Bank Risk Sentiment*

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Abstract

This paper evaluates the role of investor risk sentiments in the commercial bank lending market and their effect on macroeconomic outcomes. I create a new empirical measure of bank risk sentiment (BRS) using regulatory data covering the universe of US commercial banks and an identification scheme motivated by a novel, analytical, heterogeneous bank model. BRS is countercyclical with spikes during financial crises, but is heterogeneous at the bank level. Loan-level analysis then shows that an increase in bank-level risk sentiment is associated with a decrease in credit supply and tightening loan covenants. While at the macro-level, an increase in aggregate BRS leads to a broad-based deterioration in macroeconomic and financial outcomes. Lastly, I present evidence that BRS is distinct from corporate bond market investors' risk sentiment, and is more important in explaining economic fluctuations. I conclude that BRS plays a significant role in determining the price and quantity of bank loans and macroeconomic outcomes.

Keywords Financial Intermediaries, Credit Supply Shocks, Investor Sentiment, Loan Markets
JEL Classifications: E32, E44, G21, G32

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1 Introduction

The price and quantity of bank loans are important determinants of macroeconomic outcomes, such as output and inflation. This fact has been shown to be robust across countries and through time. For the United States in particular, bank loans are, and have long been, the primary source of credit for key engines of economic activity and innovation, households and small firms. Moreover, banks' willingness to supply credit is of interest to academics as a source of amplification in business cycle fluctuations, and policymakers as the primary transmission mechanism of monetary policy.

Meanwhile, an emerging literature has pointed to investor risk sentiment as a key factor in determining prices across several financial markets, such as the corporate bond, equity, and syndicated loan markets. In this literature, risk sentiments reflect agents' fear regarding future states of the economy, and are measured through their demanded compensation for holding risk. Investor risk sentiment has also been emphasized in explaining boom and bust credit cycles as well as financial crises, such as the Global Financial Crisis in 2008, quickly making them a keen interest of policymakers. The potential causal mechanism is straightforward: as investors' fear increases, their willingness to supply credit decreases so that the price of credit increases, and in turn, firms and households are priced out of debt markets, leading to a subsequent decline in economic activity, reinforcing the precipitant fear and the credit crunch becomes self-enforcing. A similar story can be told based on investor optimism about future states of the world, which in turn leads to a credit boom and a surfeit of debt. However, the investor risk sentiment literature has largely ignored one of most important credit markets in the United States: commercial bank lending.

This paper evaluates the role of investor risk sentiment in the US commercial bank lending market and its effect on macroeconomic outcomes. I find that, similar to investor risk sentiment in other credit markets, bank risk sentiment (BRS) plays an important role in determining the price and quantity of bank loans, and in turn, plays a prominent role in determining business cycle fluctuations in economic activity and prices. However, I show that BRS is distinct from investor risk sentiment in other markets, namely the corporate bond market, and is more important in explaining macroeconomic outcomes.

I first create an empirical measure of BRS. I will study *bank risk sentiment* as the difference between a bank's forecast of risk and its rational expectations of risk, thus I will require a structural model to guide the econometric strategy. To this end, I develop an analytical heterogeneous macro-banking model rich enough to take to the data but tractable enough to yield a closed form solution to a bank's loan pricing problem. In the context of this rich analytical setting, a bank's loan rate equation is shown to be a function of the bank's market power, capital costs, regulatory costs, and expected loan default rate —what I refer to as risk.[1] Moreover, by postulating a law of motion for risk in the economy, I can further decompose the firm's expected loan default rate into a rational expectations and sentiments component. The loan rate equation is then easily log-linearized and mapped into an estimable linear regression, such that the resulting residuals isolate a measure of the bank's risk sentiment. Using this approach, I estimate bank-level risk sentiments at a quarterly frequency for the universe of US commercial banks from 1992 to 2021 using regulatory Call Reports.

Aggregate BRS is found to spike during several financial crises (or potential financial crises), such as the Asian Financial Crisis, Russian Financial Crisis, LTCM failure, Enron and WorldCom collapses, the Global Financial Crisis, European Debt Crisis, Taper Tantrum, and COVID pandemic. Bank-level risk sentiments display a large degree of heterogeneity and the distribution of sentiments evolves over time. The underlying bank-level sentiment processes are shown to be persistent, but with fat tailed distributions over the persistence and volatility of sentiment shocks.

I then show that BRS matters for loan-level outcomes. To do so, I match bank-level risk sentiments to DealScan syndicated loan data and measure the causal relationship between BRS and loan-level outcomes

[1] The analysis is extended to also consider the role of aggregate uncertainty and a bank's time-varying risk aversion in Appendix B. Together, these variables make up the list of standard elements in financial intermediaries' loan portfolio pricing problem. The identifying assumption behind my measure of bank risk sentiment will be that variation in portfolio pricing beyond these standard factors will have to come from bank-level deviations from rational expectations.

with an identification strategy in the spirit of Khwaja and Mian (2008). In this causal setting, I find an increase in BRS leads to an increase in loan rates, decrease in loan amounts, and tightening loan covenants. These loan-level results point towards two potential channels through which BRS may affect macroeconomic outcomes: directly as a shock to the price and quantity of loans, and indirectly through tightening earnings based borrowing constraints.

Moreover, BRS is shown to matter for macro-level outcomes. I study how economic activity, prices, and financial conditions respond to unanticipated changes in BRS through the lens of a factor augmented vector autoregression (FAVAR) and a rich collection of over 200 macroeconomic variables. An increase in BRS leads to a broad based deterioration in economic outcomes. However, the shock is not felt evenly across the economy: consumption falls more dramatically than than production, and the yield curve steepens, disproportionately increasing the cost of long term credit compared to short term debt. A further inspection of granular shocks à la Gabaix (2011) shows that BRS primarily impacts the economy through small regional and community banks rather than large national lenders.

I last turn to comparing BRS to investor risk sentiment in other asset markets, specifically the corporate bond market. I proxy corporate bond market sentiment with the Excess Bond Premium (EBP) of Gilchrist and Zakrajšek (2012), and compare BRS to EBP through a VAR in the spirit of Gertler and Karadi (2015). I show that an unanticipated increase in aggregate BRS has a more persistent impact on activity, prices, and the policy rate than an analogous shock to the EBP. Moreover, in the context of a forecast error variance decomposition, fluctuations in the BRS are more important in explaining innovations in inflation and the unemployment rate than the EBP, although the EBP is more important in explaining changes in the policy rate. Finally, BRS accounts for 20 percent of the variance in the EBP, while the EBP accounts for less than 10 percent of variance in BRS.

1.1 Related Literature

My work is related to three broad, and non-mutually exclusive, strands of literature concerning: market sentiments, macro-banking, and financial accelerators. I will discuss this project's relationship with and contribution to each broad topic in turn, and then conclude by focusing on studies directly concerned with bank risk sentiment.

Market sentiments
There is a long history of discussions around market sentiments dictating credit and real business cycles alike, see for example Minsky (1977) and Kindleberger (1978) for discussions of the topic through the beginnings of the rational expectations revolution of the 1970's and 80's. The topic has since reemerged as a point of debate in the wake of the global financial crisis. One strand of literature focuses on extracting measures of investor risk sentiment by decomposing risk premia found in various asset markets, such as the corporate bond market: Gilchrist and Zakrajšek (2012), López-Salido et al. (2017) and Leiva-Leon et al. (2022), equity markets Baron and Xiong (2017) and Pflueger et al. (2020), and most recently the syndicated loan market, Saunders et al. (2021) and Kwak (2022).[2] These works find investor risk sentiment to empirically matter for explaining fluctuations in economic outcomes, such as activity and prices, as well as the credit cycle. A second strand of literature has focused on explaining the investor risk sentiment formation process through a theoretical lens. The diagnostic expectations literature was kicked off by the seminal work of Bordalo et al. (2018), and has expanded upon by Bordalo et al. (2019), Krishnamurthy and Li (2021), Bianchi et al. (2022), and Maxted (2023). See Bordalo et al. (2020) for a review of the psychological and forecasting survey based evidence for this particular departure from rationality, or Bordalo et al. (2022) for a review of overreaction in macroeconomics more broadly. This strand of literature has shown that deviations from rationality may account for the sentiment driven boom-bust patterns we observe across credit cycles.[3]

[2] Saunders et al. (2021) and Kwak (2022) both extract an EBP style sentiment indicator from the syndicated loan market. Therefore, at first glance, these may seem like a good measures of bank risk sentiment. However, works, such as Fleckenstein et al. (2020), have shown that non-bank lenders are the most prevalent actors in the syndicated loan market. So these measures are correctly interpreted as syndicated loan market sentiments, but not commercial bank lending sentiments.

[3] A separate type of financial market sentiments, namely optimism and pessimism vis-à-vis future liquidity, has also recently emerged in the international finance literature, and has been used to explain recessions and financial crisis, see for example

While the diagnostic expectations literature was a direct answer to explaining sentiment driven boom and bust credit cycles, the concept of sentiments studied in this work is more closely linked to that arising from the dispersed and noisy information problems proposed by Angeletos and La'o (2010, 2013) and further surveyed in Angeletos and Lian (2016). That is, the sentiments I study are defined as exogenous deviations from a bank's rational expectations forecast of risk, and arise from primitive shocks in the model, while the concept of sentiments in the diagnostic expectations literature arise from over-extrapolations of forecast errors and are endogenous given the agents belief-formation process. I choose this approach to defining sentiments for two reasons. First, my approach is more easily mapped to a measurement equation which can be taken to the data. Second, by treating bank-level sentiments as primitive shocks, I do not take a stand on their source, which I view as beyond the scope of this project.

My contribution to this literature is an asset price based measure of sentiment in an overlooked credit market, the commercial bank lending market. Moreover, this project will be the first to directly measure individual agent's risk sentiment based on their real world pricing decisions.

Macro-Banking

Both the theoretical and empirical macro-banking literature has expanded rapidly since the Global Financial Crisis. Early (theoretical) entries focused on more explicitly incorporating financial intermediaries into DSGE models, resulting in a Handbook chapter, Gertler and Kiyotaki (2010), and applications to unconventional monetary policy, Gertler and Karadi (2011), bank runs Gertler and Kiyotaki (2015), and shadow banking, Martinez-Miera and Repullo (2017). While a more recent wave of models has emphasized the role of heterogeneity among banks, including Coimbra and Rey (2017) which features heterogeneous value-at-risk constraints, Jamilov (2021) featuring heterogeneous portfolio return, Corbae and D'Erasmo (2021) featuring heterogeneous market power, and Bellifemine et al. (2022) or Jamilov and Monacelli (2023) featuring heterogeneous market power and idiosyncratic portfolio returns. My project joins this strand of literature by putting forth an analytically tractable macro-banking model featuring heterogeneity in banks' portfolio returns and risk sentiment processes.

A large amount of empirical work concerning the effects of bank credit supply and risk taking behavior has also been undertaken in the wake of the Global Financial Crisis. This project is most closely related to those that study liquidity and risk taking through loan-level analysis, such as Khwaja and Mian (2008), Chodorow-Reich (2014), Jiménez et al. (2014), Dell'Ariccia et al. (2017), Morais et al. (2019), Greenstone et al. (2020), Pinardon-Touati (2021), Di Giovanni et al. (2022), and Chodorow-Reich and Falato (2022). These works focus on a variety of shocks and outcomes, for example, Khwaja and Mian (2008) studies how liquidity supply shocks (stemming from Pakistani nuclear tests in the 1990's) impacted loan prices and access to credit, Pinardon-Touati (2021) studies how local government borrowing crowds out private sector loans, and Di Giovanni et al. (2022) studies how bank-level exposure to the fluctuations in the global financial cycle impacts credit access in emerging markets. However, like this work, they all do so by exploiting variation in firm-bank outcomes for multi-lender firms. This work joins this literature as the first to use the Khwaja-Mian research design to study covenant-related responses to bank-specific risk shock.[4]

Financial accelerators and macroeconomic outcomes

My work is related to the abundant literature connecting the supply of credit and financial intermediation to real economic outcomes, as well as the nascent literature on earning based borrowing constraints. The link between credit and real business cycles has been empirically documented to be robust across time and country, see Jordà et al. (2017) and Mian and Sufi (2018) for surveys of this literature. While theoretical work has additionally formalized the link between intermediation and amplification of business cycle fluctuations. Seminal work in this area includes the establishment of the financial accelerator mechanism, linking bank lending to output via intermediation frictions, such as moral hazard, as in Hart and Moore (1994) and Kiyotaki and Moore (1997), or costly state verification problems, as in Bernanke and Gertler (1989),

Perri and Quadrini (2018) or Schmitt-Grohé and Uribe (2021). This is not the style of investor sentiment this project considers.

[4] Chodorow-Reich and Falato (2022) similarly studies covenant related outcomes, however, this work studies how banks respond to covenant violations rather than supply-side shocks.

Bernanke et al. (1999), and Carlstrom and Fuerst (1997). My results will point towards two channels through which bank risk sentiment impact the economy. First, risk sentiment act directly as a shock to supply of credit, with a similar effect as the liquidity supply shocks studied by Khwaja and Mian (2008) or risk shocks studied by Christiano et al. (2014). Second, risk sentiment works indirectly as a credit constraint shock by tightening covenants regarding earning based borrowing constraints. Such constraints have been shown to be prevalent, see Lian and Ma (2021) and Caglio et al. (2021), as well as key in explaining economic fluctuations in closed economies, Drechsel (2023), and open economies, Camara and Sangiacomo (2022). That is, this work will provide further empirical evidence in favor of the emerging earning based borrowing constraints extension of the financial accelerator literature.

Bank risk sentiment

Works most closely related to my own are those that directly deal with studying the economic effects of BRS. Studies concerning bank risk sentiment can generally be divided into two categories: sentiment as time-varying risk aversion and sentiment as uncertainty.

He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) study bank risk sentiment through the lens of time-varying risk aversion of bank owner-operator households. The former argues that time-varying risk aversion is important in explaining asymmetric behavior of asset prices and the supply of credit, while the latter extends this to explain asymmetric business cycle fluctuations more broadly. These works differ from my own and others in the investor risk sentiment literature by defining sentiment based on a household's risk aversion over consumption and are theoretical, rather than empirical, studies. I present an extension of my analytical model in Appendix B that shows my measure of BRS can in fact be interpreted as sentiment in excess of time-varying risk aversion.

Bank risk sentiment has also been studied through the lens of uncertainty shocks. For example Christiano et al. (2014), considers banks that perceive risk shocks as changes in the variance of individual entrepreneurs ability, and find that an increase in risk leads to a decrease in the supply of credit. This style of risk shocks is closely related to uncertainty shocks à la Bloom (2009) or Bloom et al. (2018). Additional studies in this vein include Gilchrist et al. (2014) which studies the intersection of (corporate bond) investor risk sentiment and productivity uncertainty shocks, as well as, Akinci et al. (2022) which traces domestic uncertainty shocks to banks' willingness to lend abroad. Similar to these works, the analytical model presented in this paper can be extended to account for uncertainty, as a change in the variance of loan default rates, and in turn BRS can be defined as the loan risk premia in excess of that attributable to the forecasted mean and variance of loan defaults rate. I present evidence in Appendix B that the empirical measure of BRS is qualitatively robust to removing the influence of aggregate uncertainty.

The works most similar to mine are Ma et al. (2021) and Falato and Xiao (2022). On the one hand, Ma et al. (2021) have a similar goal to my own, to measure bank risk expectations, and in turn find similar results, an increase in perceived downside risk leads to an increase in lending costs and decrease in loan supply. On the other hand, Falato and Xiao (2022) focus first on documenting that bank expectations follow an over-extrapolative formation process —that is, deviate from rational expectations— then show that this can account for the slow recovery in credit growth after the Global Financial Crisis.

However, there are several important distinctions between these two projects and my own. First and foremost, the interests of Ma et al. (2021) and Falato and Xiao (2022) are complimented and subsumed by the focus of this work, respectively. Ma et al. (2021) focuses on bank risk expectations, while I measure sentiments over and above rational expectations of risk. Falato and Xiao (2022) similarly study deviations from rational expectations, but these authors focus specifically on deviations due to over-extrapolation, while I study the effects of the entire deviation from rationality, not just the portion due to over-extrapolation. Second, the scope of these two works are limited by data availability in comparison to this project. While both works have a direct report of bank risk expectations, they do so for only a short period of time, starting after the Global Financial Crisis, and for a small number of US banks. In comparison, my measure of risk sentiments is based on banks' revealed preferences via their loan rates and span the universe of US commercial banks since the 1990's, allowing for an examination of how sentiments have evolved through time and across a broader cross-section of banks.

1.2 Roadmap

The remainder of the paper is organized as follows: Section 2 presents the analytical model, Section 3 introduces and describes the empirical measure of BRS, Section 4 analyzes BRS effect on loan-level outcomes, Section 5 analyzes BRS effect on macro-level outcomes, Section 6 compares BRS and EBP, and Section 7 concludes.

2 Model of monopolistic competition in loan markets

I next present an analytical model of banks operating in a monopolistically competitive credit market to motivate my econometric strategy for measuring bank risk sentiment. I additionally present analytical predictions for the effect of changes in a bank's risk sentiment on bank-level loan rates, aggregate loan rates, and the aggregate supply of credit.

My analytical model takes the canonical Gertler and Kiyotaki (2010) as a foundation.[5] Risk neutral banks raise capital each period to form one-period loan portfolios, face (indirect) net worth constraints, and operate as monopolistic creditors within a segmented market. However, the analytical model will diverge from Gertler and Kiyotaki (2010) in two key respects: aggregation and regulation. First, banks operate as the sole creditor within their own Lucas (1973) style island, which in this setting may be interpreted as representing markets for differentiated credit products (e.g. commercial and industrial loans versus mortgages) or geographic regions (e.g. US counties or states). However, unlike Gertler and Kiyotaki (2010), I stop short of aggregating financial intermediaries across islands.[6] I do this to 1) facilitate a focus on individual banks, since my ultimate goal will be to derive a strategy for estimating bank-level risk sentiment, and 2) more easily allow for the inclusion of explicit bank-level time-varying mark ups in loan markets, following recent work on bank-level heterogeneity, such as Corbae and D'Erasmo (2021), Bellifemine et al. (2022), and Jamilov and Monacelli (2023). Second, I impose regulatory costs based on a bank's funding gap, rather than a moral hazard friction on raising funds as in Gertler and Kiyotaki (2010). Both frictions incorporate a bank's net worth into it lending decisions and restrict the size of loan portfolios, while the regulatory cost is more directly motivated by reality.

I will next describe the credit markets, assets, agents, and aggregate outcomes in this analytical setting.

2.1 Loan market structure

Specialist banks form monopolies by creating differentiated credit products that serve as intermediate inputs for a consumer-facing Broker who supplies loans to firms and households in a perfectly competitive asset market. Specialized banks hold risky loans on their own balance sheets, thus form expectations about default risk and price their credit products accordingly. Brokers effectively act as middlemen between Specialists and borrowers, thus are not exposed to default risk, and in turn do not form expectations of their own. Note that the Broker is not necessary for the results derived in this analytical setting, but its presence makes examining aggregate loan rates and quantities more tractable.

