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 an empirical measure of bank risk sentiment —irrational bank-level shocks to expected loan portfolio default rates— using regulatory data covering the universe of U.S. commercial banks and an identification scheme motivated by a novel, analytical, heterogeneous bank model. Aggregate bank risk sentiment (BRS) is pessimistic during financial crises and optimistic during debt-fueled asset bubbles, but is heterogeneous at the bank-level. BRS shocks act like credit supply shocks, impacting both the extensive and intensive margins of lending. Through lending markets, a pessimistic sentiment shock leads to a significant and long-lived deterioration in economic activity and prices, prompting a monetary policy easing. I also show that BRS is equally or more important in explaining macroeconomic outcomes than corporate bond market sentiment shocks (proxied by fluctuations in the Excess Bond Premium), real shocks (including generic aggregate demand and supply shocks), and U.S. monetary policy shocks. I lastly turn to a loan-level analysis to explore the potential micro-to-macro transmission mechanisms of bank-level sentiment shocks, and show that pessimistic sentiment shocks tighten earning base borrowing constraints.

Keywords Financial Intermediaries, Credit Supply Shocks, Investor Sentiment, Loan Markets
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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 the most important credit markets in the United States: the commercial bank lending market.

This paper evaluates the role of investor risk sentiment in the U.S. 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 financial markets, namely the corporate bond market, and is equally or more important in explaining macroeconomic outcomes than other financial market sentiment shocks, real shocks (including generic aggregate demand and supply shocks), and U.S. monetary policy shocks. I lastly turn to a loan-level analysis to explore the potential micro-to-macro transmission mechanisms of bank-level sentiment shocks, and show that an increase in BRS tightens earning based borrowing constraints.

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 sophisticated 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.[2] Using this approach, I estimate bank-level risk sentiments at a quarterly frequency for the universe of U.S. commercial banks from 1992 to 2021 using regulatory Call Reports.

Aggregate BRS spikes during financial crises or potential financial crises, such as the Russian Financial Crisis, the collapses of Enron and WorldCom, the Global Financial Crisis (GFC), the European Debt Crisis, the Taper Tantrum, and the COVID-19 pandemic. Conversely, it tends to be optimistic during debt-fueled asset bubbles, including the Dot-com bubble of the late 1990s and early 2000s, and the U.S. housing bubble that ultimately led to the GFC. However, bank-level risk sentiments exhibit significant heterogeneity, with dispersion in sentiments spiking during crises. The underlying bank-level sentiment processes are shown to be optimistic on average, but characterized by a fat-tailed distributions over the persistence and volatility of sentiment shocks.

Having measured and characterized BRS, I next turn to asking the question: do bank sentiment shocks actually affect loan market outcomes, and, if so, do these effects spill over to the real economy? I start answering this question by studying the effects of aggregate bank sentiment shocks across a variety of lending market characteristics and outcomes in a flexible and theoretically agnostic Jordà (2005) style local projection framework.

A pessimistic aggregate BRS acts similar to a standard negative credit supply shock. A one standard deviation BRS shock leads to a 0.8 percentage point increase in loan rates and a coinciding 2.5 percent decrease in total lending. Moreover, the sentiment shock acts

[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.

[2] The measurement strategy to decompose loan rates into a portion attributable to measurable and theoretically motivated factors, isolating an unexplained and unobservable sentiments component is largely motivated by the approach used to measure the Gilchrist and Zakrajšek (2012) Excess Bond Premium. However, as I will show, my measurement strategy can also be seen as a loan rate decomposition into supply and demand factors similar in spirit to Greenstone et al. (2020).

along both the intensive and extensive margins of lending. On the one hand, pessimistic shocks lead to an increase in the number of banks tightening loan covenants for both small and large firms —tightening the credit limits imposed on borrowers— thus tightening the extensive margin of lending. On the other hand, pessimistic shocks lead to an increase in the number of banks tightening lending standards, raising the financial health requirements for new borrowers, thereby tightening the extensive margin of lending.

I then turn to evaluating the impact and relative importance of BRS shocks on macroeconomic outcomes, focusing on activity, prices, and the policy rate. Through the lens of a structural Bayesian Vector Autoregression (BVAR) —identified with a novel combination of IV, sign, and exclusion restrictions— I compare the macroeconomic effects of five structural shocks of interest: bank risk sentiment shocks, bond market sentiment shocks, aggregate demand, aggregate supply, and monetary policy rate shocks. The comparison between bank and bond market sentiments is an especially key contribution of this work because the majority of the investor risk sentiment literature has focused on the macroeconomic impacts of bond market sentiments (see López-Salido et al. (2017), Leiva-Leon et al. (2022), and Boeck and Zörner (2023) for empirical examples, or Bordalo et al. (2018) and Maxted (2023) for theoretical examples), but, as I will show, this is not necessarily the most important source of sentiments driving macroeconomic outcomes.

Pessimistic BRS shocks lead to prolonged deterioration in economic activity, prices, and interest rates. For example, a one standard deviation pessimistic shock leads to a 0.7 percentage point decline in GDP growth which does not recover for at least five years after impact. In comparison, a one standard deviation pessimistic bond market sentiment shock only decreases GDP growth by 0.5 percentage points and fully recovers within three years after impact. In fact, a pattern emerges when comparing the responses to bank sentiment and bond market sentiment shocks: bank sentiment shocks lead to comparably sized, if not larger, and much more persistent declines in macroeconomic outcomes than analogous bond market sentiment shocks.

While BRS shocks lead to a large and sustained response in economic outcomes, they also explain a large proportion of the business cycle variation in these economic phenomena as well. In the short run —on impact of the shocks— BRS explains one third of variation in the policy rate (a plurality of the variation), one quarter of the variation in inflation (second in influence only to aggregate supply shocks), and one fourteenth of the variation GDP growth (substantially less than the real and monetary policy shocks, but five times more impactful than bond market sentiment shocks). In the long run —steady state changes in the endogenous variables— BRS continues to explain a plurality of variation in the policy rate (now down to 28.6 percent), one sixth of variation in inflation (less than real and monetary policy shocks but twice as much as bond market sentiment), and one fifth of GDP growth.

Having identified the macroeconomic effects and importance of BRS, I lastly turn to loan-level micro-data to more precisely detail the possible transmission mechanisms through which bank-level sentiment shocks may impact loans, thus the credit supply and in turn the real economy. That is, I turn an examination of the potential micro-to-macro transmission mechanisms of bank risk sentiment. 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 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.

Roadmap. The remainder of the paper is organized as follows: Section 2 discusses the related literature and enumerates this study's contributions in detail, Section 3 presents the analytical model, Section 4 introduces and describes the empirical measure of BRS, Section 5 analyzes the effects of BRS shocks on lending market outcomes, Section 6 analyzes the effect of BRS on macroeconomic dynamics, Section 7 explores BRS micro-to-macro transmission mechanisms, and Section 8 concludes.

2 Related literature

This paper 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.

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), Leiva-Leon et al. (2022), and Boeck and Zörner (2023), 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).[3] 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 observed across credit cycles.[4]

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, and an assessment of how bank sentiments impact macroeconomic outcomes. Moreover, this project is the first jointly compare the relative empirical importance of sentiment, real, and monetary policy shocks in explaining business cycle and steady state variation in macroeconomic activity, prices, and policy.

[3] 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.

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

A related literature also studies the impact of bank-level deviations from rationality, but with a more micro-oriented focus on bank-level financial outcomes. For example, similar works include Ma et al. (2021) and Falato and Xiao (2022). On the one hand, Ma et al. (2021) has 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 beyond simply the macro versus micro focus of the questions being posed. 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 U.S. banks. In comparison, my measure of risk sentiments is based on banks' revealed preferences via their loan rates and span the universe of U.S. 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.

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 (2023) 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 contributes to this 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, studies in this literature pinpoint the source of credit supply or demand shocks by either 1) using externally identified shock (for example, monetary policy shocks based on asset price surprises around policy announcements), or 2) rely on purely reduced form decomposition of changes in loan prices and quantities in the tradition of Greenstone et al. (2020). The former approach identifies the source of the shocks one is studying the credit and real response to, but it requires the researcher to have those externally identified shocks. The latter approach is more flexible and does not require an externally identified shock, but at the expense of understanding the source of the credit supply and demand fluctuations unless one is able to find a valid instrument, reimposing the externally identified shock requirement. This work contributes to the empirical macro-banking literature by proposing an alternative approach to decomposing loan prices and quantities into credit supply and demand factors, in the tradition of Greenstone et al. (2020), but with a theoretical model that allows for a structural interpretation of the fluctuations in credit supply and demand. The model based identification mitigates the need for externally identified shocks by providing a framework for decomposing loan outcomes into supply, demand, and sentiment shocks based on easily observable balance sheet and income data. The resulting ability to relate fluctuations in supply or demand to specific factors in banks' loan pricing problem allows for a level of structural interpretation that is inaccessible in the purely reduced form supply and demand decomposition pursued in the current literature.

Financial accelerators and macroeconomic outcomes

This paper is additionally 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), 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, from a macro-perspective, risk sentiment acts directly as a shock to the 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, from loan-level evidence, 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.

Alternative approaches to bank risk sentiment

Works closely related to mine are those that study the economic effects of BRS, though they adopt different approaches to defining the term. Alternative studies on bank risk sentiment can generally be categorized into two groups: those that view sentiment as time-varying risk aversion and those that interpret 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.

3 Model of monopolistic competition in loan markets

I first present an analytical model of banks operating in a monopolistically competitive credit market to concretely define BRS and to motivate my econometric strategy for measuring it. 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)

[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.

or geographic regions (e.g. U.S. 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.

3.1 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.

3.2 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.

3.3 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:

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

[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).

[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).

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

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

3.4 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]

[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.

3.5 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 bank failures.[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 $C_{i,t} = 1 + c_{i,t}$. The assumption that the capital cost of forming loans is bank-specific is motivated by recent work on banking market power in deposit markets, including Drechsler et al. (2017), Corbae and D'Erasmo (2021), Bellifemine et al. (2022), and Jamilov and Monacelli (2023).

Specialists also pay a regulatory cost based on their funding gap, $L_{i,t} - N_{i,t}$.[11] 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

[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] 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 (2023) 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.

$\Phi'(X) \geq 0$ 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 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.

3.6 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.[12] 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).[13] 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

[12] 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.

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

innate ability to manage and perceive risk) and aggregate risk (reflecting uninsurable shocks to the entire economy).[14] 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.

3.7 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)

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

- 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.

3.8 Bank risk sentiment and aggregate outcomes

I next examine the impact of bank risk sentiment in aggregate outcomes, including aggregate loan rates and quantities.

3.8.1 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.

3.8.2 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:

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

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 result 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:

$$L_t^D = P - AR_t + \pi_t \implies R_t = \frac{P - L_t - \pi_t}{A} \tag{11}$$

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

4 Measuring and characterizing Bank Risk Sentiment

I next turn to measuring bank risk sentiment. The methodology, data, and results are discussed in order.

4.1 Measurement strategy

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

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

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

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. I 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:

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

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 I estimate the linear regression:

$$r_{i,t} = \gamma_i + b_1 log\left(\frac{\theta_{i,t}}{\theta_{i,t} - 1}\right) + b_3 c_t + b_4 2r(L_{i,t} - N_{i,t}) + b_4\rho_1\lambda_{i,t-1} + b_5\rho_2\lambda_{t-1} + \epsilon_{i,t} \tag{12}$$

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, $\psi_{i,t}$. However, motivated by Equation 11, I will additionally augment Equation 12 with proxies for credit demand.

The measurement strategy to decompose loan rates into a portion attributable to measurable and theoretically motivated factors, is in part motivated by the approach used to measure the Gilchrist and Zakrajšek (2012) Excess Bond Premium. Simply put, the EBP is the residual corporate bond interest rate unexplained by measurable default risk and observable loan characteristics. In comparison, the BRS is the residual loan rate unexplained by standard loan pricing factors. While the EBP has been interpreted by some authors as a proxy for bond market risk sentiment, for example López-Salido et al. (2017), the BRS is similarly interpretable as a proxy for bank risk sentiment.

4.2 Sentiment in a credit supply and demand decomposition

While my measurement strategy is primarily motivated by Gilchrist and Zakrajšek (2012), it is also related to the credit supply and demand decomposition framework developed in Greenstone et al. (2020) and used by works such as Gilchrist et al. (2018) and Aruoba et al. (2022).

Studies in the Greenstone et al. (2020) tradition isolate the impact of credit supply and demand factors on bank-level credit outcomes, formally decomposing credit growth as:

$$\Delta L_{j,k,t} = S_{j,t} + D_{k,t} + \epsilon_{j,k,t}$$

where $\Delta L_{j,k,t}$ is the change in loans at bank j in county k at time t, $S_{j,t}$ is then the credit supplied by bank j at time t, $D_{k,t}$ is the credit demanded by households and businesses in county k at time t. A reduced form identification of S and D is achieved with a multi-county lender and multi-bank county fixed effects strategy, analogous to the multi-lender borrower approach first proposed by Khwaja and Mian (2008).

However, and as noted in Gilchrist et al. (2018), a disadvantage of the Greenstone et al. (2020) purely reduced form identification strategy is the lack of understanding regarding what the bank specific supply shock actually captures. One strategy to remedy this shortcoming is taken by Gilchrist et al. (2018) and Aruoba et al. (2022), by projecting the reduced form bank-specific credit supply measure onto externally estimated shocks.

In contrast, my identification strategy for measuring BRS can be interpreted as an alternative approach to decomposing loan outcomes into credit supply and demand factors, similar in spirit to Greenstone et al. (2020), but in a way that allows for a structural interpretation of the factors driving fluctuations in bank-level loan outcomes.

