} + g_t - \mu_t^B, \qquad \sigma_t^{P,B} - \sigma_t^P = \sigma_t^{q,B}.$$

Substituting these equations into the previous return equation implies

$$\begin{aligned}\mathrm{d}R_t^B &= \left(\mu_t^{q,B} + g_t + \bar{\imath}_t - \mu_t^B\right)\mathrm{d}t + \sigma_t^{q,B}\mathrm{d}Z_t \\ &= \left(\mu_t^{q,B} + g_t + \check{s}_t\right)\mathrm{d}t + \sigma_t^{q,B}\mathrm{d}Z_t,\end{aligned}$$

where the second line follows from the government budget constraint. This is precisely the same equation as in the baseline model with short-term bonds.[4]

Clearly, the capital return (3.5) is also unaffected by the introduction of long-term bonds. Consequently, the portfolio choice condition between bonds and capital for each individual agent must be identical as in the baseline model. Therefore, we obtain the same bond valuation equation as before for the bond wealth share ϑ_t (equation (3.23)). Also, the separation result from Proposition 9 remains valid.

As a corollary, we obtain immediately that under flexible prices, the equilibrium dynamics of q_t^B, q_t^K, u_t, and ι_t and the consumption allocation across individual agents remain unaffected by the maturity structure λ and are as in the baseline model.

[4]To see this, compare the equation with equation (3.4) and replace their $i_t - \mu_t^B$ by $\check{s}_t$ using equation (3.11).

The derivations made in the main text and the claim that all model equations are as in the baseline model, except that i_t must be replaced with $\bar{i}_t$ and q_t^B has to be split according to equation (3.38) do not require further clarification here. It is thus only left to clarify the relationship between nominal short rates i_t and the variable $\bar{i}_t$.

Specifically, we show that for given ϑ dynamics (due to portfolio separation, Proposition 9), there is in equilibrium a mapping from interest rate paths $\{i_t\}_{t=0}^{\infty}$ to paths $\{\bar{i}_t\}_{t=0}^{\infty}$ of the variable $\bar{i}$ that satisfy in addition $\inf_{t\geq 0} \bar{i}_t > -\lambda$.[5] The relationship between the two is described by the backward stochastic differential equation (BSDE)

$$\mathbb{E}_t\left[\mathrm{d}\bar{i}_t\right] = \left(\left(\lambda + \bar{i}_t\right)\left(\bar{i}_t - i_t\right) - \sigma_t^{\vartheta}\sigma_{\bar{i},t}\right)\mathrm{d}t. \tag{E.20}$$

Here, $\sigma_{\bar{i},t}$ denotes the arithmetic volatility of $\bar{i}_t$.

Before deriving this BSDE, we show how to invert the mapping, i.e., start with some desired Ito process for $\bar{i}_t$,

$$\mathrm{d}\bar{i}_t = \mu_{\bar{i},t}\mathrm{d}t + \sigma_{\bar{i},t}\mathrm{d}Z_t$$

and back out the required process for i_t to implement it. This is important, as only then it is feasible to treat $\bar{i}_t$ as the policy instrument. Given the desired Ito process for $\bar{i}_t$, we equate $\mu_{\bar{i},t}\mathrm{d}t$ with $\mathbb{E}_t\left[\mathrm{d}\bar{i}_t\right]$ in the BSDE and obtain, after solving for i_t,

$$i_t = \bar{i}_t - \frac{\mu_{\bar{i},t} + \sigma_t^{\vartheta}\sigma_{\bar{i},t}}{\lambda + \bar{i}_t}.$$

Under the assumption $\inf_{t\geq 0} \bar{i}_t > -\lambda$, the denominator in the second term is always positive, and thus i_t required to implement $\bar{i}_t$ is well-defined.

To derive BSDE (E.20), consider the portfolio choice between (long-term) government bonds and a zero-net-supply nominal bond with infinitesimal duration. Call the latter M (for money), its return is (under sticky prices, so $\sigma_t^P = 0$)

$$\mathrm{d}R_t^M = i_t\mathrm{d}t + \frac{\mathrm{d}\left(1/P_t\right)}{1/P_t} = \left(i_t - \pi_t\right)\mathrm{d}t.$$

[5] This additional restriction is natural as it is equivalent to bounded nominal bond prices P_t^B (compare equation (3.38)).

Using the return representation (E.19) for bonds and the fact $\sigma_t^P = 0$ under sticky prices to simplify that representation, the portfolio choice condition between bonds and money becomes

$$\bar{i}_t - i_t + \mu_t^{P,B} = \sigma_t^n \sigma_t^{P,B}.$$

Now, $\sigma_t^n = \sigma_t^{q^B + q^K} = \sigma_t^{q,B} - \sigma_t^{\vartheta} = \sigma_t^{P,B} - \sigma_t^{\vartheta}$ and $\bar{i}_t = \lambda \left(1/P_t^B - 1\right)$, so

$$\begin{aligned} \mathrm{d}\bar{i}_t &= \lambda \mathrm{d}\left(1/P_t^B\right) = \lambda \frac{1}{P_t^B}\left(-\mu_t^{P,B} + \left(\sigma_t^{P,B}\right)^2\right)\mathrm{d}t - \lambda \frac{1}{P_t^B}\sigma_t^{P,B}\mathrm{d}Z_t \\ &= \lambda \frac{1}{P_t^B}\left(\left(\bar{i}_t - i_t\right) + \sigma_t^{\vartheta}\sigma_t^{P,B}\right)\mathrm{d}t - \lambda \frac{1}{P_t^B}\sigma_t^{P,B}\mathrm{d}Z_t \end{aligned}$$

which immediately implies the BSDE (E.20) stated above.

We conclude this appendix by remarking that the implicit integral formula for $\bar{i}_t$ for the case without risk ($\sigma_{\bar{i},t} = 0$) stated in the main text is easily verified by taking the time derivative in this formula and comparing the result with BSDE (E.20).

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