[5]Additional ways for modeling bank risk sentiment exist, most prominently He and Krishnamurthy (2013) and Brunnermeier and Sannikov (2014) place bank's risk sentiment at the heart of their theoretical models of the economy. Bank risk sentiment in these settings are actually the risk premia due to the bank owner-operator household's time-varying risk aversion. I show in Appendix B that the empirical measure of BRS can be interpreted as controlling for time-varying risk aversion in the style of the two aforementioned works. Therefore I can choose to begin with a more tractable risk-neutral bank setting without losing a potentially important source of loan premia.

[6]This is more inline with the segmented market structure often used to explain international finance phenomenon, such as the exchange rate disconnect and UIP deviations, for example Gabaix and Maggiori (2015), Itskhoki and Mukhin (2021), and Basu et al. (2020).

2.2 Loans

The only asset in this economy is a risky, one period, loan. Loans are risky because firms and households will default with state-contingent probability λ_s, where s indexes the state of the world.[7] When loans default, they yield a gross return of zero. That is, the entire principal of the loan is lost.

2.3 Loan demand

Firms and households are not a focal point of my analysis. Therefore, I will keep consumer credit demand simple, represented by a reduced from, downward sloping, linear demand schedule:

$$L_t^D = P - AR_t + \pi_t \tag{1}$$

$$\pi_t \sim \mathcal{N}(0, \sigma_\pi^2)$$

where P is the maximum credit demand, A is the interest elasticity of loan demand, and π is an *iid* stochastic demand shifter with mean zero and variance σ_π^2. Consumers purchase loan products from the Broker.

2.4 Brokers

A Broker aggregates specialized credit products into a single consumer loan via a CES aggregator:

$$L = \left(\sum_i^B L_i^{\frac{\theta-1}{\theta}} \right)^{\alpha \frac{\theta}{\theta-1}}$$

where L is the notional value of the consumer loan, L_i is the notional value of the loan made by Specialist i, B is the number of Specialist banks, $\theta > 1$ and $\alpha \in (0, 1]$. When $\alpha = 1$ the Broker bundles Specialists' loans with a constant returns to scale technology and when $\alpha \in (0, 1)$ with decreasing returns to scale technology.

The Broker demands specialized loans to maximize profits. The formal problem is given as:

$$\max_{L_i} \; R_t L_t - \sum_i^B R_{i,t} L_{i,t} \tag{2}$$

where R is the interest rate charged on the consumer loan and R_i is the interest rate charged on Specialists i's loan. Note that the Broker does not bear risk on their own balance sheets, thus the consumer loan rate R is treated as risk free. The Broker's problem yields the following first order condition for any generic specialized loan:

$$\frac{\partial \Pi}{\partial L_{i,t}} = R_t \alpha \left(\sum L_{i,t}^{\frac{\theta-1}{\theta}} \right)^{\alpha \frac{\theta}{\theta-1} - 1} L_{i,t}^{\frac{\theta-1}{\theta} - 1} - R_{i,t} = 0$$

and in turn the following downward sloping demand schedule for any specialized loan:

$$L_{i,t} = \frac{1}{\alpha} \frac{R_t^{\theta-1}}{R_{i,t}^{\theta}} L_t \tag{3}$$

which is homothetic across the size of total loans demanded, L. That is, the percent of Specialist's loan L_i to total loans demanded by households and firms stays constant as the total level of loans demanded changes.[8]

[7] One can motivate exogenous defaults in a number of ways, for example, stochastic firm exits as in Restuccia and Rogerson (2008) or stochastic household deaths as in Huggett (1996).

[8] This assumption is key in maintaining the tractability of our measurement equation. Non-homothetic preferences over specialized loans may allow for the demand ratios for specialized loans to vary across the total demand for loans, leading to a non-linear model of loan demand and potential identification issues in isolating bank risk sentiment.

2.5 Specialized banks

The Specialist bank acts as a monopolist intermediate credit supplier that maximizes profits by solving the following pricing problem:

$$\max_{R_{i,t}} \beta E(R^p_{i,t})L_{i,t} - (L_{i,t} - N_{i,t})C_t - \Phi(L_{i,t} - N_{i,t}) \quad \text{s.t.} \tag{4}$$

$$N_{i,t} = N_{i,t-1} + \Pi_{i,t-1}$$

$$L_{i,t} = \frac{1}{\alpha}\frac{R_t^{\theta-1}}{R_{i,t}^{\theta}}L_t$$

$$E(R^p_{i,t}) = (1 - E\lambda_{i,t+1})R_{i,t}$$

where Specialists maximize the present discounted value of expected profits, $\Pi_{i,t}$, by charging loan rate $R_{i,t}$. The expected gross portfolio return rate for loans made in period t is denoted, $E(R^p_{i,t})$, and is realized at the beginning of period $t+1$. Thus, profits Π_t are known at the beginning of period $t+1$. The bank's net worth in period t is denoted $N_{i,t}$ and is simply the previous period's net worth plus realized gains or losses from the current period's loan portfolio. I will make the simplifying assumption that banks are sufficiently well funded (that is, have a sufficiently large enough $N_{i,t}$) to cover loan losses so that I may abstract away from the possibility of bankruptcies.[9] Note that Specialists are atomistic and do not internalize how a change in their interest rate R_i will change the aggregate loan rate, thus aggregate demand for credit.[10]

Specialists can use their net worth, $N_{i,t}$, to fund loans and can source deposits or other funding from an inter-bank funding market at the marginal gross cost $C_t = 1 + c_t$. The assumption that the capital cost of forming loans is common across all banks is in line with the fact that banks have access to a common, perfectly competitive, inter-bank lending market, following Gertler and Kiyotaki (2010).[11]

Specialists also pay a regulatory cost based on their funding gap, $L_{i,t} - N_{i,t}$.[12] The regulatory cost function, $\Phi(\cdot)$, will be kept general for the remainder of the presentation of the analytical model, and is assumed to be weakly convex and zero at the origin. More formally, I assume $\Phi'(X) \geq 0$ and $\Phi''(X) \geq 0$ for all $X \in \mathbb{R}$, and $\Phi(0) = 0$. Although, I will later assume a (quadratic) functional form when deriving a concrete econometric strategy for measuring BRS. The a convex regulatory costs acknowledges the real presence of such costs born by banks, as well as establishes a connection between a bank's net worth, $N_{i,t}$, and ability to make loans.

Therefore, the Specialist charges a loan interest rate:

$$R_{i,t} = \frac{1}{\beta} \cdot \underbrace{\frac{1}{1 - E\lambda_{i,t+1}}}_{\text{perceived risk}} \cdot \underbrace{\frac{\theta_{i,t}}{\theta_{i,t} - 1}}_{\text{market power}} \cdot \underbrace{(C_t + \Phi'(L_{i,t} - N_{i,t}))}_{\text{marginal cost}} \tag{5}$$

so that as the expected default rate, $E\lambda_{i,t}$, market power, $\theta_{i,t}$, cost of capital c_t, or marginal regulatory cost, $\Phi'(L_{i,t} - N_{i,t})$ increases, so does the interest rate charged to the market. Conversely, as the size of the

[9] Relaxing this assumption would not change the subsequent analysis, but would require a richer description of the Households or Government who would ultimately have to foot the bankruptcy bill.

[10] Specialists ignoring general equilibrium effect of their loan rates may also be motivated by assuming there is a continuum of banks so that any single bank has a measure zero impact on the final good price

[11] Recent work on banking market power in deposit markets, such as Drechsler et al. (2017), Corbae and D'Erasmo (2021), Bellifemine et al. (2022), Jamilov and Monacelli (2023), may motivate allowing idiosyncratic marginal funding costs. However, these works, Drechsler et al. (2017) in particular, notes that a bank's deposit mark downs are not necessarily connected to its loan rates. So we will continue in the tradition of Gertler and Kiyotaki (2010) and use a common funding cost for tractability.

[12] Various authors take up a similar object of interest when formulating regulatory costs and constraints. For example, Gabaix and Maggiori (2015) focus on a liquidity ratio while Coimbra and Rey (2017) employ a leverage ratio. I depart slightly from these antecedents by using the difference between the notional loan value and bank net worth, rather than the ratio of the two (i.e. the leverage ratio). This modeling choice does not change the spirit of the regulatory cost, but yields a more convenient log-linearization when taking the model to the data.

bank increases, $N_{i,t}$, the loan rate decreases and the quantity supplied increases. Note that while I maintain the simplifying assumption that all banks have the same market power for the presentation of this tractable model, I have expanded the notation in Equation 5 to allow for bank-specific market power. This additional flexibility will be used while empirically estimating bank-level risk sentiments.

2.6 Default rates and bank risk sentiment

I define a bank's risk sentiment as the time-varying wedge between the bank's rational expectations forecast of risk and their revealed forecast of risk. Therefore, to measure risk sentiments, I must postulate a law of motion for risk in the economy that will provide an analytical forecast to benchmark banks' expectations against.[13] It is common in the macro-banking literature to assume that a bank's portfolio return is risky and follows a reduced form Brownian motion process (if continuous time) or random walk with drift (if discrete time).[14] As a Specialist's portfolio ex-post return fluctuates according to the loan default rate, we will adopt the literature's standard approach and postulate a reduced form law of motion for risk in the economy.

In the spirit of Bellifemine et al. (2022) and Jamilov and Monacelli (2023) I will assume that a bank's specific level of default risk is a function of idiosyncratic risk (reflecting a bank's innate ability to manage and perceive risk) and aggregate risk (reflecting uninsurable shocks to the entire economy).[15] Additionally, in keeping with evidence presented in Falato and Xiao (2022), the law of motion for risk will be assumed to take on an AR(1) process. Thus, I will postulate that $\lambda_{i,t}$ follows a stochastic process with an idiosyncratic and aggregate component:

$$\lambda_{i,t} = \gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} + \omega_{i,t}, \quad \omega_{i,t} \sim \mathcal{N}(0, \sigma_\omega^2) \tag{6}$$

where $\lambda_{i,t}$ is a bank's loan default rate in time t, λ is a measure of aggregate default rates, and $\omega_{i,t}$ is an idiosyncratic and exogenous shock to default rates. I allow for a bank-specific mean default rate, Γ_i, such that $\Gamma_i = \gamma_i - \rho_1 + \rho_2$.

The rational expectations forecast of loan default rates is then:

$$E_{RE}(\lambda_{i,t}|s_{t-1}) = \gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} \tag{7}$$

which implies the following decomposition of a bank's risk expectations:

$$\begin{aligned} E(\lambda_{i,t}|s_{t-1}) &= E_{RE}(\lambda_{i,t}|\lambda_{i,t-1}) + \psi_{i,t} \\ &= \gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} + \psi_{i,t} \end{aligned}$$

where $\psi_{i,t}$ is the bank-level deviation from the rational expectation forecast of loan default rates, that is, the bank's risk sentiment. We can further expand the Specialist's loan pricing equation to explicitly reflect the presence of the bank's rational expectations and risk sentiment:

$$R_{i,t} = \frac{1}{\beta} \cdot \frac{1}{1 - (\gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} + \psi_{i,t})} \cdot \frac{\theta_{i,t}}{\theta_{i,t} - 1} \cdot (C_t + \Phi'(L_{i,t} - N_{i,t})) \tag{8}$$

Result 1. (Bank risk sentiment and loan rates)
An increase in the bank's rational expectations forecast of default rates or the bank's risk sentiment, $\psi_{i,t}$, leads to an increase in the bank loan rate.

[13] One may take a more agnostic approach to estimating an rational expectations forecast by way of combining machine learning and large data sets, as in Bianchi et al. (2023) or McCarthy and Hillenbrand (2021). However, these approaches threaten predicting the behavioral sentiment of interest in addition to the fundamental risk of interest. Such an over-prediction problem becomes an identification problem when attempting to isolate sentiment shocks. For this reason I do not adopt these agnostic approaches.

[14] See Brunnermeier and Sannikov (2014) or He and Krishnamurthy (2013) for examples in continuous time or Gertler and Kiyotaki (2010) in discrete time.

[15] Alternative laws of motion for risk are tested and discussed in Appendix A.

2.7 Competitive Equilibrium

The competitive equilibrium is characterized by the sequence of allocations $\{L_t^D, L_t, L_{i,t}, N_{i,t}\}_{t=0,i=1}^{\infty,N}$, prices $\{R_t, R_{i,t}, C_t\}_{t=0,i=1}^{\infty,N}$, and exogenous shocks $\{\psi_{i,t}, \omega_{i,t}\}_{t=0,i=1}^{\infty,N}$ such that for each period:

- Each Specialist bank i chooses $R_{i,t}$, given $N_{i,t}$, C_t, and $\psi_{i,t}$ that satisfies its profit maximization problem, Equation (4)
- The Broker sources specialized loans $\{L_{i,t}\}_{i=1}^{N}$ to create consumer loan L_t such that its profit maximization problem, Equation (2), is satisfied
- Households and Firms take out loans L_t^D according to the demand schedule, Equation (1)
- The aggregate loan markets clear, $L_t^D = L_t$, as well as the market for each specialist loan

I next turn to describing the effects of bank risk sentiment on aggregate outcomes, such as loan rates and quantities.

2.8 Bank risk sentiment and aggregate outcomes

We can next turn to characterizing the effect of bank risk sentiment on the aggregate loan rate and credit supply.

2.8.1 Aggregate loan rate

I find the aggregate interest rate on loans by combining the Broker's problem, Equation 2, and the zero expected profit condition of perfectly competitive credit markets:

$$E\Pi_t = R_t L_t - \sum_i^B R_{i,t} L_{i,t} = 0$$

which easily yields the aggregate loan rate:

$$R_t = \sum_i^B R_{i,t} \left(\frac{L_{i,t}}{L_t} \right) \tag{9}$$

That is, the aggregate loan rate is a loan-weighted average of specialized loan rates. We can further, expand this equation to find that in a given period t:

$$R_t = \frac{1}{\beta} \sum_i^B \frac{\theta_{i,t}}{\theta_{i,t} - 1} \frac{1}{1 - E\lambda_{i,t+1}} \frac{L_{i,t}}{L_t} (C_t + \Phi'(L_{i,t} - N_{i,t})) \tag{10}$$

Result 2 (Bank risk sentiment and the aggregate loan rate)
The aggregate loan rate is a loan weighted average of the Specialists' loan rates. Thus, a granular increase a single bank's risk sentiments will increase the aggregate loan rate of the economy.

2.8.2 Aggregate loan supply

I next turn to finding the effect of bank risk sentiment on the aggregate loan supply. The consumer loan market clearing condition is standard: loan quantity demanded must equal loan quantity supplied. Thus, $L_t^D = L_t$. Therefore, to examine the impact of bank risk sentiment on the aggregate loan supply, we can alternatively study its impact on aggregate loan demand.

Start with the aggregate loan demand schedule:

$$L_t^D = P - AR_t + \pi_t$$

Table 1: Summary statistics of BRS measurement equation data

	Mean	SD	p(5)	p(25)	p(50)	p(75)	p(95)
Bank characteristics							
Loan portfolio interest rate	4.730	1.260	2.832	3.719	4.749	5.607	6.69
Bank state-level loan share	0.366	0.933	0.008	0.036	0.098	0.268	1.482
Leverage	10.305	2.912	5.795	8.403	10.201	12.016	14.952
Macroeconomic environment							
Aggregate loan demand	0.425	25.844	-52.600	-11.800	1.400	17.800	41.400
Policy rate	3.049	2.132	0.128	0.893	3.384	5.096	6.133

Notes: This table reports the summary statistics for data used in estimating the bank-level BRS measure. Bank characteristics are from US Call Reports and author calculations. Aggregate loan demand is measured as the coincidence indicator of banks reporting an increase in loan demand for commercial and industrial loans, as reported by the Senior Loan Officers Survey put out by the Federal Reserve. The policy rate is measured as the one year constant maturity Treasury yield. The sample is made up of 910,093 observations, with dates ranging from 1992:Q1 through 2020:Q4. There are 117 dates and 14820 unique banks represented in the sample.

and incorporate the price of the consumer loan:

$$L_t = P - A\sum_{i}^{B} \frac{\theta_{i,t}}{\theta_{i,t}-1}\frac{1}{1-E\lambda_{i,t}}\frac{L_{i,t}}{L_t}(C_t + \Phi'(L_{i,t} - N_{i,t})) + \pi_t$$

The following proposition becomes self-evident.

Result 3. (Bank risk sentiment and the aggregate loan supply)
An increase in bank-level risk sentiments will decrease the aggregate supply of loans in the economy.

Moreover, we can further rearrange the aggregate loan demand equation to find that the market clearing price of loans will be a function of the households and firms' demand shifter:

$$L_t^D = P - AR_t + \pi_t \implies R_t = \frac{P - L_t - \pi_t}{A}$$

motivating the inclusion of a proxy for credit demand in my empirical measurement of BRS.

3 Measuring bank risk sentiment

I next turn to measuring bank risk sentiment. Aggregate BRS is shown to be countercyclical and to particularly spike during financial crises. There is also a large degree of bank-level heterogeneity in risk sentiments and their underlying processes. The methodology, data, and results are discussed in order.

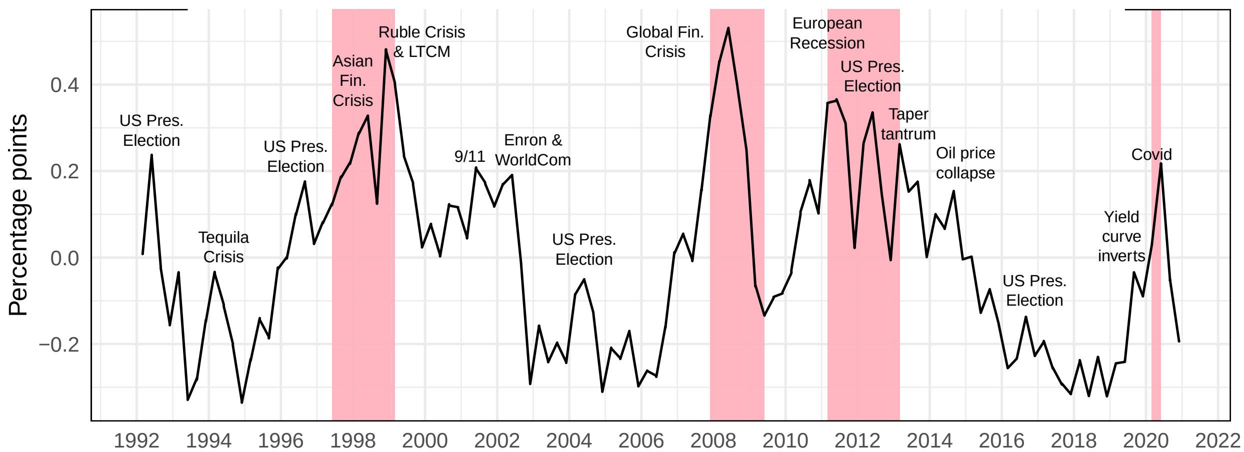
3.1 Methodology

The analytical model yields a closed-form solution for a monopolistically competitive bank's loan rate, which we can in turn use to motivate a simple econometric strategy for measuring BRS in observed data.