I first posit that banks operate in monopolistically competitive loan markets, therefore, the factors that determine their loan rate decisions in turn determine the credit supply. It follows that, through the lens of the analytical model presented in Section 3, one may measure the variance in loan rates due to the variance in the bank-level credit supply by projecting the bank-level loan rates onto market power, regulatory costs, capital costs, bank-level risk, aggregate risk, and risk sentiment. More formally the linear relationship between loan rates and the credit supply is estimable as:

$$r_{j,t} = \beta \mathbf{S}_{j,t} + \nu_{j,t}$$

where $\mathbf{S}$ is the vector of observable proxies for the factors of bank-credit supply, and $\nu_{j,t}$, by construction, is the the variance in loan rates attributable to the variance in the slope of the credit demand curve (how demand interacts with a monopolist's decision making) and unobservable bank risk sentiment. I can then additionally account for $D_{j,t}$ by directly including measures of bank-level reported changes in business and household demand for loans. This leads to the expanded decomposition:

$$r_{j,t} = \beta \mathbf{S}_{j,t} + \alpha \mathbf{D}_{j,t} + \epsilon_{j,t}$$

where $\mathbf{D}$ is the vector of observable proxies for credit demand, leaving $\epsilon_{j,t}$ as the variance in loan rates attributable to bank-level risk sentiment shock. If one rewrites $S_{j,t} = \beta \mathbf{S}_{j,t}$ and $D_{j,t} = \alpha \mathbf{D}_{j,t}$, then the formal model is rewritten as a loan rate decomposition in the Greenstone et al. (2020) tradition:

$$r_{j,t} = S_{j,t} + D_{j,t} + \epsilon_{j,t}$$

That is, the bank risk sentiment measurement equation can rewritten as a decomposition of bank loan rates into observable factors of credit supply and demand, and unobservable sentiment shocks, where fluctuations in loan rates can be concretely mapped to specific interpretable sources.

4.3 Data

Equation 12 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 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 headquarter state loan Herfindahl-Hirschman Index (HHI).[15] Regulatory costs are proxied by the bank's leverage ratio, assets divided by equity.[16] Marginal cost of capital is proxied by the bank-level interest expenses divided by total assets, that is, the average interest paid on the bank's capital assets. Realizations of bank-level risk are measured by the bank's charge-off ratio, total

[15] 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.

[16] 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.

Table 1: Summary statistics of BRS measurement equation data

	Mean	SD	p(5)	p(25)	p(50)	p(75)	p(95)
Bank characteristics							
Δ Net interest margin	-0.057	0.201	-0.393	-0.154	-0.044	0.046	0.242
Capital funds cost	0.539	0.324	0.067	0.227	0.562	0.805	1.030
Leverage ratio	10.346	2.864	5.896	8.452	10.233	12.038	14.962
Δ Charge-off / loan ratio	0.000	0.005	-0.006	-0.001	0.000	0.001	0.006
Macroeconomic environment							
Sate-level loan HHI	0.004	0.010	0.000	0.000	0.001	0.003	0.015
Demand for business loans	0.673	26.318	-51.200	-18.500	4.800	19.200	35.400
Demand for household loans	-1.296	25.784	-44.800	-20.200	-1.500	18.100	35.800

Notes: This table reports the summary statistics for data used in estimating the bank-level BRS measure. Bank characteristics are from U.S. 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 887.8 thousand observations, 14442 unique banks represented in the sample and dates ranging from 1992:Q1 through 2020:Q4.

charge-offs divided by total loans.[17] Realizations of aggregate risk are the quarterly loan weighted average of bank-level loan charge-offs. Bank-level data are collected from quarterly U.S. 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.[18]

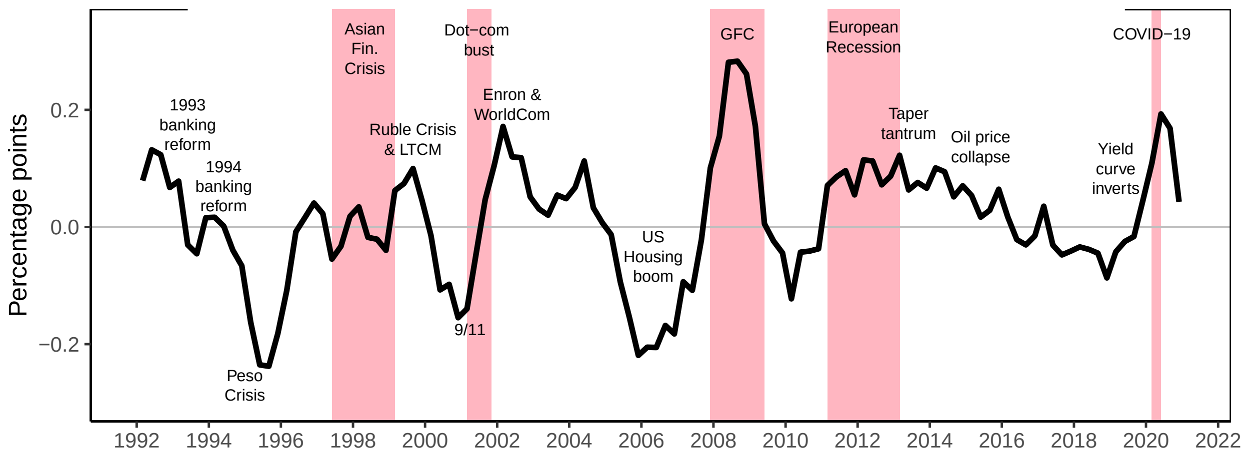
I additionally include a measure of credit demand to control for general equilibrium forces that may be influencing a bank's loan rate. Credit demand is proxied by two coincidence indicators of banks reporting an increase in credit demand for either business or household loans, as reported by the Federal Reserve System's Senior Loan Officer's Survey (SLOOS).

Table 8 summarizes the sample used to estimate the BRS panel regression. The sample includes 887.8 thousand bank-quarter observations, running from 1992 through 2020. The average bank-level net interest margin follows a downward trend during the sample period (largely mirroring the tending decline in the federal funds rate), so I use the change in bank-level net interest margins in my econometric model to ensure a the dependent variable follows a stationary process. The average change in the net interest margin is slightly negative, but close to zero, at approximately negative 5.7 basis points. However the distribution of changes indicates a large dispersion in potential outcomes across banks, with a fifth percentile near negative 40 percent and a 95th percentile near 24 percent. Bank-level characteristics also

[17]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.

[18]Standard micro-data cleaning procedures are applied. 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.

Figure 1: Bank risk sentiment

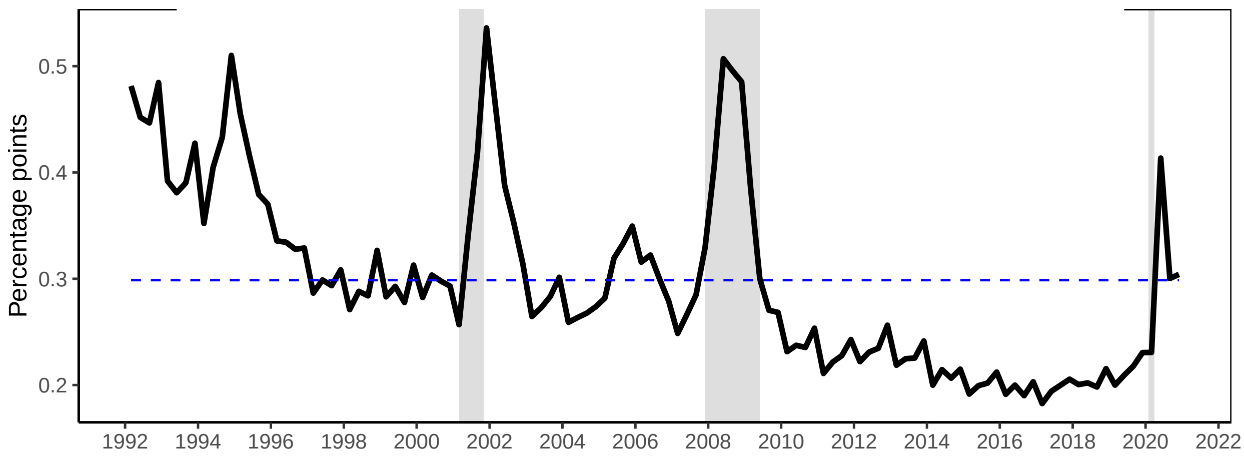


Notes: Solid black line depicts the quarterly loan-weighted average of bank-level risk sentiments. Sentiments increase as banks forecast an increase in future loan default rates, that is, a deterioration in economic conditions. Red shaded regions mark periods of financial stress: the Asian Financial Crisis extended from 1997 through 1998, the Dot-com bust was from 2001:Q1 through 2001:Q4, 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.

display large variation across the sample; state-level loan HHI are highly skewed, with a mean of 0.004, median of 0.0001 and 95th percentile near 0.0015. That is, the level of competition in the bank lending markets varies widely by state according to my proxy for banks' market power. Bank leverage ratios are likewise skewed, with a mean of approximately 10, but 5th percentile near 6 and 95th percentile of approximately 15. In contrast, bank-specific capital costs are not markedly skewed, with the mean and median of the distribution being approximately equal. Aggregate series are more symmetric across the sample. The change in loan demand for both business and household loans are approximately zero on average and have an approximately symmetric distribution within the sample. The construction details and time series of national averages for each variable in the BRS measurement equation are presented in Appendix H.

Equation 12 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.

Figure 2: Dispersion in bank risk sentiment



Notes: The solid black line depicts the dispersion in bank-level risk sentiment. Dispersion is the difference between the 90th and 10th percentiles of bank-level sentiment in a given quarter. The blue dashed line marks the historical mean level of dispersion. Data are quarterly from 1992 to 2021.

4.4 Characterizing bank risk sentiment

I next turn to presenting the aggregate measure of BRS, examining the underlying bank-level risk sentiment processes, and discussing the validity of interpreting bank risk sentiment as an exogenous shock.

Aggregate bank risk sentiment

Aggregate bank risk sentiment is characterized by sharp increases in times of financial stress and uncertainty in the U.S.. Figure 1 shows that, for example, BRS spikes during U.S. Dot-com bubble burst and sudden collapse of Enron and WorldCom in the early 2000s, the Global Financial Crisis, and COVID-19 pandemic. Moreover, bouts of optimism are often ended during times of elevated uncertainty, such as the September 11 terrorist attacks and beginning the Fed's quantitative tightening in 2018 (and subsequent yield curve inversion in 2019). Conversely, marked periods of bank sentiment optimism include the early 1990's during a period of U.S. banking reform and recovery after the S&L crisis in the late 1980's, the Dot-com bubble of the late 1990s and early 200s, and the housing boom in the mid-2000's which would later fuel the GFC.

BRS also appears to be sensitive to news of foreign crises and uncertainty. For example, Figure 1 shows pessimistic sentiment spiking during the Mexican Tequila crisis, Russian Financial crisis, and Europe's "double-dip" recession. The U.S. commercial banking sector's apparent sensitivity to foreign uncertainty is notable, as the U.S. 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 U.S. bank sentiment to negative shocks overseas suggests that even if there are not "real" channels through which foreign shocks hit the U.S., it does not matter because U.S. banks obverse those shocks, internalize the risk, and as I will show later on, decrease credit supplied to the U.S. 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 U.S., 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).

While there are common movements in sentiments across banks, there is also a wide range of sentiments across banks in any given quarter. Figure 2 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 approximately 0.3 percentage points on average. Dispersion becomes especially pronounced during U.S. recessions, that is, there is a cyclicality to the heterogeneity in bank-level sentiments. Although dispersion in sentiments began wider in 1992 and has been trending towards greater coordination in sentiments.

Bank-level sentiment processes

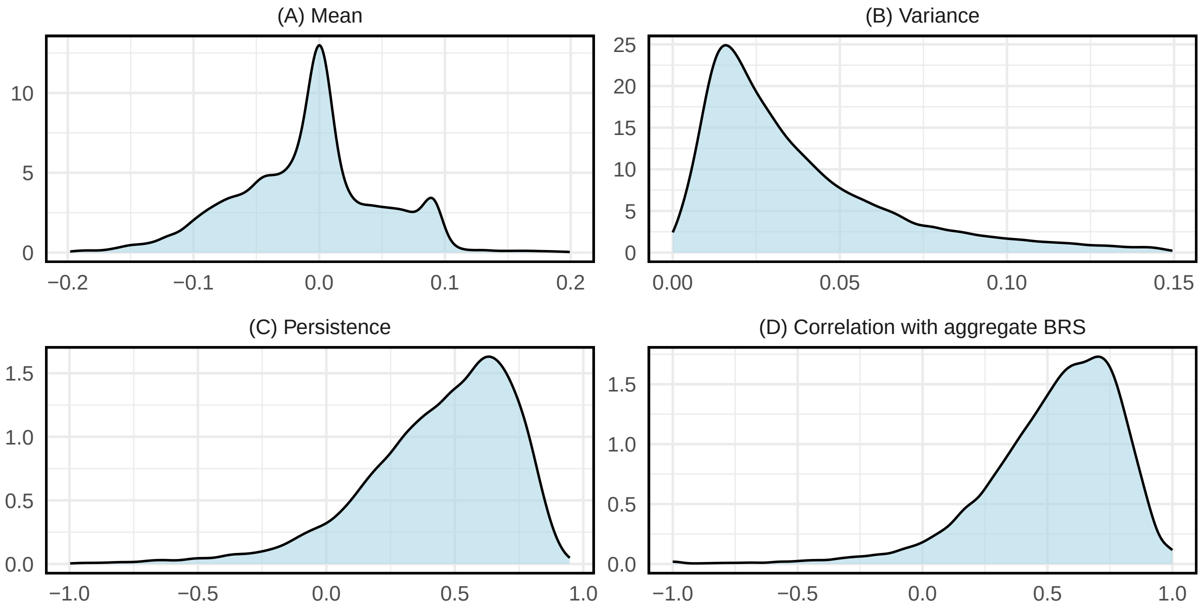
Having identified both strong co-movements and a wide dispersion in bank sentiment, I next turn to examining the bank-level sentiment processes in detail. I find there is a large degree of heterogeneity. Figure 3 shows the distributions over the first two moments of bank-level risk sentiment processes, 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 0.433 —suggesting a relatively transient sentiment process, with a half-life of only two periods.[19] However, by inspection, it is clear that the modal AR(1) coefficient is approximately 0.6. The distribution is heavily skewed

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

Figure 3: Bank-level 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 14442 banks, quarterly from 1992 through 2021; the average number of observations per bank is 61 quarters.

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 average, and the modal correlation at approximately 0.7.

In summary, most banks experience weakly 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.

Animal spirits. In the context of the analytical model presented in Section 3, bank risk sentiment is an irrational deviation from a bank's forecast of future defaults in its loan portfolio, or in the language of Angeletos and La'o (2013), an animal spirits shock. I empirically confirm that BRS behaves like animal spirits shocks by showing that 1) bank-level sentiments are systematically uninformative for forecasting loan defaults and 2) that BRS is statistically independent of generic macroeconomic shocks, such as aggregate demand, supply, and monetary policy shocks. However, I leave a full description of these exercises to Appendix D.

5 Sentiment shocks and loan market outcomes

Having measured and characterized BRS, I next turn to asking the question: do bank sentiment shocks actually affect loan market outcomes, and, if so, do these effects spill over to the real economy? I start answering this question by studying the effects of aggregate bank sentiment shocks across a variety of lending market characteristics and outcomes in a flexible and theoretically agnostic Jordà (2005) style local projection framework.

The econometric model is formally written as:

$$\Delta^h(Y_{t-1}) = \alpha^h + \theta^h BRS_t + \beta^h X_{t-1} + \epsilon_{t+h} \tag{13}$$

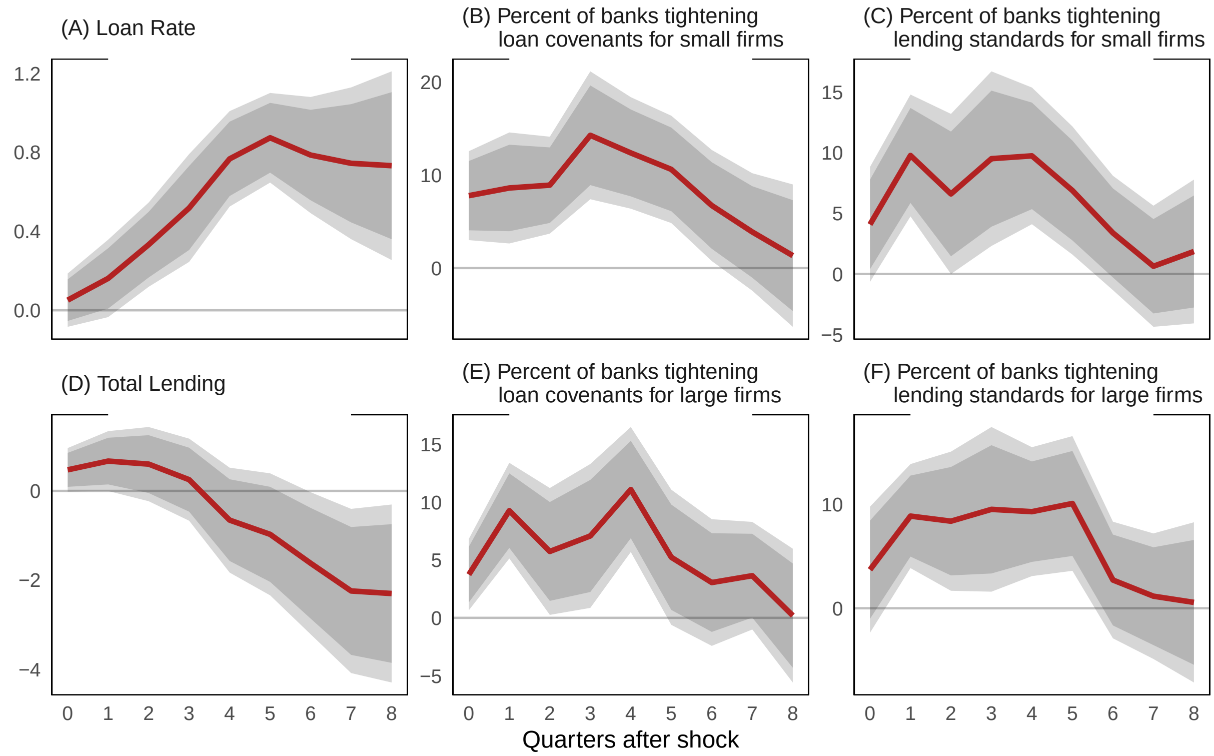
where $\Delta^h(Y_{t-1})$ is the change in the economic outcome of interest h quarters from $t-1$, BRS_t is the aggregate measure of bank sentiment, and X_t is the vector of four auto-regressive lags of the dependent variable Y, as well as lagged controls representing the state of the business cycle, including real GDP growth, core PCE inflation, and the policy rate, proxied by the one year Treasury rate (as in Gertler and Karadi 2015).[20]

I will study the impact of bank sentiment on six variables that together holistically characterize the U.S. lending market: the average loan rate, total value of loan and leases held by banks, the percent of banks tightening lending covenants for small firms, the percent of banks tightening lending covenants for medium and large firms, the percent of banks tightening lending standards for small firms, and the percent of banks tightening lending standards for large firms.[21] The first two measures describe the price and quantity of bank

[20] For concreteness, responses reported in percentage point changes imply $\Delta^h(Y_{t-1}) = Y_{t+h} - Y_{t-1}$, and for percent changes, $\Delta^h(Y_{t-1}) = 100 \cdot (Y_{t+h} - Y_{t-1})/Y_{t-1}$.

[21] Total loan and leases are taken directly from the Federal Reserve Board's H.8. table on credit in the United States, while the loan rate is measured as the loan-portfolio weighted average of implied loan rates (loan income divided by loan portfolio

Figure 4: Loan market response to bank sentiment shocks



Notes: This plot depicts the response of the U.S. bank lending market to an aggregate, pessimistic, one standard deviation bank sentiment shock. All responses are measured as percentage point changes from their pre-shock levels, except for panel (D), which is measured as a percent change. The dark gray band marks the 90-percent confidence interval and the light band marks the 95-percent confidence interval. Data is quarterly from 1992 through 2019.

loans and require little explanation, however, the latter four are less frequently discussed so I will define them here. From Broadbent et al. (2024): *lending standards* are the processes that banks follow for approving or denying loan applications, and tightening (easing) lending standards indicate an increase (decrease) in the financial health requirements faced by borrowers seeking new loans. Conversely, *loan covenants* are the specific conditions included in loan contracts, such as collateral requirements and credit limits, and tightening (easing) loan covenants indicate, among other things, more (less) restrictive borrowing constraints faced by borrowers. In that way, lending standards tend to capture variations in the extensive margin of lending, while terms are more closely related to the intensive margin.

Identification. By construction (and empirically validated in Appendix D) bank risk sentiment acts as a bank-level animal spirits shocks, estimating the causal impact of common

size) from U.S. Call Reports. The percent of banks tightening standards and covenants are collected from the SLOOS. Data runs from 1992 through 2019.

movements in bank sentiment is straightforward. I feed the vector of loan-weighted average bank risk sentiment directly into the local projection as a series of externally identified shocks, following in the tradition of works that estimate the impact of externally identified monetary policy, fiscal policy, or commodity price shocks via local projections. The resulting statistic of interest is θ^h, the direct estimate of the pseudo-elasticity of the dependent variable to a change in bank risk sentiment.

Additionally, given the lagged vector of business cycle controls —including four lags of prices, activity, and interest rates— the local projection (asymptotically) reproduces the same IRFs as the analogous VAR with structural shocks identified via short-run impact restrictions (see Plagborg-Møller and Wolf 2021). However, in this small sample setting, Li et al. (2024) point out that the local projection framework is more robust to miss-specification than a VAR, while Olea et al. (2024) prove that local projections is as accurate in its confidence intervals as a locally miss-specified VAR.

5.1 Impacts on lending outcomes

A one standard deviation increase in bank risk sentiment —a pessimistic shock— leads to a broad deterioration in bank lending.

Loan rates increase and total lending decreases. Figure 4 panel (A) shows that the sentiment shock does not initially impact loan rates —reflecting that it takes time to issue new loans in a quantity that changes the average rate on a bank's balance sheet— but increases rates by 50 basis points within three quarters and 80 basis points within 5 quarters after the shock. The increased loan rates only very slowly recover as loans originated after the shock remain on banks' balance sheets for several years. Similarly, Figure 4 panel (D) shows the total quantity of loans and leases remains unchanged by the sentiment shock for the first year after impact, but then as loan rates rise and reach their peak five quarters after impact, total lending begins to fall, and recedes by as much as 2.5 percent two years after impact. There is no sign of recovery in total lending within the two years after the shock.

Loan covenants tighten for both large and small firms. Figure 4 panel (B) and (E) show that banks tighten loan covenants when they become pessimistic. As a result, banks may set more stringent restrictions on their borrowers' leverage, for example by lowering the allowable debt to earning ratios borrowers may maintain, or require greater collateral backing for new loans. Moreover, the wave of tightening does not stop after the shock, rather it builds and the number of banks tightening covenants increase through one year after impact. It is also notable that covenants do not begin to ease (on net) after the tightening. That is, a pessimistic sentiment shock tightens loan covenants, putting stricter borrowing constraints on businesses, but then banks do not ease covenants, thus the borrowing constraints, within two years after the pessimistic shock passes.

Banks tighten lending standards. Figure 4 panel (C) and (F) show that the number of banks reporting that they tightened lending standards to small and large firms, respectively, increases on impact. That is, banks become more pessimistic and then increase the financial health required of borrowers to obtain loans. Similar to loan covenants, the wave of tightening lending standards does not stop after the period of the pessimistic shock, but rather continues through at least a year after impact. Moreover, the lending standards tightening is persistent, leaving it more difficult for new and existing borrowers alike to obtain loans for two years after the pessimistic shock.

Robustness. The point estimates for the lending standard shocks are robust to excluding the business cycle controls, but their inclusion gives the model an analogous interpretation to standard three-variable VARs as well increases the precision of the confidence intervals. The impulses are also qualitatively robust to changing the number of lags included in the set of controls.

5.2 Discussion: the transmission channels of bank sentiment shocks

This exercise in studying the lending market impacts of bank sentiment shocks highlights three, albeit closely related, potential transmission channels through which sentiment shocks may impact the real economy.

First, the increase in price and decrease in quantity follow the patterns of a standard negative supply shock. Thus bank risk sentiment shocks may be characterized as behaving like credit supply shocks, and in turn inherit the effects and consequences of such shocks enumerated in a long history of both theoretical (e.g. Kiyotaki and Moore 1997, Gertler and Kiyotaki 2010, Christiano et al. 2014, Gertler and Kiyotaki 2015) and empirical study (e.g. Bernanke et al. 1994, Amiti and Weinstein 2018, Greenstone et al. (2020)).

Second, there is additionally a long literature examining how fluctuations in lending standard shocks impact the the real economy, similar to to more generic credit supply shocks by specifically impacting the extensive margin of lending activity (see for example Lown and Morgan, 2006, Bassett et al., 2014, and Broadbent et al. (2024)). However, there is less written on what drives changes in standards. Figure 4 shows that bank sentiment shocks may be one such driver of lending standards, and by extension, real activity and prices.

Third, as a bank sentiment shocks tighten loan covenants, they are likely tightening borrowing constraints, and impacting the credit supply through the intensive margin of lending. Works such as Lian and Ma (2021), Drechsel (2023), and Caglio et al. (2022), highlight that earning based borrowing constraints are common covenant terms and are the most prevalent type of borrowing limit in the economy. Therefore, as bank risk sentiment shocks impact loan covenants, they in turn impact earning based borrowing constraints and effectively tighten or ease borrowing limits in the economy.[22] At the macro-level, shocks directly impacting financial constraint parameters follow in the tradition of works like Jermann and Quadrini (2012), which links this type of credit supply tightening with severe economic downturns.

6 Sentiment shocks and macroeconomic outcomes

I next evaluate the effects of bank sentiment shocks on macroeconomic dynamics —fluctuations in prices, activity, and monetary policy— as well as compare their importance in explaining business cycle fluctuations to sentiment shocks in other credit markets, namely the corporate bond market, as well as real demand, supply, and monetary policy shocks.

6.1 Macro-econometric model and identification strategy

I turn to a structural Bayesian VAR to better understand the macroeconomic effect of bank sentiment shocks, and their importance relative to other structural shocks of interest. I begin with the canonical three-variable representation of the macro economy —summarizing activity as real GDP growth, prices as core PCE inflation, and monetary policy as the one year Treasury rate— and build on this framework by additionally considering credit market conditions via the the Gilchrist and Zakrajšek (2012) Excess Bond Premium (EBP) as in Gertler and Karadi (2015), and total bank lending. I then postulate that the economy can be well summarized by the joint evolution of these five variables following a linear law of motion:

$$Y_t = \nu + \mathbf{A}Y_{t-1} + \mathbf{B}\epsilon_t, \quad \epsilon_t \sim \mathcal{N}(\mathbf{0}, I_K) \tag{14}$$

$$Y_t = \begin{bmatrix} y_t \\ y_{t-1} \\ \vdots \\ y_{(t-P+1)} \end{bmatrix} \quad \nu = \begin{bmatrix} \mu \\ 0 \\ \vdots \\ 0 \end{bmatrix} \quad \mathbf{A} = \begin{bmatrix} A_1 & A_2 & ... & A_{P-1} & A_P \\ I_K & 0 & ... & 0 & 0 \\ 0 & I_K & ... & 0 & 0 \\ \vdots & & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & I_K & 0 \end{bmatrix} \quad \mathbf{B} = \begin{bmatrix} B \\ 0 \\ \vdots \\ 0 \end{bmatrix}$$

[22]One may think of earning based borrowing constraints as taking the place of collateral based borrowing constraints in canonical financial accelerator models, such as Kiyotaki and Moore (1997).

where y_t is the vector of $K = 5$ endogenous states observed at time t, ϵ is the vector of structural shocks, and $P = 4$ is the lag order of the auto-regressive system, while the mean vector, ν, coefficient matrix $\mathbf{A}$, and structural shock impact matrix, $\mathbf{B}$, are all written in standard companion form. Structural shocks are assumed to be *i.i.d.* with mean zero, variance one.