From the Specialist's problem we have a closed form solution for bank-level interest rates:

$$R_{i,t} = \frac{1}{\beta}\cdot\frac{1}{1-E\lambda_{i,t+1}}\cdot\frac{\theta_{i,t}}{\theta_{i,t}-1}\cdot(C_t + \Phi'(L_{i,t} - N_{i,t}))$$

Figure 1: Bank risk sentiment



Notes: Solid black line depicts the quarterly unweighted average of bank-level risk sentiments. Sentiments increase as banks forecast an increase in future loan default rates, that is, a deterioration in economic conditions. Red shaded regions mark periods of financial stress: the Asian Financial Crisis extended from 1997 through 1990, the Global Financial Crisis is marked by the United States NBER dated recession dates from 2007:Q4 through 2009:Q2, the European "double-dip" recession extends from 2011 through 2013, and the COVID period runs the first two quarters of 2020. Data are quarterly from 1992 to 2021.

For concreteness, suppose that the regulatory cost function is simply quadratic in the funding gap, that is: $\Phi(X) = rX^2$ and $\Phi'(X) = 2rX$, where $r \in \mathbb{R}^+$ by assumption. We will also now allow for bank-specific discount rates, β_i. The pricing equation becomes:

$$R_{i,t} = \frac{1}{\beta_i} \cdot \frac{1}{1 - E\lambda_{i,t+1}} \cdot \frac{\theta_{i,t}}{\theta_{i,t} - 1} \cdot (C_t + 2r(L_{i,t} - N_{i,t}))$$

and the log-linear pricing equation is then:

$$log(R_{i,t}) = log(1/\beta_i) - log(1 - E\lambda_{i,t+1}) + log(\frac{\theta_{i,t}}{\theta_{i,t} - 1}) + log(1 + c_t + 2r(L_{i,t} - N_{i,t}))$$

which for small values of the net loan interest rate $r_{i,t}$, expected default rates $\lambda_{i,t}$, marginal funding costs c_t, and regulatory coefficient r, (approximately) yields:

$$r_{i,t} = log(1/\beta_i) + \rho_1\lambda_{i,t-1} + \rho_2\lambda_{t-1} + \psi_{i,t} + log\left(\frac{\theta_{i,t}}{\theta_{i,t} - 1}\right) + c_t + 2r(L_{i,t} - N_{i,t})$$

Therefore, if we estimate the linear regression:

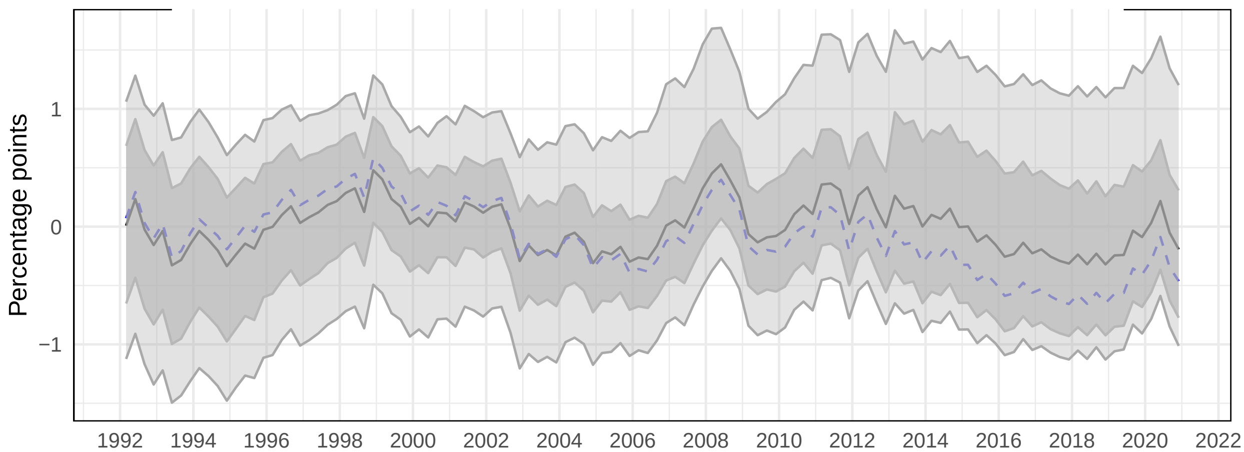
$$r_{i,t} = \gamma_i + b_1 log\left(\frac{\theta_{i,t}}{\theta_{i,t} - 1}\right) + b_3 c_t + b_4 2r(L_{i,t} - N_{i,t}) + b_4\rho_1\lambda_{i,t-1} + b_5\rho_2\lambda_{t-1} + \epsilon_{i,t} \tag{11}$$

then the bank-specific discount rate β_i will be subsumed by the bank-level fixed effect γ_i, the set of linear coefficients $b_{1:5}$ are theoretically equal to one, and the residual $\epsilon_{i,t}$ will equal the unobservable risk sentiment, $\psi_{i,t}$.

3.2 Data

Equation 11 calls for six ingredients to estimate a measure of bank-level risk sentiments: loan rates, market power, regulatory costs, capital costs, bank-level risk, and aggregate risk. Loan portfolio rates are calculated

Figure 2: Heterogeneity in bank risk sentiment



Notes: Dark gray bands shade the inter-quartile range of bank risk sentiments. Light gray bands shade the area between the 10th and 90th percentiles. The solid black line denotes the unweighted quarterly average of bank-level risk sentiment, while the dashed blue line denotes the quarterly median bank-level risk sentiment. Data are quarterly from 1992 to 2021.

directly from bank-level income statement and balance sheet data as the loan interest income divided by the notional value of the entire loan portfolio (net non-paying loans). A bank's market power is proxied by its state-level loan share.[16] Regulatory costs are proxied by the bank's leverage ratio, assets divided by equity.[17] Marginal cost of capital is proxied by the yield on the one year constant maturity Treasury bill. Realizations of bank-level risk are measured by the bank's charge-off ratio, total charge-offs divided by total loans.[18] Realizations of aggregate risk are the quarterly loan weighted average of bank-level loan charge-offs.

Bank-level data are collected from the US Call Reports, a regulatory filing required of all commercial banks in the United States, detailing a bank's balance sheet, income statement, and asset portfolio composition. Data is at the bank level and is reported quarterly. The one year Treasury yield is collected from the Federal Reserve Board's H.15. statistical report.

I additionally include a measure of credit demand to control for general equilibrium forces that may be influencing a bank's loan rate. Credit demand is proxied by the coincidence indicator of bank's reporting an increase in credit demand for medium and large firm commercial and industrial loans, as reported by the Senior Loan Officer's Survey (SLOOS), put out by the Federal Reserve System.

Bank-level data are winsorized at the 1st and 99th percentiles, negative leverage ratios are excluded, banks must be in the sample for at least 5 years (20 quarters), and seasonality in reporting is removed from loan portfolio interest rates with a four quarter moving average.

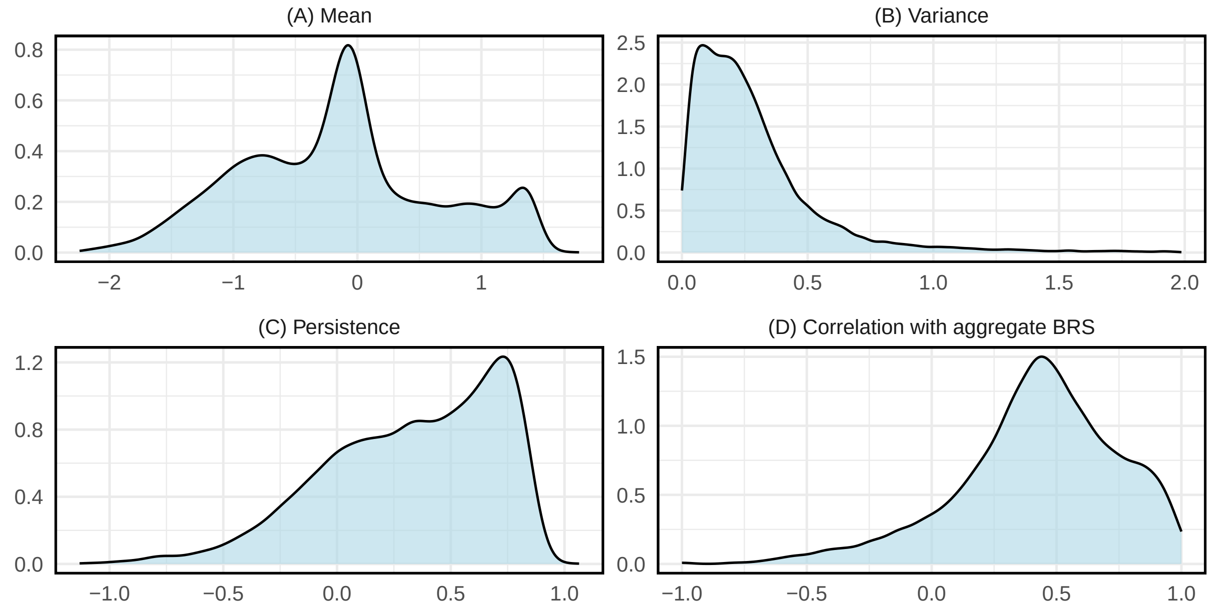
Table 2 summarizes the sample used to estimate the BRS panel regression. The sample includes approximately 910.1 thousand bank-quarter observations, running from 1992:Q2 through 2020:Q4. The average

[16] Corbae and D'Erasmo (2021)'s measure of loan mark ups have been used as robustness check. The state-level loan share requires fewer data inputs, making future cross-country comparison more accessible.

[17] Regulatory costs are analytically represented as a function of the difference between a bank's loans and net worth. However, this difference is not stationary object, so in practice I use the ratio of the values, also referred to as the leverage ratio. A measure of the bank's liquidity ratio, total repurchase agreements and Treasuries divided by total assets, is used as a robustness check.

[18] Charge-offs are measured net of recoverable assets, thus reflect the net losses to the bank due to the default of a given loan. Therefore, where the analytical model may be unrealistic in ignoring the possibility of recoverable collateral or liens, the empirical exercises allow for this realistic possibility.

Figure 3: Bank-level risk sentiment process



Notes: Light blue shaded regions show the empirical density functions of bank-specific (A) mean risk sentiments, (B) variance of risk sentiments, (C) AR(1) coefficient of risk sentiments and (D) the correlation between bank-specific and average risk sentiments. Data is an unbalanced panel of 14658 banks, quarterly from 1992 through 2021; the average number of observations per bank is 61 quarters.

loan portfolio interest rate is approximately 4.7 percent, but varies widely across banks and through time, with the 5th percentile near 2.8 and 95th percentile near 6.7 percent. Bank-level characteristics also display large variation across the sample; bank state-level loan share is highly skewed, with a mean of 0.36 percent but 95th and 99th percentiles near 1.48 and 6.8 percent, respectively. Bank leverage ratios are likewise skewed, with a mean of approximately 10, but 5th percentile near 3 and 95th percentile of approximately 15. Aggregate series are more symmetric across the sample. The change in aggregate loan demand is approximately zero on average and have an approximately symmetric distribution within the sample. The policy rate represents both Fed tightening and easing cycles, as well as the zero lower bound period (note that the one year Treasury yield is in part used instead of the federal funds rate precisely because of this period).

Equation 11 is estimated as a (within-group) fixed effects panel regression, taking into account bank- and state-level fixed effects. State-level fixed effects control for state-level regulatory costs, while bank-level fixed effects are dictated by Equation 6.

3.3 Bank risk sentiment

I next turn to presenting the aggregate measure of BRS, discussing bank-level heterogeneity, and examining the underlying bank-level risk sentiment processes.

Aggregate bank risk sentiment

Figure 1 shows the unweighted quarterly average of bank-level risk sentiment. Aggregate bank risk sentiment is characterized by sharp increases in times of financial stress and uncertainty. For example, BRS achieves local maximums within the 1997-1990 time period, which included several financial crises episodes across the globe, such as the Asian Debt Crisis (1997-1990), Ruble Crisis (1998), and the failure of LTCM (1998).

Sentiments reach their peak at the beginning of the global financial crisis. In fact, bank risk sentiment spikes during the global financial crisis prior to either the VIX or the Excess Bond Premium, widely accepted measures of investor risk sentiment. A more in depth comparison of bank risk sentiment and broader measures of investor risk sentiment is taken up in subsequent sections. Lastly, there is a period of elevated and volatile sentiments that coincides with Europe's second financial crisis (2011-2013), a US presidential election (2012), and the Taper Tantrum (2013).[19] The last sentiment spike begins with the inversion of the Treasury yield curve in the summer of 2019 and is then exacerbated by the sudden onset of the COVID pandemic and recession. Although, focusing on aggregate BRS belies a large degree of heterogeneity at the bank-level. I will next examine the distribution of sentiments and characterize bank-level sentiment processes in turn.

Heterogeneity in bank-level risk sentiment

There is a large range of BRS in the cross-section of banks in any given quarter, and the distribution of bank-level risk sentiments has evolved over time. Figure 3 shows the dispersion of bank risk sentiments from 1992 through 2020. There is a large degree of heterogeneity across bank-level risk sentiments through the entire sample period, with the range between the 10th and 90th percentiles always greater than two percentage points. Moreover, bank risk sentiments are not normally distributed. Sentiments were predominately skewed to the right prior to the global financial crisis, that is, the plurality of banks had pessimistic views of risk before to the global financial cycle. However, after the global financial crisis, the average range in risk sentiments not only expanded, but also become skewed to the left. That is, a plurality of banks began to harbor more optimistic sentiments regarding risk in the economy.

A further inspection into the panel of bank-level sentiments shows that the post-GFC shift towards "optimism" is predominantly driven by small and medium size banks. However further discussion of BRS by bank size is left to Appendix C.

Bank-level sentiment processes

There is a large degree of heterogeneity in bank-level risk sentiment processes. Figure 2 shows the distributions over the first two moments of bank-level risk sentiment processes, as well as their persistence and correlation with the aggregate BRS.

The distribution of bank-specific mean risk sentiment (panel A) is highly non-normal, and shows a wide range in sentiments. The heterogeneity holds not only for the magnitude of the sentiment, but also the sign of the sentiment. That is, there exists both a mass of optimistic banks, those with a mean negative risk sentiment, and pessimistic banks, those with a positive risk sentiment. However, a bank's risk sentiment is not necessarily static.

The persistence of of bank-specific risk sentiment processes (panel C) is measured as its AR(1) coefficient, and is on average approximately 0.331 —suggesting a relatively transient sentiment process, with a half-life of only two periods.[20] However, by inspection, it is clear that the modal AR(1) coefficient is approximately 0.75. The distribution is heavily skewed to the right, with only a quarter of its mass below zero.

Conversely, the variance of bank-level risk sentiments (panel B) is heavily skewed to the left tail, with a large mass of banks experiencing little volatility in their risk sentiment. However, similar to persistence, banks are not homogeneous, with a fat right tail of banks experiencing a large variance in their risk sentiments.

Lastly, panel D shows the distribution over bank-level sentiment correlation with the financial sector average level of bank risk sentiment. A similar pattern emerges as with the last two previously discussed moments, showing a large degree of heterogeneity across banks, with a small mass negatively correlated with the av-

[19] There is a spike in bank risk sentiments every four years, coinciding with the a US presidential election, perhaps reflecting uncertainty around future policy.

[20] One lag is almost universally the BIC and AIC minimizing lag order when estimating bank-level risk sentiment autoregressions.

Table 2: Summary statistics of matched bank-loan data

	Mean	SD	p(5)	p(25)	p(50)	p(75)	p(95)	Obs
Loan characteristics								
Loan amount	2796	13537	85	300	870	2039	9919	8119
Loan rate	209.0	139.8	45.0	116.5	190.0	275.0	450.0	7898
Max debt to EBIDTA	3.629	0.968	2.250	3.000	3.500	4.500	5.250	2765
Covenants present	51.0%							
Secured by collateral	71.1%							
Bank characteristics								
BRS	-0.268	0.788	-1.657	-0.621	-0.274	0.142	1.058	8119
Bank equity	814.7	2195	3.844	15.47	39.61	349.1	5738	8119
Firm characteristics								
Firm net worth	5183	87089	-0.015	-0.001	0.000	179.7	2500	858
Total debt to EBITDA	4.138	1.525	1.700	3.000	4.000	5.500	6.500	1581

Notes: This table reports the summary statistics for data used in estimating the loan-level impact of a change in BRS. Loan amount, bank net worth, and firm net worth are all reported in millions USD. Loan rate is the margin over reference (e.g. LIBOR), quoted in basis points. Covenant present and Secured by collateral are both binary indicators. Loan and firm characteristics are from DealScan. Bank characteristics are from US Call Reports and author calculations. Dates range from 1992:Q3 through 2020:Q4. There are 112 dates, 250 banks, and 1752 borrowers represented in the sample.

erage, and the modal correlation at approximately 0.45.

In summary, most banks experience highly persistent and low variance risk sentiment series that are only moderately, but positively, correlated with a measure of average financial sector risk sentiment. However, there is also a large mass of banks that experience very unstable sentiments, by way of either high volatility or low persistence, and others that systematically disagree with the wisdom of the crowds.

A note on international sentiment spillovers

Bank risk sentiment has been studied as the key transmission mechanism between US monetary policy and the Global Financial Cycle, see for example Kalemli-Özcan (2019) and Miranda-Agrippino and Rey (2020).[21] However, Figure 1 shows the US commercial banking sector is also clearly sensitive to international financial risks, with sentiment spiking during the Mexican Tequila crisis, Asian Financial crisis, Russian Financial crisis, and Europe's "double-dip" recession. The US is often modeled as a large economy in the international macro-finance literature, meaning that it is not affected by shocks in other countries. The sensitivity of US commercial bank sentiment to negative shocks overseas suggests that even if there are not "real" channels through which foreign shocks hit the US, it does not matter because US banks obverse those shocks, internalize the risk, and as I will show later on, increase domestic loan risk premia while decreasing credit supplied to the US economy. This is also premia facia evidence counter to the hypothesis that foreign news shocks do not affect risky asset prices and credit supply in the US, a puzzle in the search for drivers of the Global Financial Cycle (see works such as Boehm and Kroner (2023) for a discussion of this puzzle).