Identifying structural shocks. I use a combination of IV, sign restrictions, and exclusion restrictions to jointly identify five structural shocks —bank sentiment, bond market sentiment, aggregate demand, aggregate supply, and monetary policy— thereby fully identifying the structural impact matrix, B.

Bank risk sentiments shocks enter the economy as an instrumental variable impacting total bank lending. I take this approach for two reasons. The first reason is theoretically motivated: by introducing bank sentiment shocks via their impact on bank lending, I can be certain that the impact of the shock is due to one of the previously identified bank credit transmission channels discussed in Sections 5 (and later at the micro-level in Section 7). The second reason is econometrically motivated: introducing bank sentiment shocks via an IV identification strategy flexibly allows the shock to have (or not have) an a contemporaneous impact on endogenous variables while acknowledging its exogeneity.[23]

Corporate bond market sentiment shocks are identified via exclusion restrictions. Motivated by López-Salido et al. (2017) and Boeck and Zörner (2023), I will define a corporate bond market sentiment shock as a shock that increases the Excess Bond Premium with no coinciding change in real activity or alternative financial markets. That is, I define a bond market sentiment shock as a change in bond prices divorced from changes in the real economy and evaluations of risk or risk appetite in other financial markets. Based on this definition, the bond market sentiment shock is identified in the structural impact matrix by a column vector of zeros but for an impact on the EBP (similar to ordering EBP last in a Cholesky decomposition of the reduced form error variance-covariance matrix). However, I will note that some authors interpret the EBP as a broader measure of financial market frictions (for example Gertler and Karadi (2015) describe the EBP this way). Therefore an important caveat is that this identification strategy may capture the impact of bond market sentiment shocks on the real economy, as well as changes in more general aspects of investors in the corporate bond market, such as risk bearing capacity.

[23] A plausible, and perhaps more tractable, alternative identification strategy is to put bank sentiment shocks directly in the BVAR and orther them either first or last in a Cholesky decomposition of the endogenous variables. However, the former assumes that bank sentiment can either contemporaneously impact prices, activity, and interest rates (which does not appear true based on the theoretically agnostic local projections presented in Figure 8), while the latter assumes bank sentiment can be directly impacted by other variables (which does not appear true based on exogenous shock tests in Section 4.4).

Table 2: Sign restrictions identifying structural shocks

	GDP	Inflation	Policy Rate	Bond Rate	Bank Lending
Demand shock	+	+	+	-	+
Supply shock	+	-	+	-	+
Rate shock	-	-	+	+	-

I lastly turn to theoretically-motivated sign restrictions to identify the remaining structural shocks. The restrictions are as follows:

- Using GDP as quantities and inflation as prices, demand and supply shocks will be standard. A positive supply shock increases quantities and decreases prices while a positive demand shock will increase both quantity and prices. It then follows from any standard Taylor rule that monetary policy will ease, thus the policy rate will fall. I will lastly postulate that expansionary shocks induce a corresponding credit supply expansion and increased demand for working capital, leading to an increase in lending. See Uhlig (2017) for a discussion of the supply and demand shock, as well as a discussion on sign restrictions more broadly.

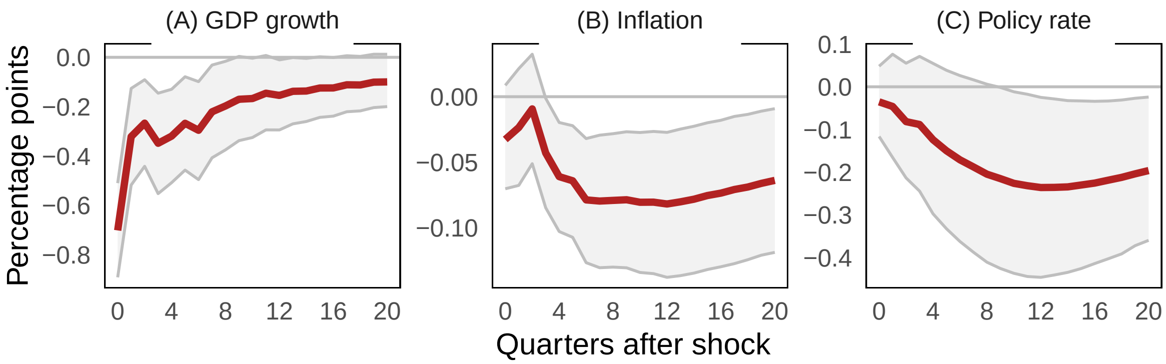
- The tightening monetary policy shock will be identified as an increase in the policy rate, and a decrease in activity, inflation and the level of credit in the economy, following work such as Uhlig (2005).

I am not the first to use an external instruments approach to identify credit sentiment shocks. López-Salido et al. (2017) and Boeck and Zörner (2023) both use a two-stage approach when identifying the impact of credit market sentiment shocks on real outcomes. While Lagerborg et al. (2023) use public shootings in the U.S. as an instrument for sentiment shocks and finds significant economic effects. However, by including the aggregate demand, supply, and monetary policy shocks, I am the first to estimate a fully identify an dynamic empirical model with real, financial, and sentiment shocks. Thus, by including the real shocks, I am able to directly compare the business cycle variance explained by sentiment, financial, and real shocks.

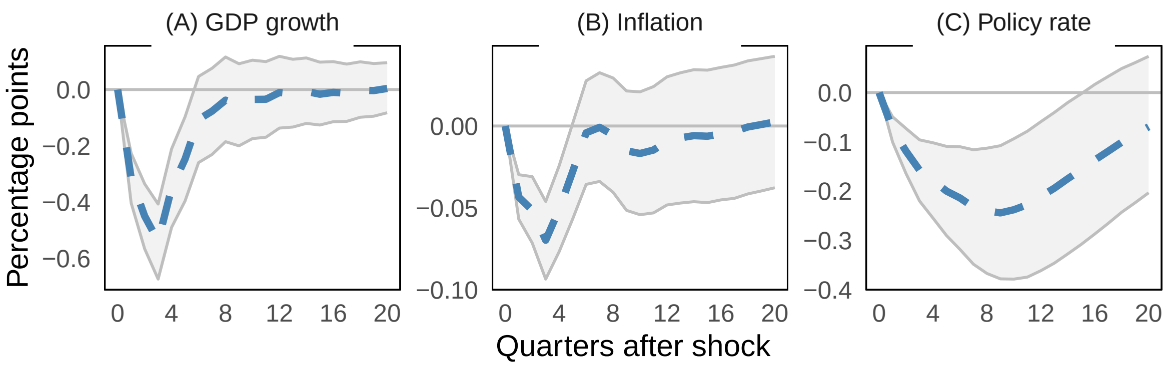
Estimation. Model parameters are estimated with the standard Minnesota priors via a Gibbs sampler with 100 thousand draws and a 50 thousand burn in. Draws are combed so that every fifth draw is accepted to reduce auto-correlation in the resulting posterior chain. A structural impact matrix is constructed for each draw with an instrumental variable, sign restrictions, and exclusion restrictions, via a combination of the algorithms put forward by Cesa-Bianchi and Sokol (2022) which combines IV and sign restrictions and detailed by Kilian and Lütkepohl (2017) which combines sign restrictions and exclusion restrictions via sub-rotations of the Cholesky decomposition of the reduced form errors. Details on identifying and estimating the structural impact matrix are discussed in Appendix E.

Figure 5: Macroeconomic response to financial sentiment shocks

(A) Bank sentiment shocks



(B) Bond sentiment shocks



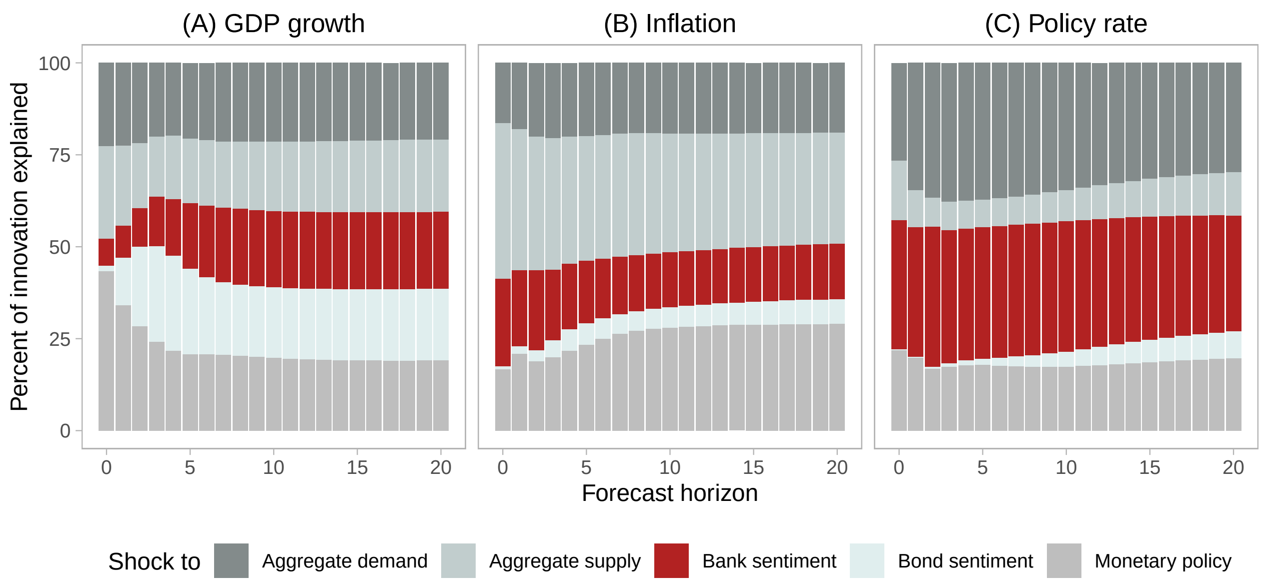
Notes: This plot shows the impulse response functions of macroeconomic activity, prices, and policy rates, to financial sentiment shocks. The solid red lines represents the mean response to a one standard deviation pessimistic BRS shock. The dashed blue line represents the mean response to a one standard deviation pessimistic bond market sentiment shock. Gray bands mark the 68 percent credible sets. Impulse response functions are estimated with a structural BVAR model with four lags and standard Minnesota priors; the posterior chain is drawn from a Gibbs sampler with 100 thousand draws and a 50 thousand burn-in period. Data is quarterly from 1992 through 2019.

Data. The macroeconomic time series used in the parsimonious BVAR are standard and discussed in more detail in Appendix H.

6.2 Examining the effects and relative importance of bank sentiment shocks

Pessimistic bank sentiment shocks induce a significant and long-lived deterioration in economic activity, slowing inflation, and sharp monetary policy easing. Figure 5 shows the macroeconomic response to a one standard deviation, pessimistic, bank sentiment shock. GDP falls by approximately 0.7 percent on impact, and only becomes statistically indistinguishable from zero two years after impact. As the economy slows, so does inflation, which

Figure 6: Variance decomposition of macroeconomic activity and prices



Notes: This plot shows the variance decomposition of activity and prices into structural shocks. Each shock's marginal contribution is calculated as the mean draw from the Gibbs sampling chain, then rows are normalized to sum to one hundred percent. Forecast errors are estimated with a structural BVAR model with four lags and standard Minnesota priors; the posterior chain is drawn from a Gibbs sampler with 100 thousand draws and a 50 thousand burn-in period. Data is quarterly from 1992 through 2019.

falls by an economically small but statistically significant 7 basis points within two years of impact. The declines in GDP and inflation are met with a sharp cut in the policy rate, which falls by approximately 0.25 percent within three years of the shock (on par with the Federal Reserve's standard 25 basis point rate cut), and remains low through at least five years after impact. It also follows from the linearity of the IRFs, that the policy rate would increase in response to an optimistic bank sentiment shock in a Leaning Against the Wind policy behavior, as discussed in works such as Svensson (2017) or Boyarchenko et al. (2024).

Given bank sentiment shock's sizable impact on GDP growth and the policy rate, it is not surprising that it also accounts for large portions of variation in these phenomena over the business cycle. Figure 6 shows the percent of variance in GDP growth, inflation, and the policy rate explained by the five structural shocks that drive this empirical economy (Table 3 the same values at selected horizons and in steady state).