Table 3: Loan-level price and quantity response to a bank risk sentiment shock

	Loan rate		Loan amount	
	(1)	(2)	(3)	(4)
BRS	0.221***	0.298***	−0.277*	−0.284*
	(0.068)	(0.055)	(0.143)	(0.149)
Refinancing only FE		✓		✓
Borrower-Quarter FE	✓	✓	✓	✓
Lender-Borrower FE	✓	✓	✓	✓
Loan characteristics	✓	✓	✓	✓
Observations	1,600	1,064	1,600	1,064
R^2	0.288	0.397	0.066	0.130
Sample composition				
Loans	785	485	785	485
Dates	92	56	92	56
Banks	126	118	126	118
Borrowers	340	215	340	215
Bank-Borrower pairs	773	522	773	522

Notes: This table reports a (within) fixed effects regression of loan outcomes onto the issuing bank's risk sentiment. Columns (1) and (2) show the response of the loan rate to a one percent change in bank-level BRS. The loan rate is measured in percentage points over the loans reference rate, eg LIBOR. Columns (3) and (4) show the response of the loan amount to a one percent change in bank-level BRS. The loan amount is measured in log-levels. All coefficients can be interpreted as elasticities. The loan rate and amount have been winsorized at the 1st and 99th percentiles. Loan characteristics are included in all regressions and include an indicator if the loan is secured by collateral and an indicator for the presence of covenants. Observations are weighted based on the lender's current share of the syndicated loan. Each borrower must be borrowing from two or more syndicated loans in a quarter. Parentheses wrap the robust standard errors, which are double clustered at bank and quarter levels, and * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

4 Sentiment shocks and loan-level outcomes

I next turn to examining the effect of changes in BRS on micro- and macro-level economic outcomes, and begin by studying the impact of bank-level risk sentiment shocks on loan-level outcomes. The analysis starts with a loan level analysis not because I am strictly interested in individual loan outcomes, but because focusing on micro-level data will allow for sharp identification of the impact of sentiment on credit, and in turn suggest potential transmission mechanisms through which BRS may impact the macroeconomy.

To this end, I study the impact of changes in bank-level risk sentiment on loan-level outcomes using DealScan data and a Kwhaja-Mian style difference-in-difference causal identification strategy, and find that an increase in a bank's risk sentiment leads to an increase in its syndicated loan rate, decrease in its lending supply, and tightening of its covenant requirements. These results suggest two potential channels through which BRS may affect the macro-economy: directly as a credit supply shock, and indirectly as a credit constraints shock. The remainder of this section discusses the method, data, and results in turn.

[21] However, these two works use the VIX as a proxy for bank risk sentiment, citing literature linking the VIX to investor risk aversion and uncertainty, such as Bekaert et al. (2013), Adrian and Shin (2014), Bruno and Shin (2015). The VIX is not a reasonable proxy for bank risk sentiment because it is based on expected volatility in equity markets, an asset not typically held by US commercial bank balance sheets.

Table 4: Loan-level covenant response to a bank risk sentiment shock

	Max debt to EBITDA (intensive margin)		Presence of covenants (extensive margin)	
	(1)	(2)	(3)	(4)
BRS	−0.077	−0.120	−0.007	0.061*
	(0.098)	(0.103)	(0.062)	(0.033)
Refinancing only FE		✓		✓
Borrower-Quarter FE	✓	✓	✓	✓
Lender-Borrower FE	✓	✓	✓	✓
Loan characteristics	✓	✓	✓	✓
Observations	571	524	1,629	1,080
R^2	0.038	0.018	0.055	0.037
Sample composition				
Loans	571	524	804	495
Dates	40	38	93	57
Banks	100	98	126	118
Borrowers	84	75	345	218
Bank-Borrower pairs	288	264	780	525

Notes: This table reports a (within) fixed effects regression of loan outcomes onto the issuing bank's risk sentiment. Columns (1) and (2) show the response of the covenant tightness to a one percent change in bank-level BRS. Covenant tightness is proxied by maximum ratio of debt to EBIDTA allowed by the contract. Columns (3) and (4) show the response of the extensive margins of covenants to a one percent change in bank-level BRS. These two regressions are interpreted as weighted linear probability models. An indicator if the loan is secured by collateral is included each model. Observations are weighted based on the lender's current share of the syndicated loan. Each borrower must be borrowing from two or more syndicated loans in a quarter. Parentheses wrap the robust standard errors, which are double clustered at bank and quarter levels, and * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

4.1 Methodology

I estimate the causal effect of a change in a bank's risk sentiment on loan-level outcomes through a weighted fixed effect regression in the spirit of Khwaja and Mian (2008). The formal specification follows:

$$y_{l,f,b,t} = \alpha + \gamma_{f,t} + \gamma_{f,b} + \delta BRS_{b,t} + \beta\Theta_t + \epsilon_{l,f,b,t} \tag{12}$$

where $y_{l,f,b,t}$ is the loan-level outcome of interest, such as loan rate, amount, and covenant requirements, indexed by loan l, firm f, bank b, and date t; $\gamma_{f,t}$ denotes a firm-quarter fixed effect, and $\gamma_{f,b}$ a borrower-lender fixed effect; $BRS_{b,t}$ is the bank risk sentiment of bank b at date t; Θ_t collects the vector of loan and firm characteristics. I assume that syndicated loan outcomes, such as loan rates, amounts, or covenants, are the share-weighted decisions of syndicate member banks. Thus, a weighted least squares regression (weighting observations based on the lenders share of the syndicated loan) will be a consistent estimator of the elasticity of an individual bank's risk sentiment onto a syndicated loan.

My elasticity of interest when evaluating Equation 12 is δ, the response of loan outcome $y_{l,f,b,t}$ to a one percentage point change in a bank's risk sentiment. I will study four loan outcomes in particular: the loan rate, log loan amount, maximum debt to EBITDA covenant, and the presence of covenants more generally. That is, I am interested in how a bank-level risk sentiment shock impact the price, quantity, and quality of loans.[22]

[22] I characterize covenants as the quality of the loan because from a borrower's perspective, tighter covenants puts the firm

Identification. I isolate the *within-firm* variation in loan outcomes attributable to variation in lenders' risk sentiment, and use this variation to estimate the *causal treatment effect* of bank-level risk sentiment shocks. To do so, I first narrow the sample of loans to those held by firms borrowing from multiple-syndicates in a given period, and in turn purge credit demand and other firm-specific factors with firm-quarter fixed effects. I then additionally control for individual borrower-lender relationships to ameliorate concerns of non-random matching in lending market, as well as loan specific characteristics, such as the presence of collateral or covenants, which may impact how lenders value loans after reassessments of risk.[23] These three steps together isolate variation in outcomes attributable to lender specific factors (ie attributable to shifts in the supply of credit). Therefore, since all confounding sources of variation have been removed, the remaining variance explained by bank-level risk sentiment shocks can be interpreted as the causal response to structural shocks.

One may note that I do not have to incorporate additional controls for non-sentiment bank-specific factors that the literature typically includes to isolate the effect of credit supply shocks. This is because, by construction, bank-level risk sentiment shocks are orthogonal to these bank-specific controls. For example, BRS is orthogonal to the size of banks' balance sheets, profitability, and other variables utilized in works such as Di Giovanni et al. (2022). Therefore, adding further bank-level covariates is unnecessary to isolate variation due to a bank-level risk sentiment shocks, if not detrimental in obtaining a precise measurement of the elasticity of interest.

4.2 Data

The loans studied in this analysis are in fact individual facilities, also known as tranches, of syndicated loans from the LPC DealScan database.[24] The data set covers nearly the universe of syndicated loans, which is in turn associated with borrowers (firms) that make up a majority of employment and production in the United States.[25] However, as I am interested in studying the impact of bank-level BRS on loan outcomes, I must narrow my study to tranches funded by lenders that can be matched to the US Call Report records used to created my measure of bank-level BRS.[26] The matched bank-loan data set ultimately includes 180.5 thousand facility observations, ranging from 1992:Q2 through 2020:Q4, representing 250 unique lenders (banks) and 1752 borrowers (firms).

The sample covers a large range of loan, borrower, and lender sizes. Table 2 reports summary statistics for data in the matched bank-loan data set that will be used as covariates in the subsequent analysis. The loan (facility) amounts vary widely. The mean facility is for 2.8 billion dollars, but the majority are for less than one billion dollars, with the median facility being for 870 million dollars and the 5th percentile worth only 85 million dollars. Banks and borrowers that participate in the syndicated loan market are likewise varied. The inter-quartile range of participating banks' net worth (i.e. equity) is approximately 334 million dollar, while the difference between the 95th and 5th percentiles is more than 5.5 billion dollars. The inter-quartile range of participating firms is similarly large at 180 million dollars, while the difference between the 95th and 5th percentiles is approximately 2.5 billion dollars.

at a higher risk of breaching the contractual obligation, which in turn may risk costly re-negotiations of loan terms with the lenders or even losing access the remaining principal of the loan yet to be paid out. That is, covenants indirectly reflect how reliable the loan will be as a continued source of funding, which one may characterize as the quality of the loan.

Additionally, I choose to focus on the the maximum debt to cash flow covenant because it is the most common type of covenant in DealScan. See Drechsel (2023) for more details.

[23]See Chodorow-Reich (2014) for a discussion of the stickiness of borrower-lender relationships and why they should be explicitly controlled for in the Khwaja-Mian research design.

[24]A *syndicated loan* is a large or niche loan that requires a consortium, or syndicate, of lenders to fulfill. The loan can be broken up into discrete pieces, referred to as *tranches*. For all intents and purposes, tranches can act as independent, smaller, loans, with their own interest rates, payment schedules, covenants, and seniority.

[25]It should be noted that DealScan does not cover small business and household lending. One should consult Caglio et al. (2021) for a more comprehensive discussion of the limitations of DealScan's loan coverage.

[26]Lenders associated with a DealScan tranche are matched with FFIEC regulated banks by name and state. An additional fuzzy matching is attempted on remaining DealScan lenders, utilizing the routine put forth by Cohen et al. (2021), but no additional matches are made.

The sample contains two types of observations, loan originations and loan refinancing agreements. However, I will primarily focus on borrowers renegotiating the terms of a loan held on a bank's balance sheet to ensure that the loan is actually held by the bank. A majority of DealScan loans are originated by commercial banks, but in turn sold to non-bank lenders. Therefore, studying how changes in BRS impacts all syndicated loans would include studying how a bank's sentiment impacts loans that it will almost immediately sell off of its balance sheet. In the context of the analytical model used to identify BRS, there should be no relationship between a bank's risk sentiment and loans not held on its balance sheet, even if it is the entity that originates the loan. For a discussion of who participates in the syndicated loan market and the origination the distribution pipeline, see Fleckenstein et al. (2020).

4.3 Results

I find a causal relationship between bank-level risk sentiment and syndicated loan-level outcomes. An increase in bank-level risk sentiment causes an increase in the price of credit, decrease in the quantity of credit, and covenant tightening (along both the intensive and extensive margins).

An increase in bank-level risk sentiments increases syndicated loan rates. Columns (1) and (2) of Table 3 present the elasticity of syndicated loan rates to a participant bank's risk sentiment shock. In the full sample, a one percent increase in a bank's risk sentiment causes a 22 basis point increase in the loan rate, and when restricting the sample to only refinancing arrangements, then the response increases to 30 basis points. As banks increase their forecasts of risk, they incorporate this into their loan rates, and demand more compensation for bearing the increased risk of default. This relationship is statistically significant at the one percent confidence level across both samples.

An increase in bank-level risk sentiment decreases syndicated loan amounts. In other words, as banks perceive an increase in risk they in turn decrease their quantity of risk. Columns (3) and (4) of Table 3 present the elasticity of syndicated loan rates to a participant bank's risk sentiment shock. A one percent increase in bank-level risk sentiment induces an approximately 28 basis point decline in the loan amount. The quantity to risk sentiment elasticity is quantitatively robust across both the full and refinancing restricted samples.

An increase in bank-level risk sentiment tightens loan covenants along both the intensive and extensive margin. First, columns (1) and (2) of Table 4 present the response of the intensive margin of covenants to a change in bank-level risk sentiment. A one percent increase in bank-level risk sentiment decreases the maximum allowable debt to EBITDA ratio by 0.8 and 0.12 ratio points among the full and refinancing-only samples respectively. Second, columns (3) and (4) of Table 4 present the response of the extensive margin of covenants to a change in bank-level risk sentiments. The use of covenants expands after an increase bank risk sentiment. In fact, the probability of including covenants during a loan refinancing increases by six percent in response to a one percent increase in bank-level risk sentiment. That is, as bank's forecast a deterioration in economic conditions (an increase in default rates more specifically), they attempt to ameliorate this risk by negotiating tighter debt to cash flow constraints for loans with extant covenants and by increasing the frequency of including covenants on loans that previously had none. However, the response in the intensive margin and full sample extensive margin are estimated precisely enough to be statistically significant.

Robustness. Results are robust to incorporating additional variables to control for firm-level risk, such as size or leverage. However, incorporating the additional data necessitates a focus on public firms and results in a severe drop in sample size, limiting the power of such exercises. An example incorporate firm leverage is presented in Appendix F.

4.4 Discussion

The loan-level analysis highlights not only how a granular bank-level risk sentiment shocks may impact individual loans, but also points towards two potential channels through which BRS shocks may impact the macroeconomy more broadly: directly through a decline in the supply of loans, and indirectly through tightening loan covenants.

An increase in bank risk sentiment acts similar to a liquidity supply shock, as studied in Khwaja and Mian (2008), by dampening the supply of credit to the economy, as well as a risk shock, à la Christiano et al. (2014), by increasing the risk premia and cost of credit. Either type of shock will directly impact the price and quantity of credit in the economy which in turn will directly impact broader prices and economic activity via the numerous channels now well established in the financial accelerator literature.

However, an increase in BRS not only dampens supply, but also tightens loan covenants. This additional effect can impact macroeconomic outcomes by further restricting firms' access to credit as an earnings based income constraint. The mechanism is simple: borrowers are allowed to borrow up to some debt-to-income ratio specified by covenants of existing loans, effectively limiting how much the firm can borrow in a given period to maintain the previously stipulated constraint. An exogenous decline in income, from for example an idiosyncratic demand shock or aggregate productivity shock will decrease the amount a firm can borrow. If the firm faces a working capital constraint, then the decrease in its borrow limit will decrease its production capacity, potentially limiting future income, and the spiral continues. See Drechsel (2023) or Camara and Sangiacomo (2022) for more thorough discussion of earning based borrowing constraints in closed and open economies, respectively.

5 Sentiment shocks and macro-level outcomes

Having identified potential channels through which BRS may affect the macroeconomy, I next turn to examining if BRS shocks actually do change macroeconomic conditions in an empirically meaningful manner. Using a FAVAR and a collection of over 200 macro and financial variables, I find that an unanticipated increase in aggregate BRS leads to a broad based deterioration in economic activity, prices, and lending. Moreover, I document that the shock is not felt evenly across the economy: consumption falls more dramatically than production, and the yield curve steepens, disproportionately increasing the cost of long term credit compared to short term debt. I next discuss the methodology, data, and results in turn.

5.1 Methodology

The FAVAR is a dynamic factor model that represents the economy with a parsimonious set of latent states, so-called factors, that are mapped to a large and nuanced collection of observables (in this case more than 220 macro and financial variables). The parsimony of the latent states allows for a precise estimation of their joint law of motion, even with limited data, while the linear combination of several states in turn allows for rich dynamics to emerge in the corresponding observables.

Written in its state-space formulation the model is:

$$Y_t = \Lambda X_t + \eta_t, \quad \eta_t \sim N(0, \Sigma_\eta) \tag{13}$$

$$X_t = A X_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_\epsilon) \tag{14}$$

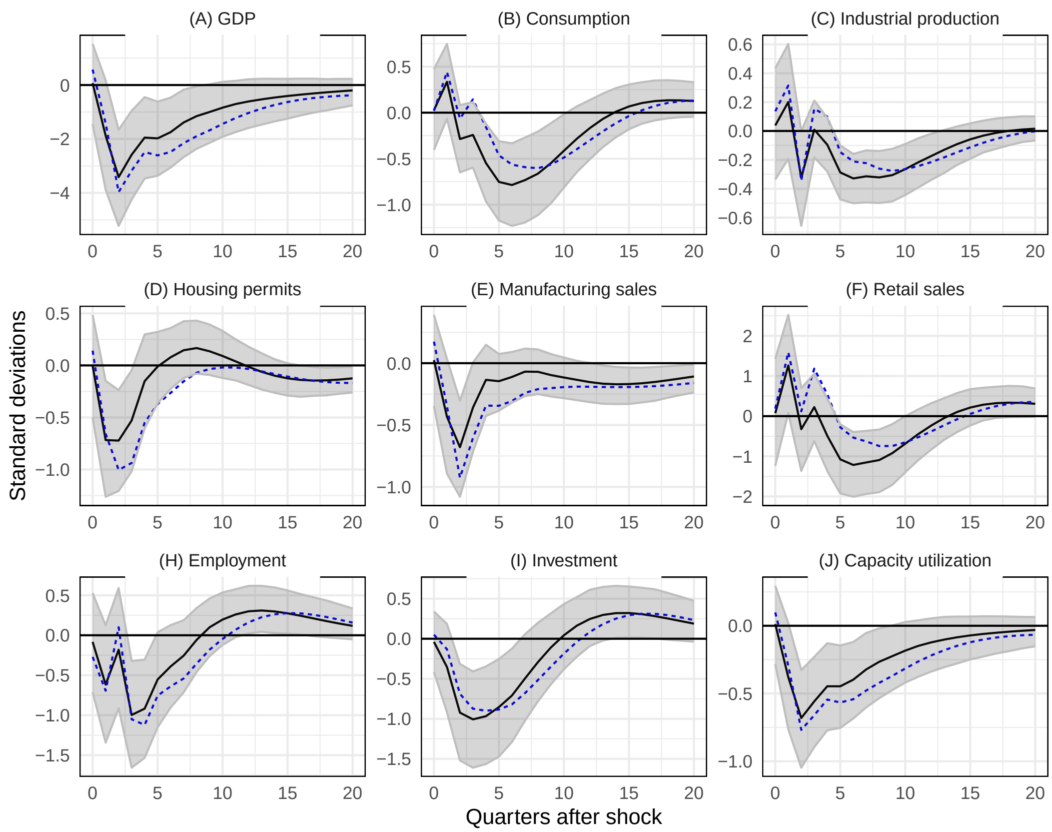
where Y_t is the collection of observable variables and X_t is the collection of latent states. Equation 13 is the measurement equation, relating latent states to observable macroeconomic variables, spanning real activity, financial activity, and prices. Equation 14 is the state law of motion, written in companion form, tracing the evolution of economy as an VAR(2) process.[27] Reduced form disturbances vectors, η_t and ϵ_t are assumed to be *iid* and drawn from normal distributions with variance-covariance matrices Σ_η and Σ_ϵ respectively.