Across all horizons, bank sentiment explains a plurality of variation in the policy rate. Bank sentiment explains as much as 33 percent of the variation of the policy rate on impact, and continues to explain more than 30 percent of the variation over the subsequent 5 years, before

Table 3: Variance decomposition of macroeconomic activity and prices by structural shocks

		Percent of innovations explained by:				
Endogenous Variable	Horizon (Quarters)	Bank Sentiment	Bond Sentiment	Aggregate Demand	Aggregate Supply	Monetary Policy
GDP growth	0	7.37	1.36	21.5	29.4	40.3
	4	15.6	25.8	18.8	20.1	19.6
	8	20.6	19.4	20.6	20.6	18.8
	12	20.8	19.1	20.7	21.1	18.2
	16	20.9	19.3	20.6	21.3	17.9
	20	20.8	19.4	20.3	21.4	18.1
	∞	20.5	18.7	20.2	21.6	18.9
Inflation	0	24.7	0.824	18.6	38.3	17.6
	4	17.8	5.88	21.1	32.7	22.6
	8	15.3	5.39	19.8	31.7	27.8
	12	15.1	5.96	19.6	30.4	29.0
	16	15.2	6.48	19.4	29.6	29.3
	20	15.4	6.86	19.2	29.1	29.4
	∞	16.6	7.31	19.4	27.9	28.8
Policy rate	0	33.1	0.132	26.8	15.7	24.3
	4	33.9	1.42	37.6	7.98	19.1
	8	34.1	3.18	36.0	8.48	18.2
	12	33.2	5.12	33.5	9.73	18.4
	16	31.8	6.58	31.2	11.2	19.3
	20	30.5	7.39	29.7	12.3	20.1
	∞	28.6	7.89	28.0	14.4	21.1
Corp. Bond Premium	0	0	100	0	0	0
	4	13.4	56.5	9.81	10.7	9.56
	8	15.6	48.9	12.2	12.9	10.4
	12	16.4	46.5	13.9	13.3	9.96
	16	17.2	45.0	14.8	13.2	9.78
	20	17.3	44.7	14.8	13.3	9.94
	∞	16.3	44.4	14.6	13.9	10.9
Bank Lending	0	48.6	0.131	41.1	5.10	5.13
	4	22.1	5.17	17.9	27.0	27.9
	8	18.8	19.4	17.0	22.0	22.7
	12	19.0	20.5	17.0	21.3	22.2
	16	18.8	20.6	17.6	21.3	21.6
	20	19.4	19.7	18.8	21.1	21.0
	∞	20.9	17.5	20.3	21.0	20.3

Notes: This plot shows the variance decomposition of activity and prices into structural shocks. Each shock's marginal contribution is calculated as the mean draw from the Gibbs sampling chain, then rows are normalized to sum to one hundred percent. Forecast errors are estimated with a structural BVAR model with four lags and standard Minnesota priors; the posterior chain is drawn from a Gibbs sampler with 100 thousand draws and a 50 thousand burn-in period. Data is quarterly from 1992 through 2019.

falling to 28.6 percent in steady state. In comparison, real and policy shocks account for less but still substantial amounts of variation in policy rates in the short run. Aggregate demand, supply, and monetary policy shocks account for 26.8, 15.7 and 24.3 percent of the variation in the policy rate on impact. Lastly, and most insignificantly, bond market sentiment shocks account for less than one percent of variation in policy rates on impact. However, the weak relationship between bond sentiment and the policy rate in the short run is by construction, given that bond sentiments are defined as shocks that only move the EBP. This limitation does not restrict the influence of bond sentiment shocks in steady state, but bond sentiment shocks remain the least influential of any shocks, accounting for less than eight percent of steady state variation in policy rates.

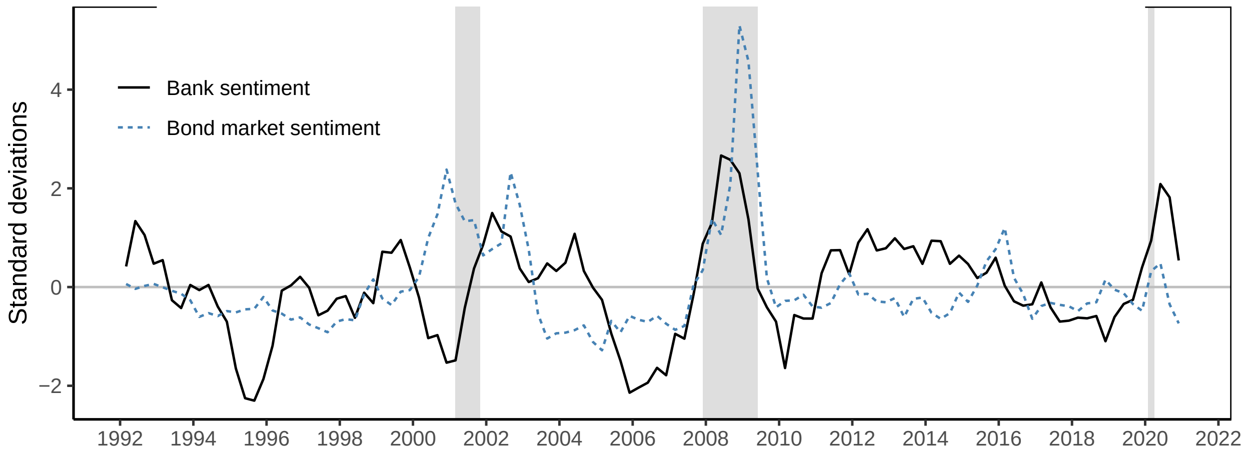
In comparison, variation in inflation is instead primarily driven by aggregate supply shocks on impact, then almost equally across aggregate supply and monetary policy shocks in steady state. Bank sentiment shocks explain a quarter of the variation in inflation on impact before falling to only 16.6 percent in steady state. However, again, analogous bond market sentiment shocks explain less than one percent of the variation in inflation on impact and then still less than half of the amount of variation explained by bank sentiment shocks in steady state.

Lastly, GDP is predominately driven by monetary policy and real shocks in the short run, with aggregate supply, demand, and policy shocks accounting for more than 90 percent of variation in output on impact. However, sentiments across both financial markets then quickly increase in importance, with bond market sentiment explaining the plurality of variation one year after the shocks, and bank sentiment increasing in importance to account for approximately 20 percent of variation in output in steady state.

Additional analysis. Further inspection of the BVAR also shows that bank sentiments most prominently influence interest rates during periods of crisis, and are the single largest contributor to the decline in GDP growth during the COVID-19 recession. However, I leave more detailed discussions of the historical decomposition of endogenous variables to Appendix F.

I additionally conduct a more nuanced analysis of the macroeconomic response to BRS shocks. Using a dynamic factor model 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, trade, prices, and financial assets. However, I document that the shock is not felt evenly across the economy: consumption falls more dramatically

Figure 7: Comparing sentiment across financial markets



Notes: This plot compares the evolution of sentiment in the bank lending and corporate bond markets. Bank sentiment is measured by the BRS and corporate bond sentiment by the excess bond premium of Gilchrist and Zakrajšek (2012). Both measures are expressed in standard deviations from their historical mean. Data is quarterly from 1992 through 2020. Gray shaded regions denote NBER dated recessions.

than production, and the yield curve steepens, disproportionately increasing the cost of long term credit compared to short term debt. This analysis is presented in Appendix G.

6.3 Comparison to bond market sentiment shocks

I next turn to more specifically comparing the effects of BRS shocks to sentiment shocks in other financial markets, namely the corporate bond market. 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.[24] 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.[25] As a result, a joint analysis of these market sentiments will represent the most comprehensive analysis of how investor risk

[24] See, for example López-Salido et al. (2017) and Boeck and Zörner (2023), 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 **??** for more examples.

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

sentiments effects U.S. macroeconomic outcomes in the extant literature.[26]

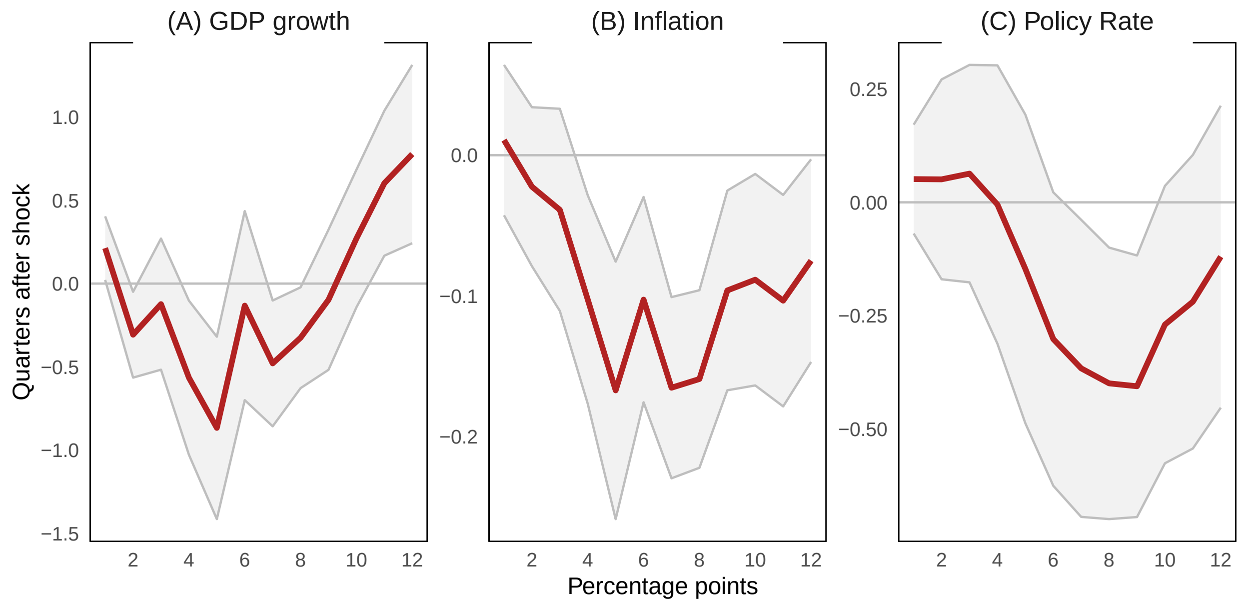
Before comparing the effects of bank and bond market sentiment shocks, I will first discuss the differences in the sentiments themselves. Figure 7 compares aggregate bank risk sentiment, which reflect bank lending sentiment, to the EBP as a proxy for corporate bond market sentiment. While both instruments 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 one quarter before the EBP, suggesting that banks were more quickly aware of the banking crisis before agents in other sectors of the economy. BRS was more optimistic during the Dot-com and housing bubbles, while the EBP was in fact pessimistic leading into the Dot-com bubble, suggesting that the BRS may be a better early warning signal for excessive optimism or even pricing bubbles in financial markets. BRS was also much more pessimistic during the depths of the COVID-19 recession while EBP remained relatively neutral.

Turning to comparing the effects of sentiment shocks, bank sentiment shocks induce longer lived recessions in economic activity and prices along with longer monetary policy easings than analogous bond market sentiment shocks. Figure 5 shows that a one standard deviation bond market sentiment shock actually induces a shallower fall in GDP than a bank sentiment shock, decreasing activity by approximately 0.5 percent compared to approximately 0.7 percent. Moreover, GDP growth recovers from a bond sentiment shock within 1.5 years after impact compared to more than two years for a bank sentiment shock. Likewise both inflation and the policy rate fall a comparable amount after either sentiment shock, but again, both recover faster after a bond market sentiment shock.

Also, and as previously highlighted in Table 3, bank sentiment shocks explain considerably more variation in both monetary policy and inflation than bond market sentiment shocks. Although bond market sentiment shocks explain more variation in GDP growth than bank sentiment shocks in the medium run, before both account for similar proportions of changes in activity in steady state.

[26] 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 U.S..

Figure 8: Macroeconomic response to a bank risk sentiment shock, local projections



Notes: This plot shows the impulse response functions of macroeconomic activity, prices, and policy rates, to financial sentiment shocks. The solid red lines represents the mean response to a one standard deviation pessimistic BRS shock. Gray bands mark the 90 percent confidence intervals. Standard errors are Newey-West adjusted. Impulse response functions are estimated with a local projection with 4 lags and five controls: GDP growth, core PCE inflation, one year Treasury rate as a proxy for the policy rate, aggregate bank risk sentiment, and the excess bond premium. Data is quarterly from 1992 through 2019.

6.4 Local projections as a robustness check

As a robustness check, I additionally consider the impacts of bank sentiment shocks through the lens of a local projection framework, in the same spirit as the empirical exercises presented in Section 5. To be more specific, I will continue with the local projection model specified by Equation 13, but now focus on an alternative set of outcomes of interest: activity, prices, and monetary policy. I will also augment the set of control variables to include the EBP as a proxy for bond market sentiment, as in López-Salido et al. (2017), and financial market conditions more broadly.

The macroeconomic response to bank sentiment shocks is qualitatively consistent across both local projection and BVAR exercises, but larger when estimated via local projections. Figure 8 shows that the bank sentiment shock leads to an approximately one percent decline in GDP growth within five quarters of impact, which only recovers two and a half years after impact. Inflation additionally falls, reaching the zenith of its deterioration five quarters after impact, falling by as much as 18 basis points. Lastly, the policy rate experiences a more delayed response to a bank sentiment shock, but ultimately declines by approximately half of a percent by two years after impact —signaling what would be two standard 25 basis point rate cuts by the central bank in response to the sentiment shock.

6.5 Discussion: comparing sentiment across agents

Much of the financial sentiments literature has focused on bond rate spreads as a proxy for investor sentiment, see for example López-Salido et al. (2017) and Boeck and Zörner (2023). However, I find distinct economic responses to sentiment shocks depending on in which financial market they originate. When sentiment shocks occur in the bank lending market, thus primarily reflect banks' sentiment, the response is longer lived than the response to an analogous shock representing the sentiment of corporate bond investors.

Moving beyond narrowly focusing on financial market sentiment, Lagerborg et al. (2023), measure sentiment shocks via consumer confidence —implicitly focusing on household sentiment. Bank sentiment shocks have a much larger impact on the economy. For example, these authors find a consumer confidence shock, instrumented by a mass shooting, results in a 5 basis point Federal Funds Rate decline and 10 basis point decline in industrial production, while I find a nearly 70 basis point decline in GDP and 25 basis point decline in the policy rate. While these are certainly not apples-to-apples comparisons, the results do hint at a much larger effect of bank sentiment shocks than household sentiment shocks, which may be further and more directly evaluated in future research.