I summarize the economy with four latent states, F^M, chosen to balance parsimony with explanatory power. A four factor model explains approximately 52 percent of variance within the collection of observable vari-

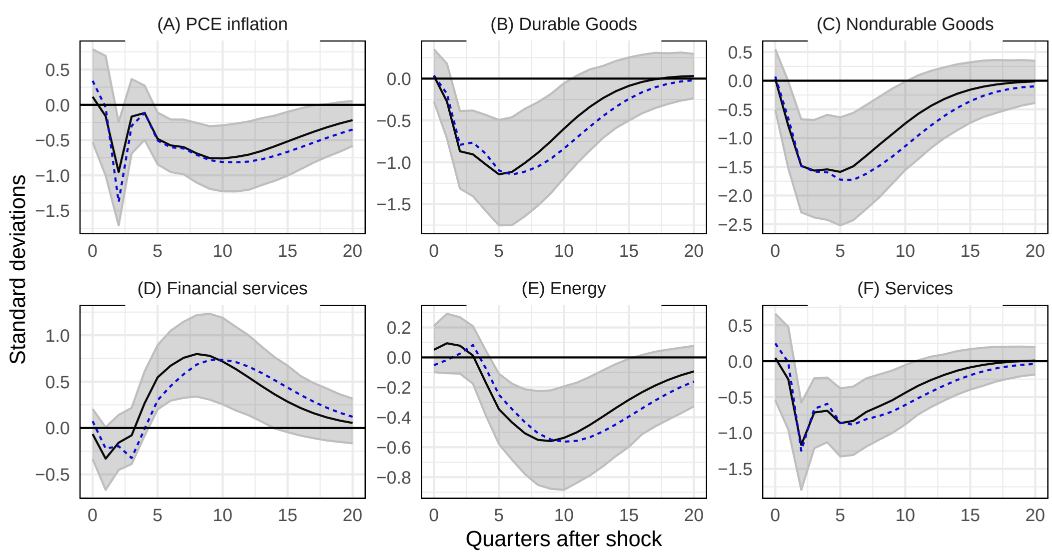
[27] Two lags are chosen by both AIC and BIC criterion for the full sample, as well as in the bootstrapping algorithm used to calculate confidence intervals. The results presented are robust to using four lags.

Figure 4: Macroeconomic response to a bank risk sentiment shock

(A) Economic activity



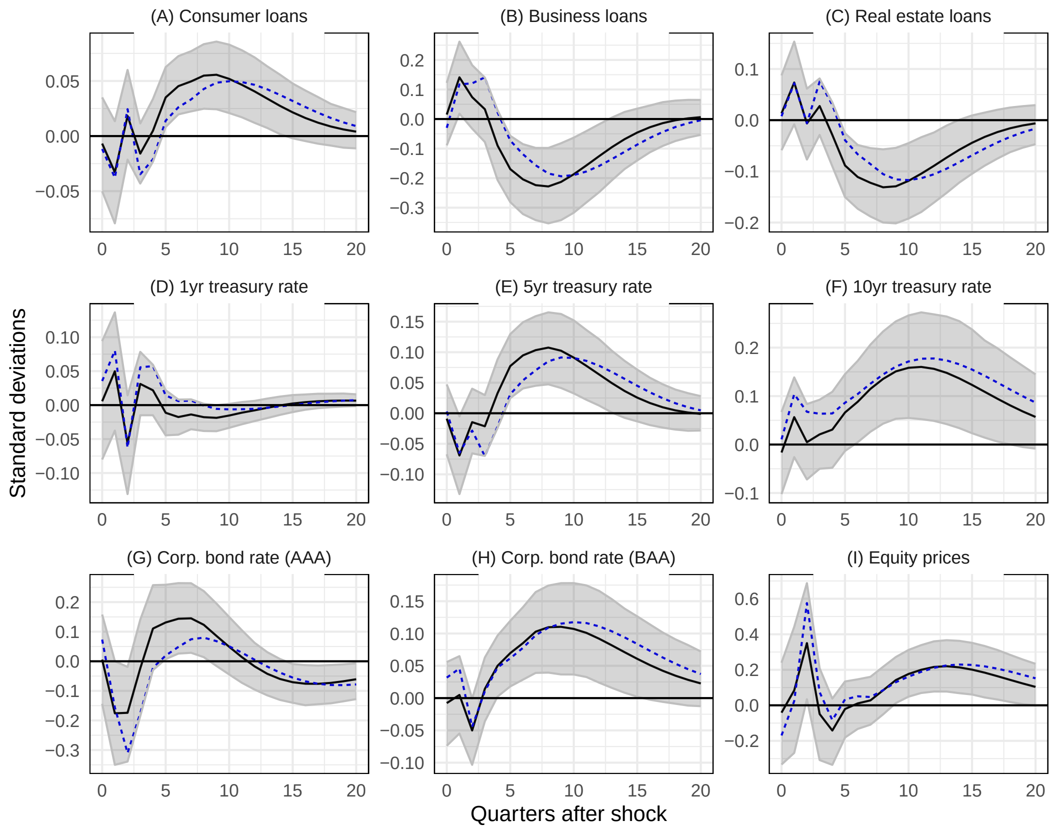
(B) Prices



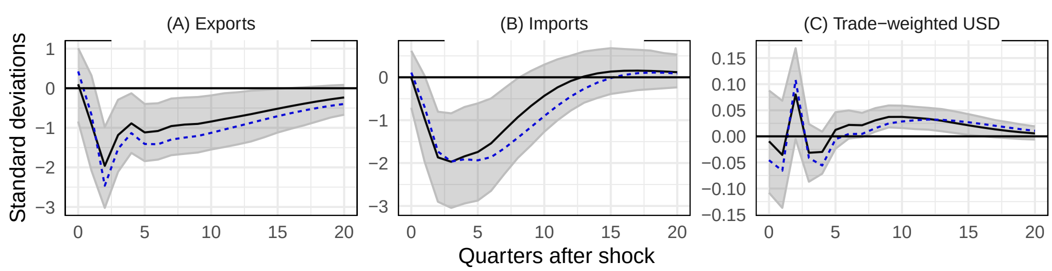
Notes: This figure reports the impulse response functions of select macroeconomic and financial variables to an unanticipated one percentage point increase in aggregate BRS. Solid black lines represent the responses to the equally weighted aggregate BRS, dotted blue lines represent responses to loan weighted aggregate BRS. Gray bands represent the 90 percent confidence intervals around the response to changes in the equally weighted aggregate BRS, based on 1000 bootstrapped samples which account for both state and measurement equation uncertainty. Data is quarterly from 1992 to 2021.

Figure 12: Macroeconomic response to a bank risk sentiment shock (continued)

(c) Financial sector and asset markets



(D) Trade



Notes: This figure reports the impulse response functions of select macroeconomic and financial variables to an unanticipated one percentage point increase in aggregate BRS. Solid black lines represent the responses to the equally weighted aggregate BRS, dotted blue lines represent responses to loan weighted aggregate BRS. Gray bands represent the 90 percent confidence intervals around the response to changes in the equally weighted aggregate BRS, based on 1000 bootstrapped samples which account for both state and measurement equation uncertainty. Data is quarterly from 1992 to 2021.

ables, while the marginal variance explained by an additional factor falls below four percent.[28]

Identification and estimation. Identification is achieved by restricting factor loadings such that banks risk sentiments are partitioned from macroeconomic observables.

$$X_t = \left[BRS,\ F^M\right]' \quad \Lambda = \begin{bmatrix} I & 0 \\ 0 & \Pi \end{bmatrix} \quad Y = \left[BRS,\ Y^M\right]'$$

where Π is estimated via principal components and A is an unrestricted coefficient matrix, estimated via OLS as a standard VAR(2) process. Note that the partitioning over Λ follows directly from the analytical model, which asserts that BRS is exogenous to economic developments. As a result, a Cholesky decomposition of the variance-covariance matrix of reduced from residuals yields an identified exogenous shock to bank risk sentiments, in other words, a sentiment shock. Moreover, ordering an externally identified exogenous shock first in a Cholesky decomposition (the BRS shock in this case) is equivalent to using the shock as an instrument in an Proxy-SVAR setting according to Plagborg-Møller and Wolf (2021). I encourage the reader to consult Stock and Watson (2016) for a more detailed discussion of issues and strategies for estimating and identifying dynamic factor models.

Impulse response functions (IRF) and confidence intervals (accounting for uncertainty in both state and measurement equations) are discussed in Appendix D.

5.2 Data

I study the effects of a BRS shock on macroeconomic outcomes in a "big data" context, utilizing the McCracken and Ng (2020) quarterly database.[29] The McCraken and Ng dataset is an unbalanced panel of 248 macro and financial variables which span production, labor markets, prices, investments, credit, and asset prices. While data is available from 1959:Q1, my measure of BRS does not begin until 1992:Q1, so I restrict my analysis to the 220 variables present from that point onwards. Data is not necessarily reported as a stationary series, but are subsequently detrended via prescribed transformations laid out in McCracken and Ng (2020).

5.3 Results

I find that an unanticipated increase in BRS leads to a broad-based deterioration in economic activity and prices, as well as a decline in financial activity and asset prices. However the shock is not felt evenly across the economy, with consumption falling greater than production, and the yield curve steepening, decreasing the price of long term assets greater than short term assets. BRS shocks are also shown to spill over into the international economy via declines in imports, exports, and an appreciating US dollar.

Economic activity deteriorates. Figure 12 presents selected IRFs to an unanticipated one standard deviation increase in the aggregate BRS. Panel A shows a broad based slow down in economic activity. At the headline level, real GDP growth declines a stark 3 standard deviations within one year of impact, and only returns to steady state after five years. We can further dissect the effect of the BRS shock within the supply and demand sides of the economy. On the demand side, there is a persistent decline in consumption, falling as much 3/4 a standard deviation within two years after impact, which does not fully recover before four years after the shock. The decline in consumption is broad, with housing permits, retail sails, and manufacturing sales all decreasing after a surprise increase in BRS. However, the decline is not homogeneous across all sectors, evident by juxtaposing the short lived and relatively shallow decline in housing permits and manufacturing sales —both decline approximately half of a standard deviation and recover within a year

[28]The choice of four factors can be motivated by appealing to McCracken and Ng (2020), which similarly models the dataset with four factors. Although the Bai and Ng (2002) information criterion would select a one factor model for the data at hand. Since my goal is to trace the impact of a BRS shock through the macroeconomy, rather than out-of-sample forecasting, I adopt the richer four factor model specification.

[29]I will leave my discussion of this large dataset relatively sparse and instead direct interested readers to the introductory paper, McCracken and Ng (2020), which thoroughly details the database and its individual series.

after impact— with the deeper and more long lived fall in retail sales —which falls as much as 1.5 standard deviations before recover only four years after impact. On the supply side, there is an analogous decline in output (proxied by industrial production) and factor inputs such as employment and investment. In fact, both employment and investment decline by more than one standard deviation before recovering within one and two years after impact, respectively. Moreover, not only does production decline due to a decrease in factor inputs, but there is also a decrease in capacity utilization. That is, business slow down their purchases of new materials, machines, and labor, while also scaling back the use of their existing stock of resources.

Overall price levels decrease. Panel B shows that going hand-in-hand with the broad based slow down in economic activity, prices decline upon a one standard deviation increase in BRS. Moreover, the deterioration in prices appears to be similarly broad based. Headline PCE inflation decreases by almost one standard deviation within a year after impact. Although the decline in inflation does not become statistically significant until two years after impact, at which point inflation remains persistently half a standard deviation lower than its pre-shock level. At the same time, prices fall in unison across almost all sectors, including durable and nondurable goods, services, and energy. The exception to the pattern is in financial and insurance services, which appears to increase in price after an unanticipated increase in BRS, which is itself may be characterized as a positive financial services price shock.

Financial activity declines. Panel C shows a one standard deviation positive BRS shock leads to a decline in aggregate commercial bank loans for real estate and businesses. I also find an increase in consumer loans. The former result is implied by both the loan level analysis in Section 4 as well as any theoretical model that ties production to credit, such as financial accelerator models or those with working capital constraints. The latter result is similarly implied by economic theory; any model featuring permanent income consumers will predict that consumers borrow to smooth consumption during economic downturns and declines in income, such as the recession we see induced by a positive BRS shock.

Risky asset prices fall and the yield curve steepens. Panel C shows that a BRS shock impacts lending on an aggregate level, and spills over into financial asset markets. Investors' risk appetite broadly declines in tandem with the economic deterioration set off by a BRS shock. For example, corporate bond yields (both investment grade and high yield) increase in a statistically significant manner a year and a half after a BRS shock, when GDP, consumption, and production are at their troughs. That is, investors' risk premia increases during the BRS induced recession, increasing their demanded compensation for holding risk during the economic down turn, which in turn manifests as an increase in corporate bond yields. Additionally, we can observe the yield curve steepening in response to a BRS shock: the near end of the yield curve (represented by the one year constant maturity Treasury rate) is unmoved by the BRS shock, while the medium and long term portions of the yield curve (represented by the 5 and 10 year constant maturity Treasury rates, respectively) increase, with the 10 year rate increasing more than the 5 year rate. This suggests that investors observe banks increase their expectations of risk and in turn investors revise down their medium and long term expectations of the economy, leading them to demand a greater risk premia to hold bonds with these maturities. Lastly, I will note a puzzle in equity markets, which see an increase in prices upon a BRS shock and the ensuing economic down turn. This last observation is included for both completeness as well as highlighting that a BRS shock does not homogeneously impact all segments of the financial sector and asset markets.

Gross trade declines and the dollar modestly appreciates in the medium term. Panel D shows that as the economy broadly shrinks, so do gross trade flows. Both import and export growth declines an economically and statistically significant two standard deviations within a year of the BRS shock. While at the same time, movements in the US dollar are imprecisely estimated until a modest appreciation against a trade-weighted basket of global currencies emerges approximately two to three years after impact. These results suggest that a sentiment induced recession may spread globally in the medium term, and in response global investors purchase "safe" assets, such as the US dollar, bidding up the price of the currency.

Robustness. These results are robust to using 3 to 6 latent states (i.e. factors), as well as using a loan-weighted measure of aggregate BRS rather than an unweighted average. Results are also robust to using 1 to 4 quarterly lags.

5.4 Discussion

Aggregate BRS shocks have an economically and statistically significant impact on the supply of credit to the economy. I find that unanticipated changes in bank risk sentiment have significant effects on macroeconomic activity and overall prices, as well as credit and risk premia. However I leave it to future research to decompose the quantitative importance of the direct effect of BRS on the supply of credit versus its impact on covenant tightness in transmitting BRS shocks to the macro-economy. Moreover, many studies in macro-finance now emphasize the non-linear relationship between financial risk and macroeconomic activity (see, for example, Brunnermeier and Sannikov (2014), or Adrian et al. (2019), and Leiva-Leon et al. (2022) for a discussion of non-linear dynamics between activity and in corporate bond market sentiments.). While this work has focused on a symmetrical and linear relationship between BRS and macroeconomic activity, fruitful research may be done in the future examining the potential non-linear relationship between these two phenomena.

A note on granular sentiment shocks and macroeconomic outcomes

In Appendix E I additionally examine the potential macroeconomic impact of granular sentiment shocks to the largest banks in the US, in the spirit of Gabaix (2011) and Gabaix and Koijen (2020). Using the same FAVAR framework as presented in this section, I find that granular sentiment shocks to the top ten largest commercial banks operating in the US do not yield statistically significant responses in macroeconomic outcomes. However, the influence of these shocks has increased over time. The limited influence of the largest banks —as shown by similarity between the unweighted and loan weighted aggregate BRS, as well as the muted response of macroeconomic outcomes to granular shocks— suggests that aggregate BRS is an important determinant of economic outcomes because of its affect on community and regional banks. A potential explanation for this conclusion is that large banks typically service large firms, which can more easily substitute bank loans for corporate bonds if its lender receives a sentiment shock and wants to increase loan rates, while small firms and households are limited in their ability to substitute sources of credit and must absorb the full sentiment-based change in the supply of credit.

6 Comparing bank and investor risk sentiments

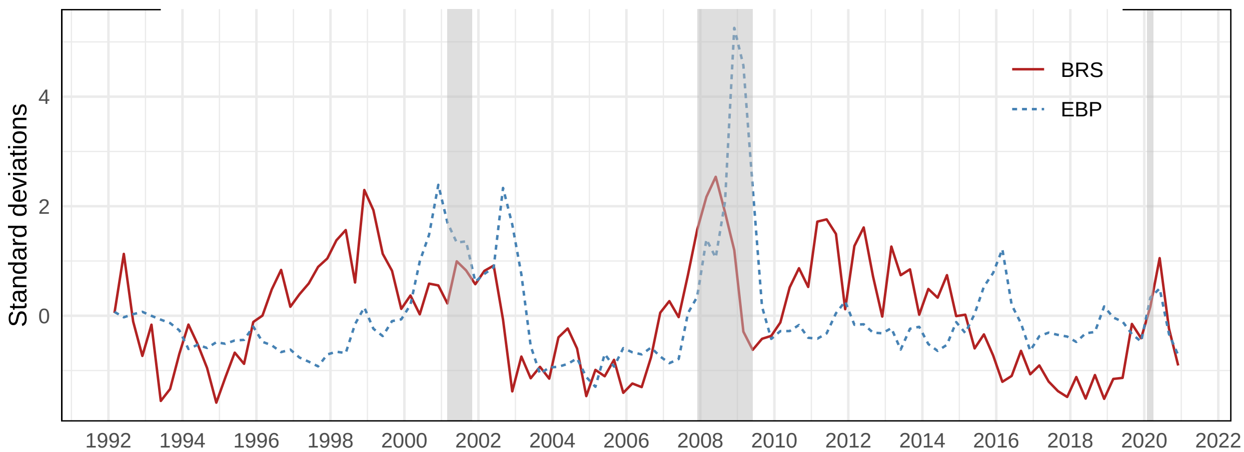
Having established that BRS matters for both loan- and macro-level economic outcomes, I next turn to compare the importance of BRS to investor sentiments in other financial markets, namely the corporate bond market. I will first present and discuss the two sentiment series side-by-side, then move to a formal comparison of their effect on and importance to the evolution of macroeconomic outcomes.

The corporate bond market is a natural place to focus my comparison for three reasons. First, the corporate bond market is the asset market most often analyzed in studies of investor risk sentiment.[30] Second, the corporate bond market is accessible exclusively to large corporations, and is favored by these agents, while commercial bank lending is in turn utilized by those agents unable to access the corporate bond market. Therefore, a source of heterogeneity across large and small firms (and households) may be the type of investors risk sentiment they are exposed to in credit markets. Comparing bank lending and corporate bond market sentiments will provide suggestive evidence whether or not this source of heterogeneity matters for firm- and macro-level outcomes. Third, together the corporate bond and bank lending markets make up a majority of private credit in the United States.[31] As a result, a joint analysis of these market sentiments will represent the most comprehensive analysis of how investor risk sentiments effects US macroeconomic

[30] See, for example, early influential works Gilchrist and Zakrajšek (2012) and López-Salido et al. (2017), as well as recent theoretical work Maxted (2023), which, despite explicitly including bank risk sentiment in the form of diagnostic expectations, calibrates sentiment to outcomes in the corporate bond market. See Section 1.1 for more examples.

[31] This fact is easily verified with US Flow of Funds statistics put out by the Federal Reserve Board.

Figure 5: Comparing bank lending and corporate bond sentiment



Notes: The solid red line depicts the average unweighted bank risk sentiment in a given quarter. The dotted blue line depicts the Excess Bond Premium measure of Gilchrist and Zakrajšek (2012). Both series have been standardized with mean zero, variance one. Shaded regions indicate NBER dated recessions. Data is quarterly from 1992:Q1 through 2020:Q4.

outcomes in the extant literature.[32]

Figure 5 compares aggregate bank risk sentiment, which reflect bank lending sentiment, to a measure of corporate bond market sentiment, the Gilchrist and Zakrajšek (2012) Excess Bond Premium (EBP). While both instruments use asset prices to measure investors' risk sentiment, they do so for different actors and different markets in the economy. The EBP captures risk sentiment for all agents trading in the corporate bond market, which may include financial institutions such as pension, hedge, and mutual funds, as well as households and firms. Conversely, BRS reflects the risk sentiment in the bank lending market, thus of a single type of agent, commercial banks. While either set of market sentiments may be useful in understanding credit and business cycle fluctuations, they may be useful for understanding different aspects of either phenomenon. For example, BRS spikes during the global financial crisis two quarters before the EBP, suggesting that banks were more quickly aware of the banking crisis before agents in other sectors of the economy. Additionally, BRS was more sensitive to the Asian and Russian Financial crises than the EBP. Although, the EBP sent a stronger warning signal of the 2001 US recession, which was predominantly ignored by BRS.

6.1 Methodology and data

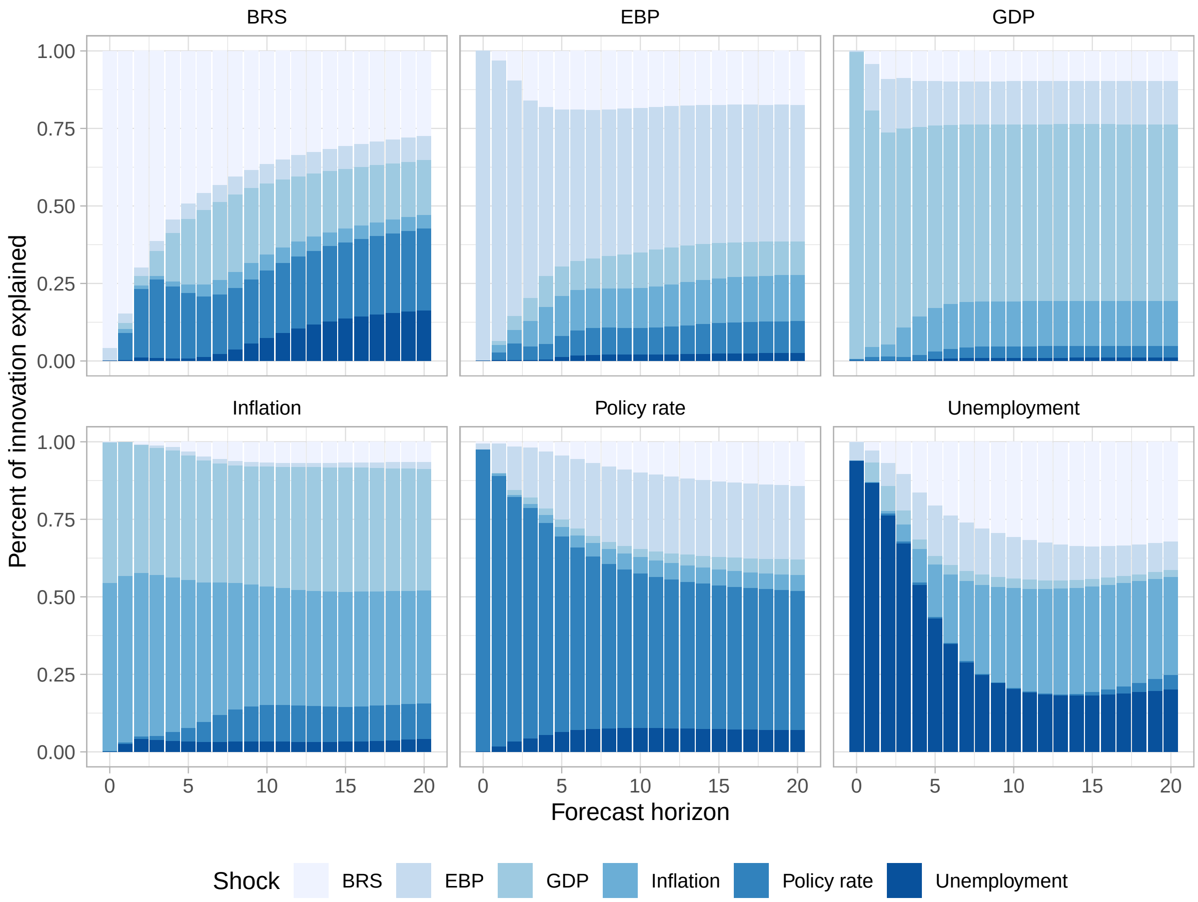
I will next compare BRS and EBP through the lens of a six variable structural VAR. More precisely, I postulate that the economy can be well summarized by the joint evolution of six variables following a linear law of motion:

$$Y_t = AY_{t-1} + B\epsilon_t \tag{15}$$

where the vector of endogenous states, Y_t, and coefficient matrix A are written in the standard companion form, while B is the impact matrix for structural shocks ϵ_t. The vector Y will contain four lags, the standard when working with quarterly data.

[32] Comprehensive in the sense that bank lending and corporate bond market sentiments together represent investor sentiments for the two largest markets of private debt in the US.

Figure 6: Comparing the role of bank lending and corporate bond sentiment shocks, FEVD



Notes: The stacked bar charts depict the forecast error variance decomposition from the one quarter through five year horizon. 100 percent of the forecast error is explained at a given horizon. Forecast frequency is quarterly. Data is quarterly from 1992:Q1 through 2019:Q4.

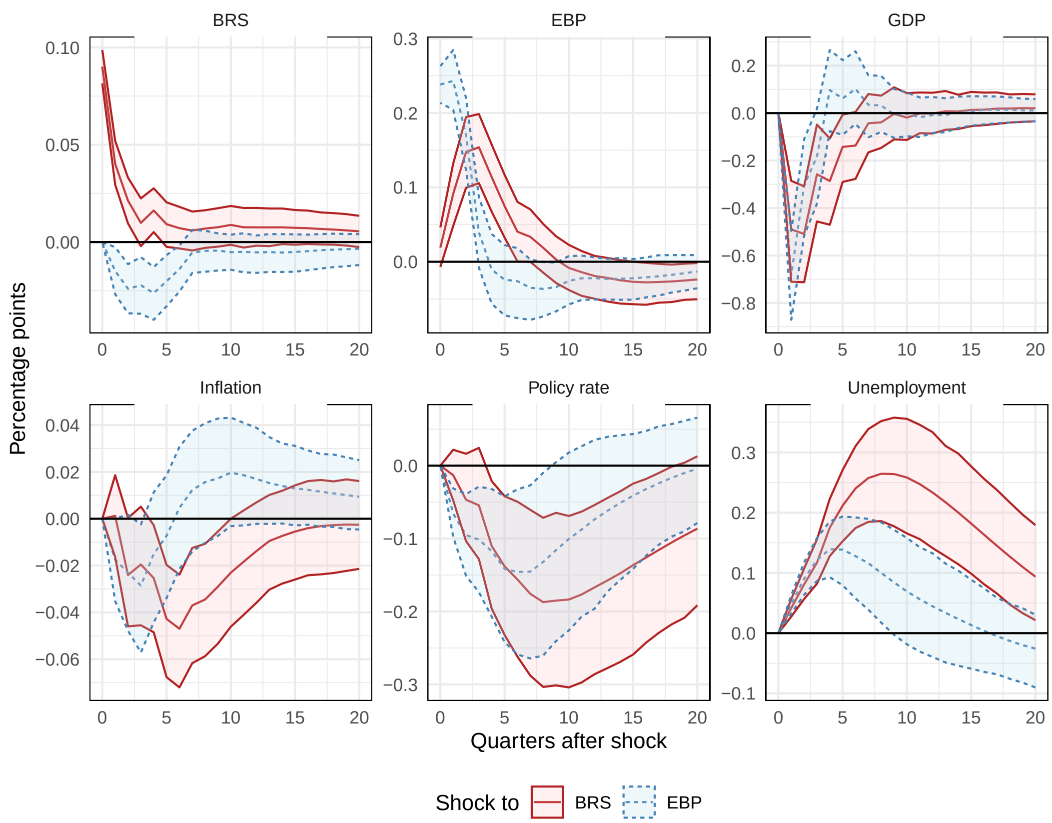
In the spirit of Gertler and Karadi (2015), my VAR tracks sentiment, measured as BRS and EBP, activity, measured as the unemployment rate and real GDP growth rate, prices, measured as core PCE inflation, and monetary policy, measured as the one year constant maturity Treasury yield. Identification will be achieved via short run restrictions on the propagation of shocks, implemented through the standard Cholesky decomposition of the reduced form error variance-covariance matrix. Variables enter the model in the order they are introduced in this paragraph. Data are quarterly from 1992 through 2019.

6.2 Results

I next examine activity, policy, and prices' dynamic response to either type of sentiment shock, as well as the average contribution of sentiment to macroeconomic fluctuations over time.

The forecast error variance decomposition (FEVD) of the VAR described by equation 15 shows that both BRS and EBP are important in explaining macroeconomic fluctuations, but BRS is often the more important sentiment. Figure 6 presents the FEVD and highlights four results in particular. First, sentiments inform one another, however, BRS influences the EBP approximately twice as much the EBP influences BRS. That is, BRS grows to explaining approximately 20 percent of innovations in the EBP while the EBP

Figure 7: Comparing the role of bank lending and corporate bond sentiment shocks, IRF



Notes: The red line depicts an impulse response to a unit BRS shock; the red shaded region covers the 90 percent confidence interval. The blue dotted line depicts an impulse response to a unit EBP shock; the blue shaded region covers the 90 percent confidence interval. Shock identification is achieved via short-run restrictions, implemented by a standard Cholesky decomposition over the impact matrix with variable ordering: inflation, GDP, unemployment, policy rate, BRS, EBP. Confidence intervals are based on 500 standard bootstraps. Data is quarterly from 1992:Q1 through 2019:Q4.

explains less than 10 percent of innovations of BRS at its maximum influence. Second, BRS explains a much larger portion of inflation and the unemployment rate than EBP. BRS explains approximately 10 percent of inflation two years after the initial shock and approximately 30 percent of unemployment two years after the initial shock. In fact, BRS is second only to inflation in explaining the level of the unemployment rate two to five years after the initial shock. Third, EBP explains a larger portion of the policy rate than BRS. Fourth, BRS and EBP explain comparable portions of GDP growth, with EBP explaining less than five percent more.

Moreover, the impulse response functions from the same VAR show that an unanticipated increase in BRS yields a more persistent, and often larger, response from activity, prices, and policy, than an analogous shock to the EBP. Figure 6 shows IRFs to both BRS and EBP shocks.

However, a more nuanced description of the responses is justified. First, a BRS shock induces an increase in the EBP, but the converse is not true. Meanwhile, an EBP shock has a slightly larger impact on GDP, with output growth falling by approximately 70 basis points within a year of the shock, while a BRS induces a 50 basis point decline. Although, a BRS shock has a more persistent effect on GDP growth; GDP recovers within three quarters of an EBP shock while it does not full recover from a BRS shock until five quarters after the shock. Next, a BRS shock has a larger and more persistent impact on inflation, albeit neither sentiment shock induces an economically meaningful decline in prices. This may be due to the relative persistence in inflation over the time period studied. Then, a BRS shock has a larger and more persistent impact on the policy rate. A shock to BRS leads to a 20 basis point drop in the policy rate, a 25 percent greater decline than following an EBP shock. Moreover, the policy rate only recovers four years after a BRS shock, compared only 10 quarters after an EBP shock. Lastly, a BRS shock leads to a larger and more persistent increase in the unemployment rate than an EBP shock. An EBP shock increases the unemployment rate by approximately 15 basis points within a year after impact, which recovers within 10 quarters after impact. A BRS shock leads to a 25 basis point increase (166 percent of the EBP maximum effect) within two years of impact, which does not recover before 5 years.

Robustness. These results are robust to using an unweighted or loan weighted measure of aggregate BRS. Estimating the VAR with only one sentiment series at a time (making it a five variable VAR). Estimating impulse response functions via local projection à la Jordà (2005). As well as reordering sentiments within the sentiment block, or moving the sentiments to the end of the variable ordering.

6.3 Discussion

I show that an unanticipated increase in aggregate BRS has a more persistent impact on activity, prices, and the policy rate than an analogous shock to the EBP. Moreover, in the context of a forecast error variance decomposition, fluctuations in the BRS are more important in explaining innovations in inflation and the unemployment rate than the EBP, although the EBP is more important in explaining changes in the policy rate. Finally, BRS accounts for 20 percent of the variance in the EBP, while the EBP accounts for less than 10 percent of variance in BRS.

However, these results raises the question: why does the BRS matter as much or more than EBP in explaining economic fluctuations? As pointed out in previous sections, BRS affects the economy through two channels, directly through the price of loans, and indirectly through the earning based borrowing constraint. Both of these channels are more likely to impact small firms and households, because unlike large firms, these agents lack access to alternative credit markets, such as the corporate bond market. Therefore, even though there are fewer loans (in dollar value), they make up the majority of credit utilized by small firms (engines of productivity and employment growth) and households (the agents who actually consume final goods and services). Although a quantitative comparison of commercial bank and corporate bond market sentiments and their transmission to the macroeconomy is left for future research.

7 Conclusion

This paper introduces a novel measure of bank risk sentiment and evaluates its effect on both loan-level and macroeconomic outcomes. Using regulatory data covering the universe of US commercial banks, I construct an empirical measure of BRS, identified in the context of an analytical heterogeneous bank model. I find that aggregate BRS is countercyclical with spikes during financial crises, but features a large degree of heterogeneity at the bank-level. Loan-level analysis then shows that an increase in BRS is associated with a decrease in credit supply and tightening loan covenants, two potential transmission channels to the macroeconomy. In turn, an increase in aggregate BRS leads to a broad-based deterioration in activity, financial conditions, and prices. I compare BRS to the Gilchrist and Zakrajšek (2012) EBP (a proxy for investor risk sentiment in corporate bond markets), and find BRS is distinct from corporate bond market investors' risk sentiment, and is more important in explaining economic fluctuations.

These findings have important implications for both academics and policy makers. For academics, my findings suggest that risk sentiments should be considered as a factor in loan pricing and bank lending. For policy makers, my findings suggest that they should be aware of the potential for bank risk sentiments to lead to a credit crunch, and they should take steps to mitigate this risk when necessary.

I have measured bank risk sentiment and shown it to matter for both micro- and macro-level economic outcomes. However, I have not addressed the source of bank risk sentiment, and leave this question open to future research. Additional avenues for future work also include examining the quantitative importance of BRS as a credit supply shock versus a credit constraint shock, how sentiments propagate among investors, the potential feedback loop between US bank risk sentiment and international financial conditions, and a broader assessment of how various financial market risk sentiments impact the macroeconomy and their quantitative importance.

References

Adrian, T., N. Boyarchenko, and D. Giannone (2019). Vulnerable growth. *American Economic Review 109*(4), 1263–89.

Adrian, T. and H. S. Shin (2014). Procyclical leverage and value-at-risk. *The Review of Financial Studies 27*(2), 373–403.

Akinci, O., Kalemli-Özcan, and A. Queralto (2022). Uncertainty shocks, capital flows, and international risk spillovers. Technical report, National Bureau of Economic Research.

Angeletos, G.-M. and J. La'o (2010). Noisy business cycles. *NBER Macroeconomics Annual 24*(1), 319–378.

Angeletos, G.-M. and J. La'o (2013). Sentiments. *Econometrica 81*(2), 739–779.

Angeletos, G.-M. and C. Lian (2016). Incomplete information in macroeconomics: Accommodating frictions in coordination. In *Handbook of macroeconomics*, Volume 2, pp. 1065–1240. Elsevier.

Bai, J. and S. Ng (2002). Determining the number of factors in approximate factor models. *Econometrica 70*(1), 191–221.

Baron, M. and W. Xiong (2017). Credit expansion and neglected crash risk. *The Quarterly Journal of Economics 132*(2), 713–764.

Basu, M. S. S., M. E. Boz, M. G. Gopinath, M. F. Roch, and M. F. D. Unsal (2020). *A conceptual model for the integrated policy framework*. International Monetary Fund.

Bekaert, G., M. Hoerova, and M. L. Duca (2013). Risk, uncertainty and monetary policy. *Journal of Monetary Economics 60*(7), 771–788.

Bellifemine, M., R. Jamilov, and T. Monacelli (2022). Hbank: Monetary policy with heterogeneous banks.

Bernanke, B. and M. Gertler (1989). Agency costs, net worth, and business fluctuations. *The American Economic Review 79*(1), 14–31.

Bernanke, B. S., M. Gertler, and S. Gilchrist (1999). The financial accelerator in a quantitative business cycle framework. *Handbook of macroeconomics 1*, 1341–1393.

Bianchi, F., C. Ilut, and H. Saijo (2023, 02). Diagnostic Business Cycles. *The Review of Economic Studies*. rdad024.

Bianchi, F., S. C. Ludvigson, and S. Ma (2022). Belief distortions and macroeconomic fluctuations. *American Economic Review 112*(7), 2269–2315.

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

Bloom, N., M. Floetotto, N. Jaimovich, I. Saporta-Eksten, and S. J. Terry (2018). Really uncertain business cycles. *Econometrica 86*(3), 1031–1065.

Boehm, C. E. and T. N. Kroner (2023). The us, economic news, and the global financial cycle. Technical report, National Bureau of Economic Research.

Bordalo, P., N. Gennaioli, Y. Ma, and A. Shleifer (2020). Overreaction in macroeconomic expectations. *American Economic Review 110*(9), 2748–82.

Bordalo, P., N. Gennaioli, R. L. Porta, and A. Shleifer (2019). Diagnostic expectations and stock returns. *The Journal of Finance 74*(6), 2839–2874.

Bordalo, P., N. Gennaioli, and A. Shleifer (2018). Diagnostic expectations and credit cycles. *The Journal of Finance 73*(1), 199–227.

Bordalo, P., N. Gennaioli, and A. Shleifer (2022). Overreaction and diagnostic expectations in macroeconomics. *Journal of Economic Perspectives 36*(3), 223–44.

Brunnermeier, M. K. and Y. Sannikov (2014). A macroeconomic model with a financial sector. *American Economic Review 104*(2), 379–421.

Bruno, V. and H. S. Shin (2015). Capital flows and the risk-taking channel of monetary policy. *Journal of monetary economics 71*, 119–132.

Caglio, C. R., R. M. Darst, and Kalemli-Özcan (2021, April). Collateral heterogeneity and monetary policy transmission: Evidence from loans to smes and large firms. Working Paper 28685, National Bureau of Economic Research.