7 Micro-to-macro transmission channels

I lastly turn to loan-level micro-data to more precisely detail the possible transmission mechanisms through which bank-level sentiment shocks may impact loans, thus the credit supply and in turn the real economy. That is, I next turn an examination of the potential micro-to-macro transmission mechanisms of bank risk sentiment.

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.

7.1 Micro-econometric model and identification

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:

$$y_{l,f,b,t} = \alpha + \gamma_{f,t} + \gamma_{f,b} + \delta BRS_{b,t} + \beta\Theta_t + \epsilon_{l,f,b,t} \tag{15}$$

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.

My elasticity of interest when evaluating Equation 15 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.[27]

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.[28] These three steps together isolate variation in outcomes attributable to lender specific factors (i.e. 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-

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

[28] 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.

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.

Data. The loans studied in this analysis are in fact individual facilities, also known as tranches, of syndicated loans from the LPC DealScan database.[29] 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.[30] 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 U.S. Call Report records used to created my measure of bank-level BRS.[31] 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). However, my estimation samples will be subsamples of this matched-data set, with observations only being included if all model variables being present. The data is more thoroughly discussed and summary statistics are presented in Appendix H.

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).

[29]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.

[30]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.

[31]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.

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

	Max debt to EBITDA (intensive margin)			Presence of covenants (extensive margin)		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank sentiment	-0.433^{**}	-0.558^{**}	-0.554^{**}	0.131	0.128^{*}	0.136^{**}
	(0.200)	(0.229)	(0.228)	(0.082)	(0.069)	(0.068)
Refinancing only		✓	✓		✓	✓
Borrower-Quarter FE	✓	✓	✓	✓	✓	✓
Lender-Borrower FE	✓	✓	✓	✓	✓	✓
Loan characteristics	✓	✓	✓	✓	✓	✓
Bank characteristics			✓			✓
Observations	2,426	2,169	2,169	5,812	3,924	3,924
Within-R^2	0.078	0.108	0.110	0.012	0.021	0.023
Sample composition						
Loans	785	672	672	2713	1702	1702
Dates	60	57	57	106	76	76
Banks	139	138	138	190	179	179
Borrowers	281	237	237	931	605	605
Bank-Borrower pairs	974	868	868	2201	1540	1540

Notes: This table reports a (within) fixed effects regression of loan outcomes onto the issuing bank's risk sentiment. Columns 1-3 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 4-6 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. A measure of the lenders net worth is also included as a bank characteristic in specifications (3) and (6). Observations are weighted by loan size. 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.

7.2 Loan-level impacts of bank-level sentiment shocks

A bank-level sentiment shock tightens both the intensive and extensive margin of loan covenants and borrowing constraints, while simultaneously increasing the price and decreasing of loans, although the latter effect is not precisely estimated.

On the one hand, Table 4 shows that bank sentiment shocks tighten both the intensive and extensive margin of loan covenants. First, loans are 12.8 percent more likely to be issued with covenants dictating the restrictions on future financing choices of the borrower. A 12.8 percent increase in the number of loans subjecting firms to borrowing constraints is both economically significant, as well as statistically significant at the 10 percent level. Moreover, the average maximum allowable debt to earnings before interest, taxes, debt, and amorti-

Table 5: Loan-level price and quantity response to a bank sentiment shock

	Loan rate			Loan amount		
	(1)	(2)	(3)	(4)	(5)	(6)
Bank sentiment	0.318*	0.124	0.071	0.043	−0.073	−0.056
	(0.173)	(0.155)	(0.149)	(0.284)	(0.270)	(0.279)
Refinancing only		✓	✓		✓	✓
Borrower-Quarter FE	✓	✓	✓	✓	✓	✓
Lender-Borrower FE	✓	✓	✓	✓	✓	✓
Loan characteristics	✓	✓	✓	✓	✓	✓
Bank characteristics			✓			✓
Observations	5,654	3,831	3,831	5,654	3,831	3,831
Within-R^2	0.117	0.215	0.235	0.013	0.051	0.053
Sample composition						
Loans	2618	1647	1647	2618	1647	1647
Dates	106	76	76	106	76	76
Banks	189	178	178	189	178	178
Borrowers	922	599	599	922	599	599
Bank-Borrower pairs	2179	1523	1523	2179	1523	1523

Notes: This table reports a (within) fixed effects regression of loan outcomes onto the issuing bank's risk sentiment. Columns 1-3 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 4-6 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. A measure of the lenders net worth is also included as a bank characteristic in specifications (3) and (6). Observations are weighted by loan size. 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.

zation (EBITDA) ratio declines by 0.558 ratio points. The average ratio is 3.403, meaning the shock produces a 16.4 percent decline from the average. As discussed in works such as Lian and Ma (2021), Drechsel (2023), and Caglio et al. (2022) these earning based borrowing constraints are the most prevalent borrowing limits in the economy, and effectively take the place of borrowing constraints in canonical financial accelerator models, such as Kiyotaki and Moore (1997). So as a bank sentiment shock makes these constraints both tighter and more common, these shocks can be seen as acting on both the intensive and extensive margin of firm-level borrowing constraints.

On the other hand, Table 5 shows that loan rates increase and loan quantities are renegotiated lower. A one percentage point increase in bank-level sentiment in turn increases loan rates by 12 basis points while decreasing loan amounts by 0.07 log points, among renegotiated loans (see columns 2 and 5 respectively). However, these effects are not precisely estimated. That is, a bank-level pessimistic sentiment shock acts similar to a negative credit supply shock —increasing prices and decreasing quantity— but with too much variation in its impact to precisely estimate the local average treatment effect.

Robustness. Tables 4 and 5 additionally show that results are robust to controlling for bank-level characteristics, despite the additional noise they introduce to the estimation of the treatment effects (see columns 3 and 6 of each table).

8 Conclusion

This paper introduces a novel measure of bank risk sentiment and evaluates its effect on lending market and macroeconomic dynamics. Using regulatory data covering the universe of U.S. 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 counter-cyclical with spikes during both domestic and foreign financial crises and optimism during asset bubbles, but features a large degree of heterogeneity at the bank-level. I then ask how BRS might impact the credit supply and real macroeconomic outcomes in turn. BRS acts as a standard credit supply shock, whereby a pessimistic bank sentiment shock leads to an increase in loan rates and decrease in loan quantities through impacting both the intensive and extensive margin of lending. Pessimistic BRS shocks, through the credit supply channel, also cause persistent declines in macroeconomic activity, prices, and the policy rate. Moreover, I find that BRS shocks are more important in explaining variation in the policy rate, in both the short run and steady state. Comparing BRS shocks to sentiment shocks in other credit markets, namely the corporate bond market, I find BRS is distinct from corporate bond market investors' risk sentiment, yields comparably sized impacts but more persistent effects on macroeconomic outcomes of interest, and is substantially more important in explaining inflation and the policy rate. I lastly turn to a loan-level analysis to explore the potential micro-to-macro transmission mechanisms of bank-level sentiment shocks, and show that an increase in BRS is associated with a decrease in credit supply and tightening loan covenants, two potential transmission channels to the macroeconomy.

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 (via covenant restrictions), how sentiments propagate among investors, the potential feedback loop between U.S. 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.

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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 3.

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 3: 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:

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

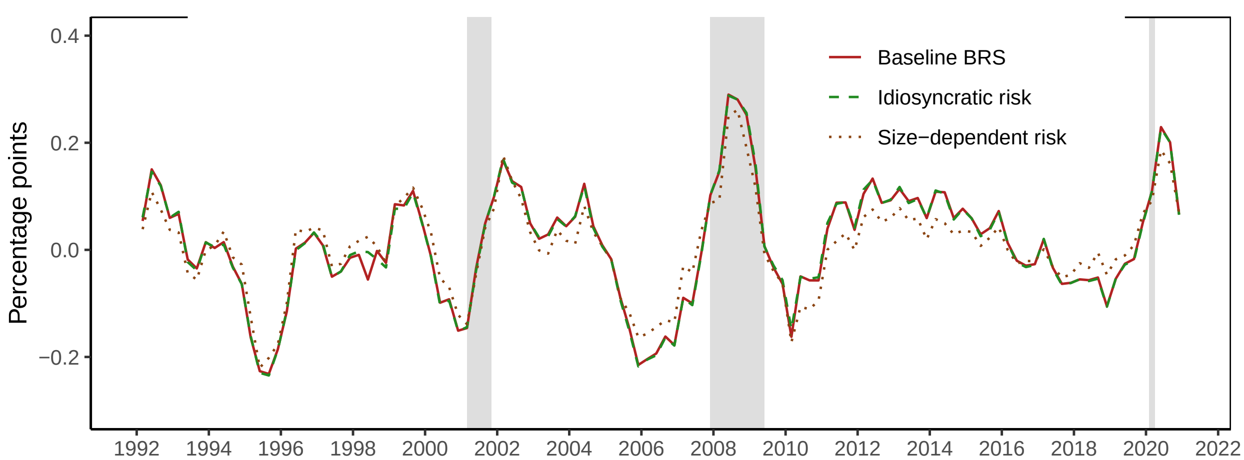
and the corresponding rational expectations forecast of risk is:

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

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 4, except now replacing $E_{RE}(\lambda_{i,t}|s_{t-1})$ with the rational expectations forecast implied by the alternative laws of motion. Figure 9 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 3).

Figure 9: Bank risk sentiment with alternative default law of motion assumptions



Notes: Solid red line depicts the baseline quarterly loan-weighted average of bank-level risk sentiments (LoM 2). The dashed green depicts BRS calculated assuming a loan default law of motion only based on bank specific risk (LoM 1). The gold dotted line depicts BRS calculated assuming a loan default law of motion with bank specific risk, aggregate risk, and bank-size aggregate-risk interaction (LoM 3). The correlation coefficients among the different BRS series are: Cor(LoM 1, LoM 2) = 0.999, Cor(LoM 3, LoM 2) = 0.951. Gray bars are NBER dated recessions. Data are quarterly from 1992 to 2021.

B Potential sources of BRS

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 3 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 3, but now let banks be owned and funded by a risk averse household and consider the existence of a risk free bond.[32] 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 variance of the risky asset, $\sigma_{R^p}^2$. The Household's expected return each period can then be written:

$$\begin{aligned} E_t(R_{t+1}) &= (1-\alpha(\gamma_t, \sigma_{R^p}^2))R_{t+1}^f + \alpha(\gamma_t, \sigma_{R^p}^2)E_t(R_{t+1}^p) \\ &= R_{t+1}^f + \alpha(\gamma_t, \sigma_{R^p}^2)\left[E_t(R_{t+1}^p) - R_{t+1}^f\right] \end{aligned}$$

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

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

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:

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

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

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

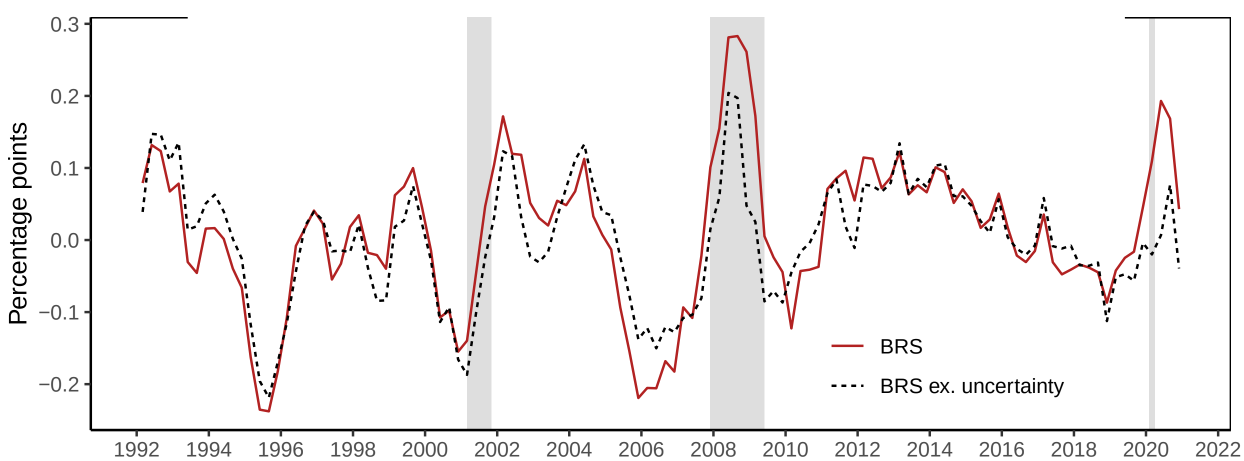
$$E(R^p_{i,t}) = (1 - E\lambda_{i,t+1})R_{i,t}$$

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.[33] That is, as the Household becomes more risk averse, its demanded compensation for holding risk increases.

Figure 10: Bank risk sentiment with and without uncertainty



Notes: Solid red line depicts the quarterly loan-weighted average of bank-level risk sentiments. The black dashed line is the quarterly loan-weighted average bank-level risk sentiments, controlling for aggregate uncertainty. Gray bars are NBER dated recessions. The correlation coefficient between the two series is 0.86. Data are quarterly from 1992 to 2021.

[33]If $\alpha = 0$ then the bank is not funded and will make no loans.

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.