Camara, S. and M. Sangiacomo (2022). Borrowing constraints in emerging markets. *arXiv preprint arXiv:2211.10864*.

Carlstrom, C. T. and T. S. Fuerst (1997). Agency costs, net worth, and business fluctuations: A computable general equilibrium analysis. *The American Economic Review*, 893–910.

Chodorow-Reich, G. (2014). The employment effects of credit market disruptions: Firm-level evidence from the 2008–9 financial crisis. *The Quarterly Journal of Economics 129*(1), 1–59.

Chodorow-Reich, G. and A. Falato (2022). The loan covenant channel: How bank health transmits to the real economy. *The Journal of Finance 77*(1), 85–128.

Christiano, L. J., R. Motto, and M. Rostagno (2014). Risk shocks. *American Economic Review 104*(1), 27–65.

Cohen, G. J., J. Dice, M. Friedrichs, K. Gupta, W. Hayes, I. Kitschelt, S. J. Lee, W. B. Marsh, N. Mislang, M. Shaton, et al. (2021). The us syndicated loan market: Matching data. *Journal of Financial Research 44*(4), 695–723.

Coimbra, N. and H. Rey (2017). Financial cycles with heterogeneous intermediaries. Technical report, National Bureau of Economic Research.

Corbae, D. and P. D'Erasmo (2021). Capital buffers in a quantitative model of banking industry dynamics. *Econometrica 89*(6), 2975–3023.

Dell'Ariccia, G., L. Laeven, and G. A. Suarez (2017). Bank leverage and monetary policy's risk-taking channel: evidence from the united states. *the Journal of Finance 72*(2), 613–654.

Di Giovanni, J., Ş. Kalemli-Özcan, M. F. Ulu, and Y. S. Baskaya (2022). International spillovers and local credit cycles. *The Review of Economic Studies 89*(2), 733–773.

Drechsel, T. (2023). Earnings-based borrowing constraints and macroeconomic fluctuations. *American Economic Journal: Macroeconomics 15*(2), 1–34.

Drechsler, I., A. Savov, and P. Schnabl (2017). The deposits channel of monetary policy. *The Quarterly Journal of Economics 132*(4), 1819–1876.

Falato, A. and J. Xiao (2022). Expectations and credit slumps. Technical report, Tech. rep., Federal Reserve Board of Governors and University of Notre Dame ....

Fleckenstein, Q., M. Gopal, G. Gutierrez Gallardo, and S. Hillenbrand (2020). Nonbank lending and credit cyclicality. *NYU Stern School of Business*.

Gabaix, X. (2011). The granular origins of aggregate fluctuations. *Econometrica 79*(3), 733–772.

Gabaix, X. and R. S. Koijen (2020). Granular instrumental variables. Technical report, National Bureau of Economic Research.

Gabaix, X. and M. Maggiori (2015). International liquidity and exchange rate dynamics. *The Quarterly Journal of Economics 130*(3), 1369–1420.

Gertler, M. and P. Karadi (2011). A model of unconventional monetary policy. *Journal of monetary Economics 58*(1), 17–34.

Gertler, M. and P. Karadi (2015). Monetary policy surprises, credit costs, and economic activity. *American Economic Journal: Macroeconomics 7*(1), 44–76.

Gertler, M. and N. Kiyotaki (2010). Financial intermediation and credit policy in business cycle analysis. In *Handbook of monetary economics*, Volume 3, pp. 547–599. Elsevier.

Gertler, M. and N. Kiyotaki (2015). Banking, liquidity, and bank runs in an infinite horizon economy. *American Economic Review 105*(7), 2011–2043.

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

Gilchrist, S. and E. Zakrajšek (2012). Credit spreads and business cycle fluctuations. *American economic review 102*(4), 1692–1720.

Greenstone, M., A. Mas, and H.-L. Nguyen (2020). Do credit market shocks affect the real economy? quasi-experimental evidence from the great recession and" normal" economic times. *American Economic Journal: Economic Policy 12*(1), 200–225.

Hart, O. and J. Moore (1994). A theory of debt based on the inalienability of human capital. *The Quarterly Journal of Economics 109*(4), 841–879.

He, Z. and A. Krishnamurthy (2013). Intermediary asset pricing. *American Economic Review 103*(2), 732–770.

Huggett, M. (1996). Wealth distribution in life-cycle economies. *Journal of Monetary Economics 38*(3), 469–494.

Itskhoki, O. and D. Mukhin (2021). Exchange rate disconnect in general equilibrium. *Journal of Political Economy 129*(8), 2183–2232.

Jamilov, R. (2021). A macroeconomic model with heterogeneous banks. *Available at SSRN 3732168*.

Jamilov, R. and T. Monacelli (2023). Bewley banks. *Available at SSRN 3732172*.

Jiménez, G., S. Ongena, J.-L. Peydró, and J. Saurina (2014). Hazardous times for monetary policy: What do twenty-three million bank loans say about the effects of monetary policy on credit risk-taking? *Econometrica 82*(2), 463–505.

Jordà, Ò. (2005). Estimation and inference of impulse responses by local projections. *American economic review 95*(1), 161–182.

Jordà, Ò., M. Schularick, and A. M. Taylor (2017). Macrofinancial history and the new business cycle facts. *NBER macroeconomics annual 31*(1), 213–263.

Kalemli-Özcan, 2019). Us monetary policy and international risk spillovers. Technical report, National Bureau of Economic Research.

Khwaja, A. I. and A. Mian (2008). Tracing the impact of bank liquidity shocks: Evidence from an emerging market. *American Economic Review 98*(4), 1413–1442.

Kindleberger, C. P. (1978). History of financial crises.

Kiyotaki, N. and J. Moore (1997). Credit cycles. *Journal of political economy 105*(2), 211–248.

Krishnamurthy, A. and W. Li (2021). Dissecting mechanisms of financial crises: Intermediation and sentiment. *Available at SSRN 3554788*.

Kwak, S. (2022). How does monetary policy affect prices of corporate loans? *FEDS Working Paper*.

Leiva-Leon, D., G. Perez-Quiros, H. Sapriza, E. Zakrajšek, et al. (2022). Introducing the credit market sentiment index. *Richmond Fed Economic Brief 22*(33).

Lian, C. and Y. Ma (2021). Anatomy of corporate borrowing constraints. *The Quarterly Journal of Economics 136*(1), 229–291.

López-Salido, D., J. C. Stein, and E. Zakrajšek (2017). Credit-market sentiment and the business cycle. *The Quarterly Journal of Economics 132*(3), 1373–1426.

Lucas, R. E. (1973). Some international evidence on output-inflation tradeoffs. *The American economic review 63*(3), 326–334.

Ma, Y., T. Paligorova, and J.-L. Peydro (2021). Expectations and bank lending. *University of Chicago, Unpublished Working Paper*.

Martinez-Miera, D. and R. Repullo (2017). Search for yield. *Econometrica 85*(2), 351–378.

Maxted, P. (2023). A macro-finance model with sentiment. *Review of Economic Studies*, rdad023.

McCarthy, O. and S. Hillenbrand (2021). Heterogeneous investors and stock market fluctuations. *Available at SSRN 3944887*.

McCracken, M. and S. Ng (2020). Fred-qd: A quarterly database for macroeconomic research. Technical report, National Bureau of Economic Research.

Mian, A. and A. Sufi (2018). Finance and business cycles: The credit-driven household demand channel. *Journal of Economic Perspectives 32*(3), 31–58.

Minsky, H. P. (1977). The financial instability hypothesis: An interpretation of keynes and an alternative to "standard" theory. *Challenge 20*(1), 20–27.

Miranda-Agrippino, S. and H. Rey (2020). Us monetary policy and the global financial cycle. *The Review of Economic Studies 87*(6), 2754–2776.

Morais, B., J.-L. Peydró, J. Roldán-Peña, and C. Ruiz-Ortega (2019). The international bank lending channel of monetary policy rates and qe: Credit supply, reach-for-yield, and real effects. *The Journal of Finance 74*(1), 55–90.

Ottonello, P. and T. Winberry (2020). Financial heterogeneity and the investment channel of monetary policy. *Econometrica 88*(6), 2473–2502.

Perri, F. and V. Quadrini (2018). International recessions. *American Economic Review 108*(4-5), 935–84.

Pflueger, C., E. Siriwardane, and A. Sunderam (2020, 03). Financial Market Risk Perceptions and the Macroeconomy*. *The Quarterly Journal of Economics 135*(3), 1443–1491.

Pinardon-Touati, N. (2021). The crowding out effect of local government debt: Micro-and macro-estimates.

Plagborg-Møller, M. and C. K. Wolf (2021). Local projections and vars estimate the same impulse responses. *Econometrica 89*(2), 955–980.

Restuccia, D. and R. Rogerson (2008). Policy distortions and aggregate productivity with heterogeneous establishments. *Review of Economic dynamics 11*(4), 707–720.

Saunders, A., A. Spina, S. Steffen, and D. Streitz (2021). Corporate loan spreads and economic activity. *NYU Stern School of Business Forthcoming*.

Schmitt-Grohé, S. and M. Uribe (2021). Multiple equilibria in open economies with collateral constraints. *The Review of Economic Studies 88*(2), 969–1001.

Stock, J. H. and M. W. Watson (2016). Dynamic factor models, factor-augmented vector autoregressions, and structural vector autoregressions in macroeconomics. In *Handbook of macroeconomics*, Volume 2, pp. 415–525. Elsevier.

A BRS under alternative laws of motion

I define a bank's risk sentiment as the wedge between its forecast of future default rates and the rational expectations forecast of default rates. However, to measure such an object, I have to postulate a true law of motion for risk in the economy to in turn define the rational expectations forecast. One may expect BRS to therefore be sensitive to choice of postulated law of motion for risk in the economy. I next show that BRS is qualitatively robust to two sensible alternative laws of motion of risk.

Postulated laws of motion

I will first propose two alternative laws of motion for risk in the economy, one more and less restrictive than the baseline specification employed in Section 2.

Loan default law of motion 1: idiosyncratic risk
Postulate that the bank-level default process follows a Markov process or AR(1):

$$\lambda_{i,t} = \rho\lambda_{i,t-1} + \pi_{i,t}$$

and that the default rate is a sufficient statistic to describe the state of the world, that is, there is an isomorphic mapping from $\lambda_s \to S$. Thus, the rational expectation forecast of the default rate is given as:

$$E_{RE}(\lambda_{i,t}|s_{i,t-1}) = E_{RE}(\lambda_{i,t}|\lambda_{i,t-1}) = \rho\lambda_{i,t-1}$$

We can then rewrite our bank expectations equation

$$\begin{aligned} E(\lambda_{i,t}|s_{i,t-1}) &= E_{RE}(\lambda_{i,t}|\lambda_{i,t-1}) + \psi_{i,t} \\ &= \rho\lambda_{i,t-1} + \psi_{i,t} \end{aligned}$$

where $\psi_{i,t}$ is the bank-level deviation from the rational expectation forecast of loan default rates. Since we have recovered an estimate of $E\lambda_{i,t}$ using the model outlined in the previous section, we can estimate bank risk sentiment as the residual of the regression specified above.

Loan default law of motion 2: idiosyncratic and size-dependent aggregate risk
Next I will loosen the assumption that the bank-level loan default rate $\lambda_{i,t}$ homogeneously loads on aggregate risk. That is, I will allow banks to scale their loading on the aggregate component of loan default rates based on size. This additional flexibility is meant to recognize that small and large banks may have a different relationship with the aggregate economy. For example, loan defaults for a community bank that primarily operates within one county is more likely to be driven by the idiosyncratic fluctuations of that county, compared to the very largest banks who issue loans across every state and are most likely not very affected by the idiosyncratic fluctuations of any single county. The postulated law of motion is then:

$$\lambda_{i,t} = \rho_1\lambda_{i,t-1} + \rho_2\lambda_{t-1} + \rho_3(\text{bank size})_t + \rho_4[(\text{bank size})_t \times \lambda_{t-1}] + \psi_{i,t}$$

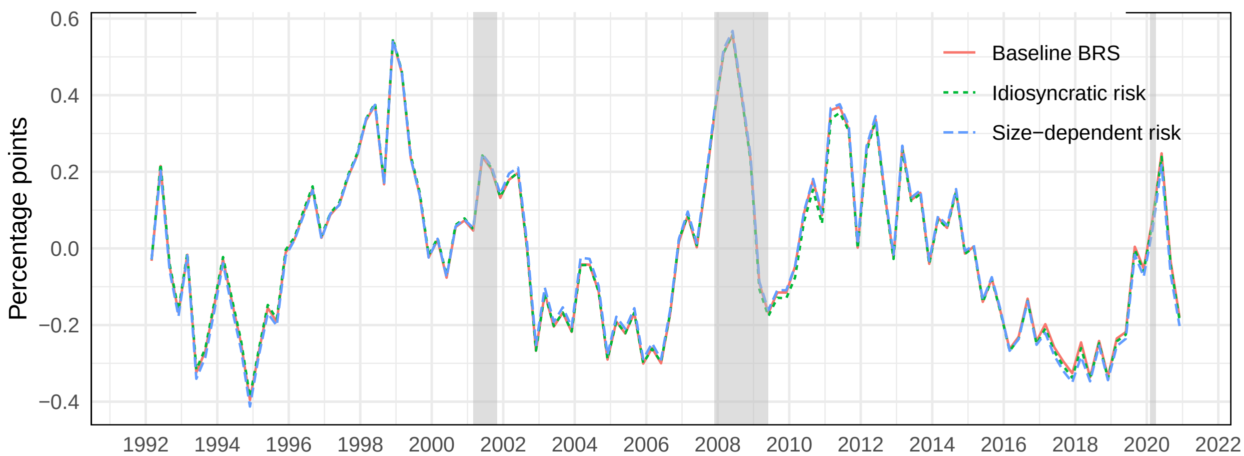
and the corresponding rational expectations forecast of risk is:

$$E_{RE}(\lambda_{i,t}|s_{t-1}) = \rho_1\lambda_{i,t-1} + \rho_2\lambda_{t-1} + \rho_3(\text{bank size})_t + \rho_4[(\text{bank size})_t \times \lambda_{t-1}]$$

Comparing sentiments

Aggregate bank risk sentiment is qualitatively robust to sensible alternative laws of motion for risk in the economy. I estimate a new empirical measure of BRS following the same procedure as in Section 3, except now replacing $E_{RE}(\lambda_{i,t}|s_{t-1})$ with the rational expectations forecast implied by the alternative laws of motion. Figure 8 shows baseline and alternative aggregate BRS: the solid red line corresponds to the baseline BRS, the dotted green line corresponds to the idiosyncratic risk only law of motion (model 1), and the dashed blue line corresponds with the size-dependent aggregate risk law of motion (model 2).

Figure 8: Bank risk sentiment under alternative laws of motion



Notes: Solid black line depicts the quarterly unweighted average of bank-level risk sentiments. The orange dashed line is the quarterly unweighted average bank-level risk sentiments, controlling for aggregate uncertainty. Gray bars are NBER dated recessions. Data are quarterly from 1992 to 2021.

B Potential sources of sentiment, time-varying risk aversion and uncertainty

I examine two potential sources of bank risk sentiment, time-varying risk aversion and uncertainty. First, I show that time-varying risk aversion is already controlled for in the measurement of BRS. Second, I show that BRS is qualitatively robust to controlling for the effects of aggregate uncertainty, although with modest attenuation during select crises.

B.1 Time-varying risk aversion

Perhaps the leading alternative framework for measuring bank risk sentiment is based on an intermediary's time-varying risk aversion, in the spirit of He and Krishnamurthy (2013) or Brunnermeier and Sannikov (2014). However, I can eliminate time-varying risk premia as a source of the empirically estimated bank risk sentiment. I next present a short extension of the analytical model presented in Section 2 and show that time-varying risk aversion is in fact already controlled for in the measurement of bank risk sentiment.

Take the economic setting presented in Section 2, but now let banks be owned and funded by a risk averse household and consider the existence of a risk free bond.[33] Households then have to allocate their wealth over a risky and non-risky asset at the beginning of each period. The risk free asset is the aforementioned risk free bond, which pays a gross return R_t^f, while the risky asset is a loan portfolio, formed and executed by the specialized bank owned by the Household, and pays gross return R_t^p as before. The exact timeline for the Household's bank funding decision in period t is thus: 1) realize previous period's loan portfolio return, R_{t-1}^p, 2) update wealth w_t, 3) allocate fraction α of wealth w_t to bank operations, 4) bank forms risky portfolio of loans.

The Household's risk aversion is thus manifest in its allocation between risky an risk free assets. The risk averse Household's portfolio allocation problem is standard. Thus, the solution is standard, and the Household will allocate a fraction of its wealth, α, as a function of its time-varying risk aversion, γ_t, and

[33] Households will own the banks, but will still be banks be run by a separate risk-neutral operator.

variance of the risky asset, $\sigma^2_{R^p}$. The Household's expected return each period can then be written:

$$\begin{aligned} E_t(R_{t+1}) &= (1-\alpha(\gamma_t,\sigma^2_{R^p}))R^f_{t+1} + \alpha(\gamma_t,\sigma^2_{R^p})E_t(R^p_{t+1}) \\ &= R^f_{t+1} + \alpha(\gamma_t,\sigma^2_{R^p})\Big[E_t(R^p_{t+1}) - R^f_{t+1}\Big] \end{aligned}$$

where the second line is the typical risk premia representation of a risky portfolio return.

Moreover, the Household will direct the risk-neutral bank operator to maximize $\alpha(\gamma_t,\sigma^2_{R^p})E_t(R^p_{t+1})$, which extends the Specialist bank's problem to be:

$$\max_{R_{i,t}} \beta\alpha(\gamma_t,\sigma^2_{R^p})E_t(R^p_{t+1})L_{i,t} - (L_{i,t}-N_{i,t})C_t - \Phi(L_{i,t}-N_{i,t}) \quad \text{s.t.} \tag{16}$$

$$\begin{aligned} N_{i,t} &= N_{i,t-1} + \Pi_{i,t-1} \\ L_{i,t} &= \frac{1}{\alpha}\frac{R_t^{\theta-1}}{R_{i,t}^{\theta}}L_t \\ E(R^p_{i,t}) &= (1-E\lambda_{i,t+1})R_{i,t} \end{aligned}$$

and the solution is augmented with a new time-varying risk aversion term:

$$R_{i,t} = \frac{1}{\beta}\underbrace{\frac{1}{\alpha(\gamma_t,\sigma^2_{R^p})}}_{\text{risk aversion}}\cdot\underbrace{\frac{1}{1-E\lambda_{i,t+1}}}_{\text{perceived risk}}\cdot\underbrace{\frac{\theta_{i,t}}{\theta_{i,t}-1}}_{\text{market power}}\cdot\underbrace{(C_t+\Phi'(L_{i,t}-N_{i,t}))}_{\text{marginal cost}} \tag{17}$$

where $\alpha \in [0,1]$ is assumed to be decreasing in risk-aversion, γ_t, so that as risk aversion increases the loan rate increases.[34] That is, as the Household becomes more risk averse, its demanded compensation for holding risk increases.

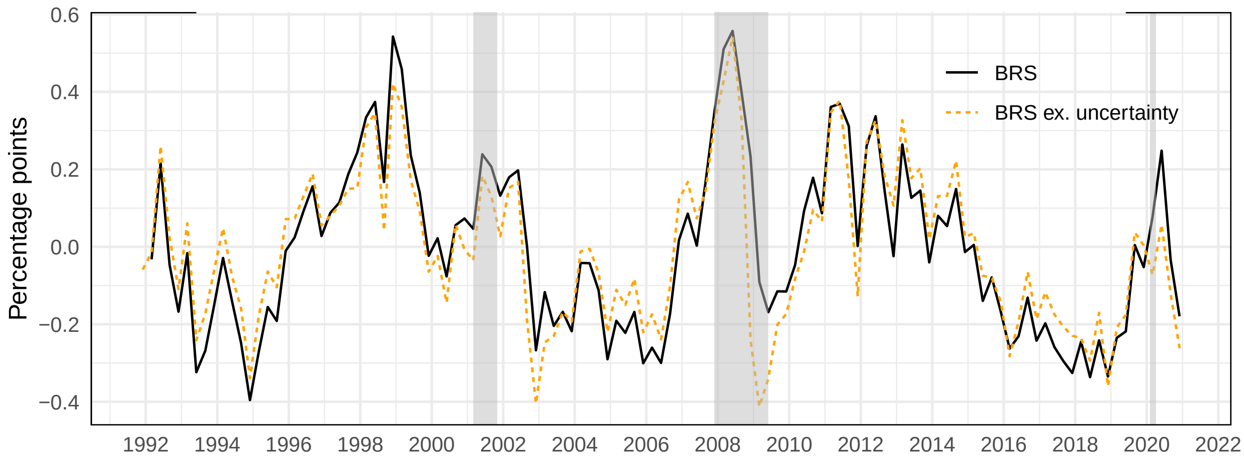
It follows that the risk-aversion augmented measure of BRS needs to be measured via Equation 17. However, if I assume that a bank's asset portfolio reflects the preferences of its owners, then the risky asset-to-net worth fraction on a bank's balance sheet may act as a proxy for the bank owner's time-varying risk aversion. This fraction is recognizable as a leverage ratio, which is in fact already included in the baseline measurement equation for BRS. That is, the empirical measure of bank risk sentiment, already controls for time-varying risk aversion.

B.2 Uncertainty

Motivated by works such as Christiano et al. (2014) and Akinci et al. (2022), I test for how BRS may be explained by uncertainty. While the inclusion of uncertainty can be motivated by in a number of ways, for example postulating a log-normal process driving loan default rates, I abstract from theoretical specifics for the following presentation. Instead, I move directly to including a measure of aggregate uncertainty, the VIX, into the BRS measurement equation.

Figure 9 compares the baseline BRS and sentiment removing the effect of aggregate uncertainty. BRS appears qualitatively unchanged by removing aggregate uncertainty. However, select crisis periods appear to be significantly driven by uncertainty. For example, BRS is attenuated during both the Ruble crisis and COVID recession when one removes the impact of uncertainty. Moreover, sentiment recovers both more quickly and bottoms out at much lower levels in the second half of the GFC if one removes the effect of uncertainty.

Figure 9: Bank risk sentiment with and without uncertainty



Notes: Solid black line depicts the quarterly unweighted average of bank-level risk sentiments. The orange dashed line is the quarterly unweighted average bank-level risk sentiments, controlling for aggregate uncertainty. Gray bars are NBER dated recessions. Data are quarterly from 1992 to 2021.

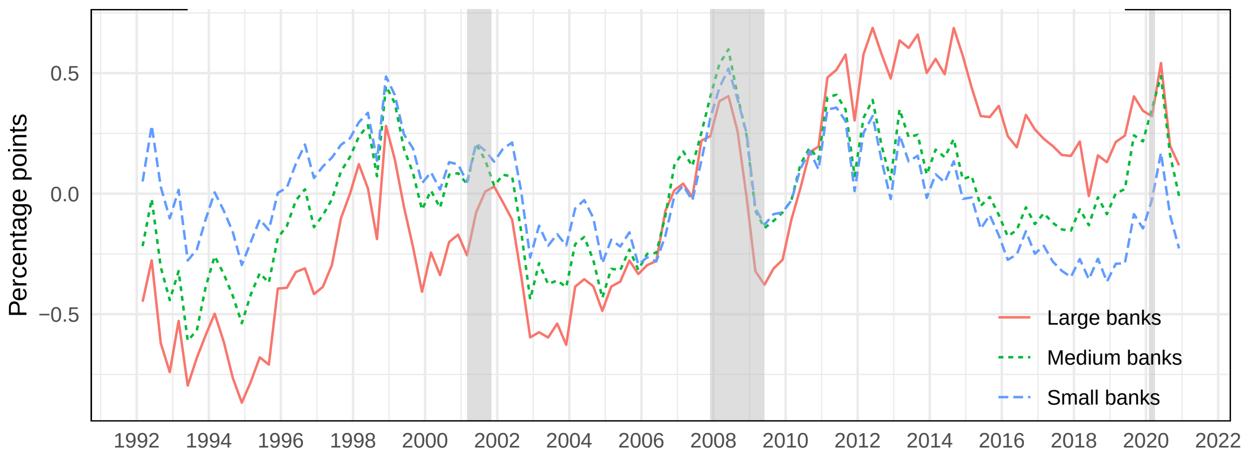
C BRS by bank size

Figure 10 shows the unweighted average bank risk sentiment by bank size. The solid red line shows the average risk sentiment of the top one percent of banks by net worth in a given quarter. The small size of the cohort reflects the fact that there are between five and ten systemically important banks in the United States that dominant the financial sector. The dashed blue line shows the small banks, those in the bottom 84 percentiles of the size distribution. The large size of this cohort reflects the fact that the majority of banks in the US are small community banks, most only operating within one state. The dotted green line captures mid-sized banks, for example the now defunct Silicon Valley Bank. These banks are multi-state operators, much larger than the average community bank, but not large enough to be labeled systemically important by regulators.

Figure 10 shows that risk sentiment varies by the size of a bank. For example, the risk sentiment of small banks is relatively elevated through the 1990's. Recall that the US Savings and Loans crisis –a period defined by a large number of small bank failures and subsequent regulatory reform– did not end until 1995. In comparison, large banks held relatively low risk sentiments. That is, until the international financial crises occurred. Large banks experienced noticeably larger spikes in sentiment during the Tequila crisis, Asian Financial crisis, and Russian Financial crisis. Additionally, prior to the GFC, small banks systematically had higher risk sentiments than large banks, and recovered to pre-crisis sentiment levels by 2016. However, since 2010, large banks have held persistently higher risk sentiments, which never recovered after the GFC. One interpretation of this fact is that large banks were more deeply scarred by the GFC than small banks. Perhaps the failure of Lehman Brothers made large banks question the implicit insurance policy that the Government would bail them out in times of distress, and this decrease in insurance has made them bias their risk assessments upwards. However, no matter the source, large banks now charge a larger risk premia due to risk sentiments than prior to the GFC.[35]

[34]If $\alpha = 0$ then the bank is not funded and will make no loans.
[35]The change in large banks' sentiment after the GFC appear robust to controlling for the post-crisis regulatory regime shift.

Figure 10: Bank risk sentiment by bank size



Notes: Solid red line depicts the unweighted average of the top 1% of banks by net worth in a given quarter, medium size banks are defined as the 85th through 99th percentile of banks by net worth, and small banks are those below the 85th percentile. Gray shaded regions are NBER dated recessions. Data are quarterly from 1992 to 2021.

D IRFs in a dynamic factor model

I define the dynamic factor model's impulse response functions and their confidence intervals in the following manner.

Impulse responses. The impulse response function of states to an exogenous unit shock to state j is

$$E(X_{t+h}|e_i) = A^{h-1}Be_j$$

while the impulse response of observables to an exogenous unit shock to BRS is

$$E(Y_{t+h}|e_1) = \Lambda^{-1}A^{h-1}Be_1$$

Therefore Λ must be invertible, but is guaranteed to be as a full rank matrix of sorted Eigenvectors.

Confidence intervals. Confidence intervals are based on 1000 standard bootstraps that take into account uncertainty in both the state and measurement equation estimation. The bootstrapping algorithm follows:

For l draws of the latent factors

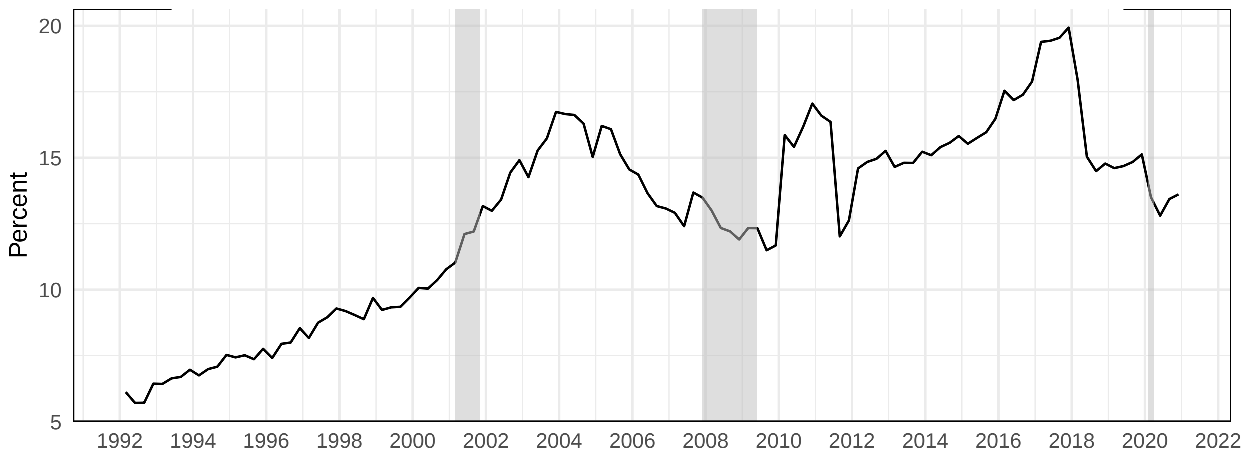
1. randomly draw p percent of observations (along the time dimension, we keep the number of observables constant throughout),
2. estimate factors via principal components,
3. estimate state equation,
4. draw m standard bootstrapped impulse response functions

Calculate the 10th and 90th percentile IRF per horizon over all bagged IRFs

End.

where I present results setting $l = 100$, $p = 80$, and $m = 10$.

Figure 11: Loan share of the top ten largest banks operating in the US



Notes: Solid black line depicts that loan share of the top ten largest banks, by total loans, operating in the US in a given period. Data is quarterly from 1992 to 2021. Source: US Call Reports.

E Macroeconomic impact of granular sentiment shocks

I examine the potential macroeconomic impact of granular sentiment shocks to the largest banks in the US, in the spirit of Gabaix (2011) and Gabaix and Koijen (2020). Using the same FAVAR framework as presented in Section 5, I find that granular sentiment shocks to the top ten largest commercial banks operating in the US do not yield statistically significant responses in macroeconomic outcomes. However, the influence of these shocks has increased over time.

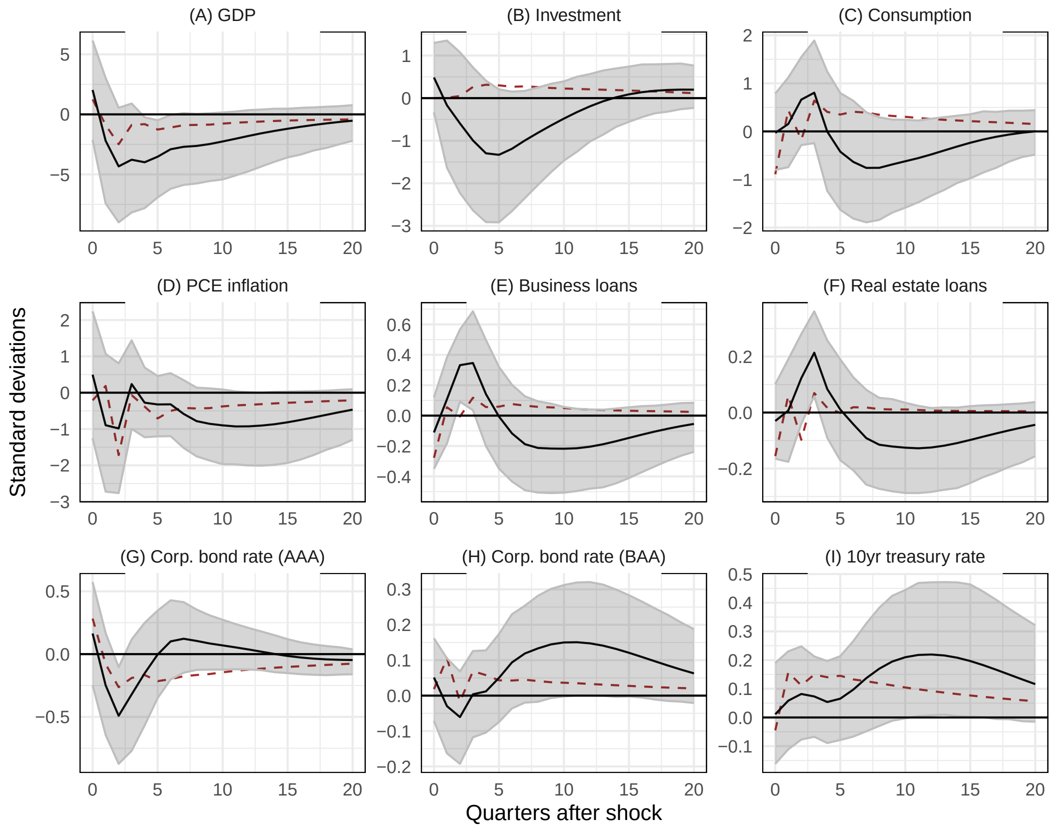
Figure 11 shows the loan share of the ten largest commercial banks in the US in a given quarter. The loan share of the largest banks has been increasing over time, suggesting that granular sentiment shocks in the first half of the sample will impact a smaller percentage of total loans in the financial system. As a result, I estimate the macroeconomic response to granular sentiment shocks across two samples, 1) the full history, from 1992 through 2021, and 2) post-GFC only, from 2010 through 2021.

Figure 12 shows the macroeconomic response to an unanticipated percentage point increase in the BRS of the ten largest banks. The dotted brown line shows the response estimated over the entire sample history, and suggests that granular shocks are not statistically or economically impactful on macroeconomic outcomes. However, the solid black line (and its associated 90 percent confidence interval) shows that the granular shocks have a much more economically, if not statistically, significant impact on economic conditions in the post-GFC period. It is perhaps unsurprising that the influence of the granular shocks increase, given that the total loan market represented by the largest banks goes from as low as five and a half percent pre-GFC to approximately 15 percent on average post-GFc. Moreover, the responses to the granular shocks post-GFC are qualitatively similar to those based on the full aggregate BRS over the entire sample history studied in Section 5.

F The robustness of loan-level outcomes

Table 5 present the results of a loan-level analysis following the same specification as those outlined in Section 4. However, these exercises additionally control for firm-level risk by including a binary indicator for high or low levels of firm-level book leverage (more specifically, if the firm is in the upper or bottom half of the leverage distribution). Leverage data is collected at the quarterly frequency for public firms from

Figure 12: Macroeconomic response to a risk sentiment shock to the largest banks



Notes: This figure reports the impulse response functions of select macroeconomic and financial variables to an unanticipated one percentage point increase in the bank risk sentiment of the ten largest banks, by loans, in a given period. The solid black line depicts the response to a BRS shock in the post-GFC period, 2010 through 2021; the dotted brown lines depict the response to a BRS shock estimated over the entire sample history. Gray bands represent the 90 percent confidence intervals around the responses estimated in the post-GFC period, based on 1000 bootstrapped samples which account for both state and measurement equation uncertainty. Data is quarterly from 1992 to 2021.

Compustat. Leverage is a natural control for considering risk, as it is closely related to a firm's probability of default, and it has been shown to determine loan level characteristics, such as price and quantity. One may turn to Caglio et al. (2021) or Ottonello and Winberry (2020) for further discussion of leverage and corporate financing outcome.

The loan-level results presented in the body of the text hold. Table 5 shows that upon a one percent bank-level risk sentiment shock, the loan rate increases, amount decreases, and covenants tighten - all at a statistically significant level when narrowing the sample to re-negotiations. This exercise confirms that the demand-side factors of credit outcomes are accounted for in the loan-level analysis. However, the stark decline in sample size may warrant some caution in extrapolating these results too broadly from the current analysis.

Table 5: Loan-level response to a bank risk sentiment shock, controlling for firm leverage

	Loan rate		Loan amount		Covenant tightness	
	(1)	(2)	(3)	(4)	(5)	(6)
BRS	0.203*	0.223*	−0.274	−0.403**	−0.242**	−0.254*
	(0.114)	(0.125)	(0.263)	(0.187)	(0.111)	(0.145)
Refinancing only FE		✓		✓		✓
Borrower-Quarter FE	✓	✓	✓	✓	✓	✓
Lender-Borrower FE	✓	✓	✓	✓	✓	✓
Loan characteristics	✓	✓	✓	✓	✓	✓
Firm characteristics	✓	✓	✓	✓	✓	✓
Observations	222	137	222	137	93	73
R^2	0.412	0.408	0.412	0.441	0.390	0.458
Sample composition						
Loans	105	64	105	64	38	32
Dates	38	26	38	26	13	12
Banks	47	39	47	39	28	25
Borrowers	48	29	48	29	17	14
Bank-Borrower pairs	106	69	106	69	44	36

Notes: This table reports a (within) fixed effects regression of loan outcomes onto the issuing bank's risk sentiment. Columns (1) and (2) show the response of the loan rate to a one percent change in bank-level BRS. The loan rate is measured in percentage points over the loans reference rate, e.g. LIBOR. Columns (3) and (4) show the response of the loan amount to a one percent change in bank-level BRS. The loan amount is measured in log-levels. Columns (5) and (6) show the response of the covenant tightness to a one percent change in bank-level BRS. Covenant tightness is proxied by maximum ratio of debt to EBIDTA allowed by the contract. All coefficients can be interpreted as either elasticities or psuedo-elasticities (in the case of covenant tightness). The loan rate and amount have been winsorized at the 1st and 99th percentiles. Loan characteristics are included in all regressions and include an indicator if the loan is secured by collateral and an indicator for the presence of covenants (except when covenant tightness is the dependent variable). Observations are weighted based on the lender's current share of the syndicated loan. Each borrower must be borrowing from two or more syndicated loans in a quarter. Parentheses wrap the robust standard errors, which are double clustered at bank and quarter levels, and * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.