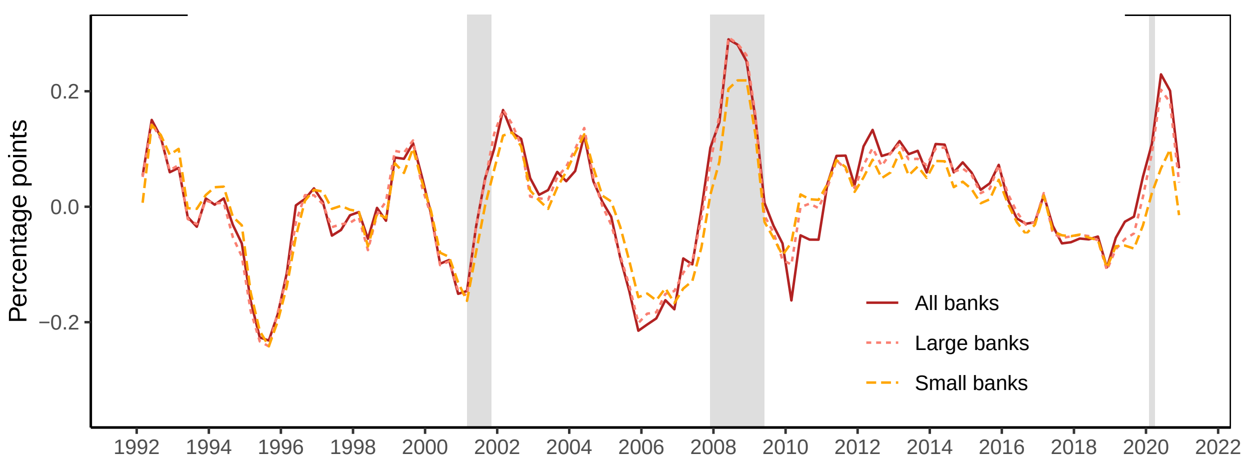
Figure 10 compares the baseline BRS and sentiment removing the effect of aggregate uncertainty. BRS appears qualitatively unchanged by removing aggregate uncertainty. However, select crisis periods appear to be significantly driven by uncertainty. For example, BRS is attenuated during both the Ruble 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.

C Additional aggregate BRS robustness checks

Measuring aggregate BRS is robust to a number of modifications and across various subsamples. I consider if BRS varies by bank sizes, if aggregate dynamics change by weighting schemes, and the importance of respecting real-time bank-level information sets.

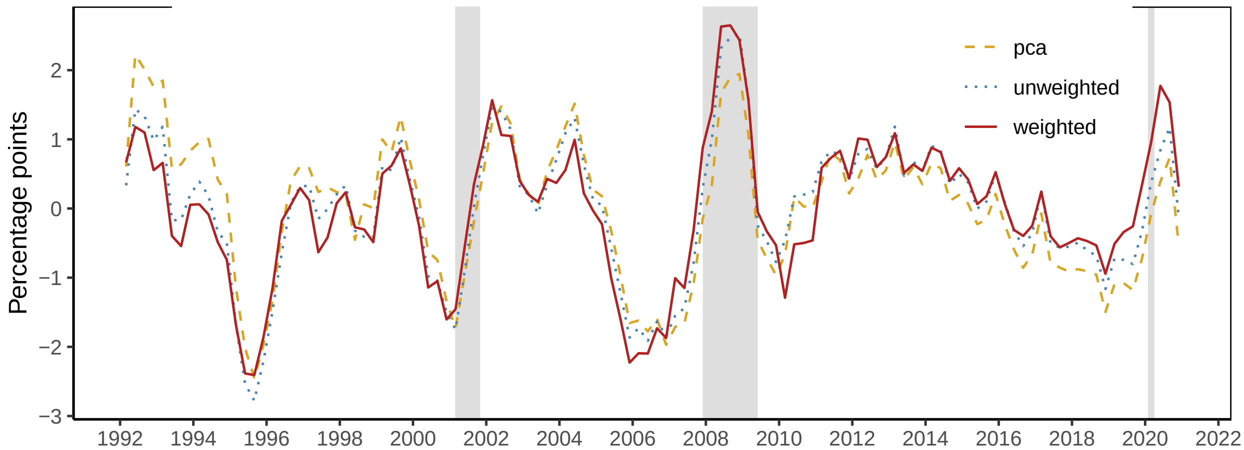
First, there is little difference in the aggregate BRS when comparing sentiments across large banks and small banks. Figure 11 shows the quarterly loan-weighted average bank-level risk sentiments for large banks (those in the top 15 percent of banks, in a quarter, by total assets), small banks (those in the bottom 85 percent of banks, in a quarter, by total assets), and all banks. This robustness check predominately confirms that the effect of size-based regulations and their associated costs have been fully controlled for in the measurement equation and do not exert a lingering influence on my measure of bank risk sentiments. This conclusions is drawn from the fact that larger banks are subject to more stringent regulations, following banking reforms in the late 1980's and early 1990's, including the Basel Accords, and then again in the 2010s following the GFC, for example the Dodd-Frank act. However, despite the differential regulatory costs, sentiments appear to move similarly across different bank size categories.

Figure 11: Bank risk sentiment by bank size



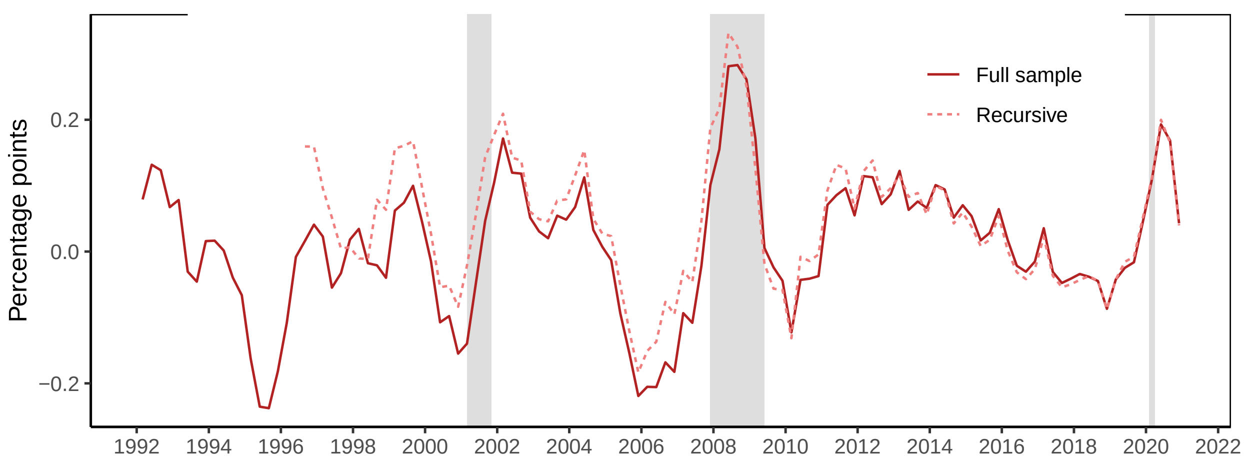
Notes: Solid red line depicts the loan-weighted average bank-level risk sentiments. The pink dashed line depicts the loan-weighted average bank-level risk sentiments of the top 15% of banks by net worth in a given quarter, while the orange long-dashed line depicts the loan-weighted average bank-level risk sentiments of the bottom 85% of banks by net worth in a given quarter. The correlation coefficients among the different BRS series are: Cor(all banks, large banks) = 0.985, Cor(all banks, small banks) = 0.934, Cor(large banks, small banks) = 0.959. Gray shaded regions are NBER dated recessions. Data are quarterly from 1992 to 2021.

Figure 12: Bank risk sentiment by alternative aggregation schemes



Notes: Solid red line depicts the quarterly loan-weighted average of bank-level risk sentiments. The blue dotted depicts the quarterly unweighted average of bank-level risk sentiments. The gold dashed line depicts depicts the quarterly first principal component of bank-level risk sentiments (restricting the sample of banks to those that are present for the entire history). The correlation coefficients among the different BRS series are: Cor(weighted, unweighted) = 0.954, Cor(pca, weighted) = 0.838. Gray bars are NBER dated recessions. Data are quarterly from 1992 to 2021.

Figure 13: Bank risk sentiment with real-time bank-level information



Notes: Solid red line depicts the quarterly loan-weighted average of bank-level risk sentiments, estimated with the full sample. The pink dashed line depicts the quarterly loan-weighted average of bank-level risk sentiments, estimated one quarter at a time with an expanding window information set. The correlation coefficient between the two BRS series is 0.9182. Gray bars are NBER dated recessions. Data are quarterly from 1992 to 2021.

Second, there is little difference in aggregate BRS when using different weighting schemes to average over bank-level sentiments. Figure 12 shows the quarterly quarterly loan-weighted average, unweighted average, and first principal component weighted, bank-level risk sentiments. The loan-weighted measure is the baseline aggregate BRS series used for the macroeconomic analysis presented in the paper, because it reasonably captures the varying importance of different banks in the financial sector (using assets as a proxy for importance in the loaning market) while also allowing for banks to come in and out of the sample. The unweighted series allows banks to entry or exit the sample, but it does not reflect the varying importance of individual banks, thus their sentiment, in lending markets. Alternatively, the first principal component of sentiments is the series that describes the most variation across the entire bank-level of sentiments, but it is restricted to a balanced panel in which banks cannot enter or exit the sample.

Third, there is little difference in aggregate BRS between using the full sample to estimate bank-level risk sentiments with one fixed effects model versus estimating bank-level sentiments one quarter at a time with an expanding window information set. Figure 13 shows there aggregate BRS estimated with the full sample compared to aggregate BRS estimated one quarter at a time. There may be a concern that estimating bank-level sentiments with the full sample will misrepresent the banks' rational expectations forecasts of loan default rates because it is contaminating their information sets with future data —this is a common problem in evaluating forecast performance without "real-time" information sets. However, when I estimate the bank-level sentiments model one quarter at a time with an expanding information set, that is, attempting to preserve the pseudo-real time forecasting information structure of the banks, I find that sentiments still aggregate to closely align with the full sample estimated analog.

D Bank risk sentiment as an animal spirits shock

In the context of the analytical model presented in Section 3, the bank risk sentiment shock is an irrational deviation from a bank's forecast of future defaults in its loan portfolio, or in the language of Angeletos and La'o (2013), an animal spirits shock. While I cannot observe a bank's rational expectations forecast of its future defaults in its loan portfolio, and therefore cannot definitively verify BRS as an exogenous sentiment shock, I can test that bank risk sentiment shocks 1) do not contain systematically useful loan default information, and 2) do not respond to macroeconomic shocks. The former condition tests that the shocks are systematically uninformative, thus irrational to include in a bank's forecast of loan defaults. The latter condition tests that the shocks are statistically independent of macroeconomic shocks, thus may be themselves considered an "exogenous" shock for the purposes of my subsequent macro-level empirical analysis.[34]

First, to test that bank-level risk sentiment does not contain any systematically useful loan default information, I conduct a simple in-sample forecasting exercise: I project the next quarter's realized loan portfolio default rate onto the current period's bank-level risk sentiment.[35] If the coefficient on bank sentiment is statistically significant, then my measure of bank sentiment contains systematically useful information for forecasting loan defaults, thus is actually an information shock and contributes to the rational expectations forecast of loan defaults.

Table 6: (In-sample) Bank-level loan portfolio defaults forecasting information content of bank sentiment

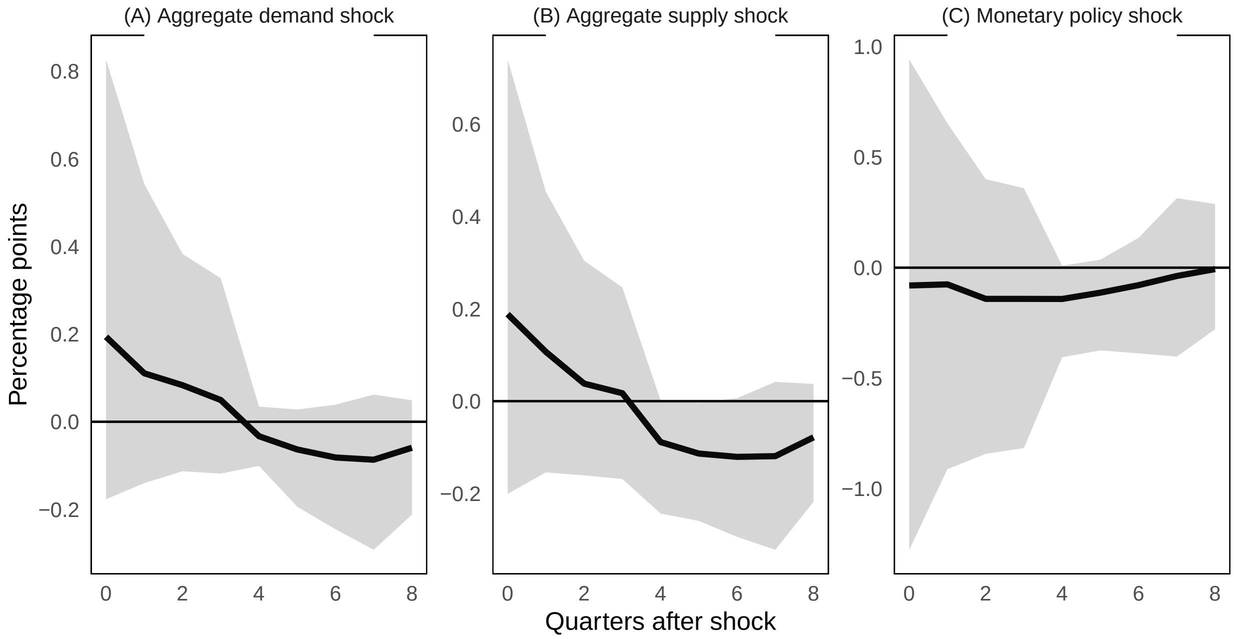
Bank risk sentiment	−0.009	−0.011	−0.010	0.002
	(0.006)	(0.007)	(0.006)	(0.002)
Bank FE		✓		✓
Date FE			✓	✓
Obs. (thousands)	873.4	873.4	873.4	873.4
R^2	0.000	0.000	0.000	0.000

Notes: This table presents the coefficients from an in-sample forecasting regression, predicting the change in bank-level charge off ratios with bank-level risk sentiment. 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.

[34]Note that an economic fluctuation is "exogenous" if and only if it is independent of all other changes in the economy, as defined in the context of a specific economic model. Therefore, if BRS is shown to be statistically independent of the exogenous shocks in a specific model, then BRS can be called exogenous in the context of that specific model of the economy.

[35]The realized portfolio default rate is taken as the level of loan and lease charge-offs divided by the total value of the loan portfolio.

Figure 14: Bank sentiment response to structural shocks



Notes: This plot shows the response of aggregate bank risk sentiment to various macroeconomic shocks. The solid black line depicts the mean response and the gray bands shows the 68 percent credible set. Impulse responses are estimated with a structural BVAR with shocks identified via standard sign restrictions. The endogenous variables includes: BRS, core PCE inflation, real GDP growth, and the one year Treasury rate as a proxy for the policy rate. The model is estimated with standard Minnesota priors and a Gibbs sampler with 50 thousand draws after a 50 thousand burn-in period. Data is quarterly from 1992 to 2021.

Table 6 shows that, when accounting for bank and date fixed effects, bank sentiment does not have a statistically significant covariance with future loan default rates (or one might alternatively say that it does not "Granger cause" loan defaults). That is, BRS does not contain systematically useful information for forecasting loan defaults, thus is not a part of the rational expectations forecast of loan defaults even though they are incorporated into the bank's loan pricing decisions.

Second, to test if BRS is statistically independent of generic macroeconomic shocks, I estimate the response of BRS to demand, supply, and monetary policy shocks. The necessary impulse response functions are estimated with a parsimonious structural BVAR, described in more detail in Section 6, while shocks are identified with standard, theoretically motivated, sign restriction scheme.

Figure 14 shows how aggregate bank risk sentiment responds to a generic demand, supply, and monetary policy shock. Bank sentiment does not respond to any of these three standard exogenous macro shocks in any statistically significant manner. This in turn implies that bank risk sentiment is independent of supply, demand and interest rate shocks, and all shocks that are subsumed by these generic shocks. Therefore, we might conclude that (aggregate) bank risk sentiment is itself an “exogenous” economic phenomenon, or at least may treat it as an exogenous shock in the following examination of its impact on the macroeconomy without fear of accidentally identifying the effect of a lurking aggregate demand, supply, or monetary policy shocks.

E Details on BVAR identification and estimation

The BVAR utilized in the macroeconomic analysis of this paper is standard in every way, except for the identification of its structural impact matrix, B. I identify B with IV, sign restrictions, and exclusion restrictions. To do so, I combine the IV-sign restriction identification procedure proposed by Cesa-Bianchi and Sokol (2022) with the sub-rotations procedure for combining sign and exclusion restrictions outlined by Kilian and Lütkepohl (2017).

Structural impact matrix estimation algorithm

Suppose there are K endogenous variables, l instrumented shocks, m sign restricted shocks, and n exclusion restriction shocks. For each draw of the Gibbs sampler:

1. Set $C = chol(\Sigma)$, where Σ is the variance-covariance matrix of the reduced form errors.
2. Estimate the IV columns of B, keep the $((K-n) \times l)$ sub-matrix s.
3. Set $s^1 = C^{-1}[s' \; 0_n']$. This scales the impact columns by the (approximate) variance of the reduced form shocks, so future re-scaling of the full impact matrix recovers the IV estimated columns.
4. Draw random columns that make a $(K-n) \times (K-m-n)$ matrix, call this matrix q. Draw the elements of q from a standard normal distribution to use the Haar prior common in the sign restriction literature.
5. Combine matrices s and q so that $\bar{W} = [s \; q]$, then take the QR decomposition of $\bar{W}$, $\bar{W} = \bar{Q}R$, so that $\bar{Q}$ is an orthonomoral matrix.
6. Construct the candidate rotation matrix: $Q = \begin{bmatrix} \bar{Q} & 0 \\ 0 & I_n \end{bmatrix}$.
7. Define $B = CQ$.
8. Check that the sign restrictions are satisfied. If so, then end and move to the next draw of the Gibbs sampler. If not, then discard candidate B and start over from step (4).

End.

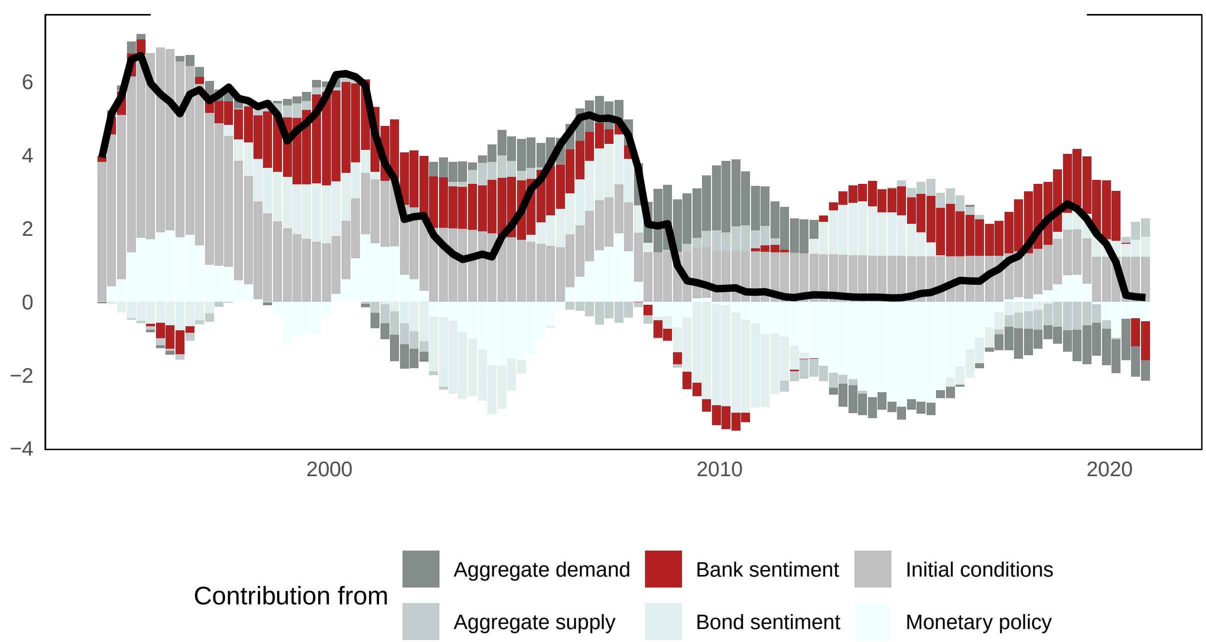
Note that, by construction, the linear mapping between structural shocks and reduced form errors is preserved such that: $BB' = CQQ'C' = CC' = \Sigma$.

F The historical effects of BRS shocks

In addition to the impulse response functions and forecast error variance decompositions, the structural BVAR can also decompose macroeconomic activity, prices, and policy rates into the historical contributions of the five shocks of interest: bank risk sentiment, bond market sentiment, aggregate demand, aggregate supply, and monetary policy.

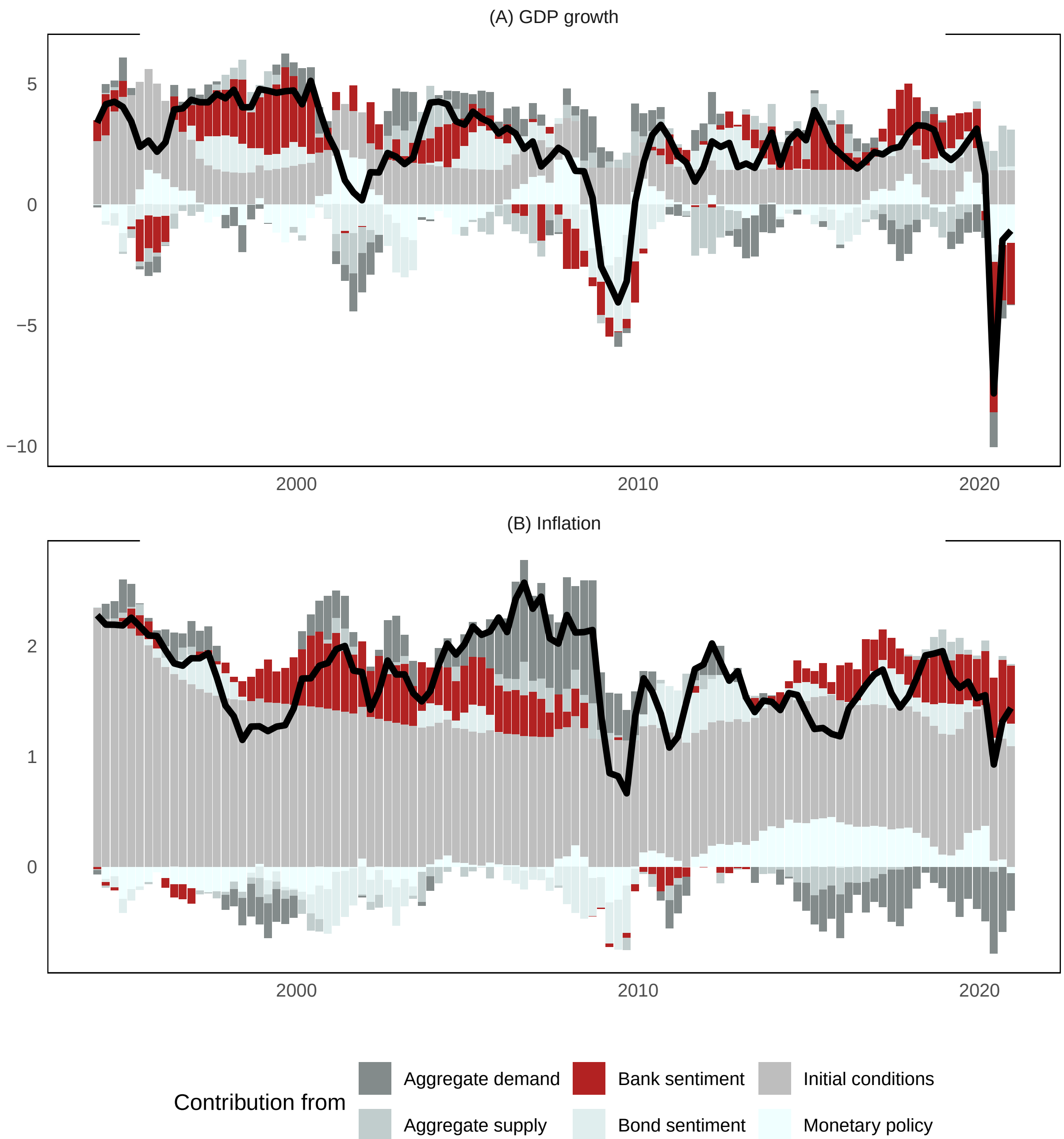
BRS plays a prominent role in determining the policy rate. Figure 15 shows the historical decomposition of the one year Treasury rate into contributions from initial conditions, aggregate demand, supply, monetary policy, bond market sentiment, and bank risk sentiment shocks. The policy rate appears to be actively leaning against the wind. That is, the policy rate is typically being increased by BRS shocks when aggregate BRS is either neutral or optimistic. For example, BRS has an increasing and positive effect pushing up the policy rate during the Dot-com asset bubble, the late 1990s and early 2000s, when BRS was itself optimistic. In comparison, When BRS was pessimistic during the GFC or COVID pandemic, then it was pushing the policy rate rate towards a more accomodative level. The policy rate

Figure 15: Historical decomposition of interest rates



Notes: This plot presents the historical decomposition of the policy rate into the effects of structural shocks. The red bars indicate the cumulative contribution of BRS shocks. The policy rate is proxied by the one year Treasury rate. The decomposition is estimated with a structural BVAR model with four lags and standard Minnesota priors; the posterior chain is drawn from a Gibbs sampler with 100 thousand draws and a 50 thousand burn-in period. Data is quarterly from 1992 through 2019.

Figure 16: Historical decomposition of macroeconomic activity and prices



Notes: This plot presents the historical decomposition of GDP growth and core PCE inflation into the effects of structural shocks. The red bars indicate the cumulative contribution of BRS shocks. The decomposition is estimated with a structural BVAR model with four lags and standard Minnesota priors; the posterior chain is drawn from a Gibbs sampler with 100 thousand draws and a 50 thousand burn-in period. Data is quarterly from 1992 through 2019.

is also largely influence by monetary policy shocks, which push the interest rate towards the zero lower bound during the recovery after the GFC.

BRS is mostly an expansionary influence on GDP growth and inflation. Through the mid-1990s until the the GFC —a period characterized by two asset bubbles and BRS optimism— the cumulative effects of BRS shocks are typically increasing GDP and inflation, as depressed loan prices fuel economic expansion. In comparison, BRS has a small impact on GDP in the GFC and little to no effect on inflation in both the GFC and COVID crises. However, BRS does have a large impact on GDP growth during the COVID crisis, in fact it is the single largest contribution to the decline in GDP of any shock studied in the decomposition.

G Sentiment shocks and detailed macroeconomic outcomes

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.

G.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:

$$Y_t = \Lambda X_t + \eta_t, \quad \eta_t \sim N(0, \Sigma_\eta) \tag{18}$$

$$X_t = AX_{t-1} + \epsilon_t, \quad \epsilon_t \sim N(0, \Sigma_\epsilon) \tag{19}$$

where Y_t is the collection of observable variables and X_t is the collection of latent states. Equation 18 is the measurement equation, relating latent states to observable macroeconomic variables, spanning real activity, financial activity, and prices. Equation 19 is the state law of motion, written in companion form, tracing the evolution of economy as an VAR(2) process.[36] Reduced form disturbances vectors, η_t and ϵ_t are assumed to be *i.i.d.* and drawn from normal distributions with variance-covariance matrices Σ_η and Σ_ϵ respectively.

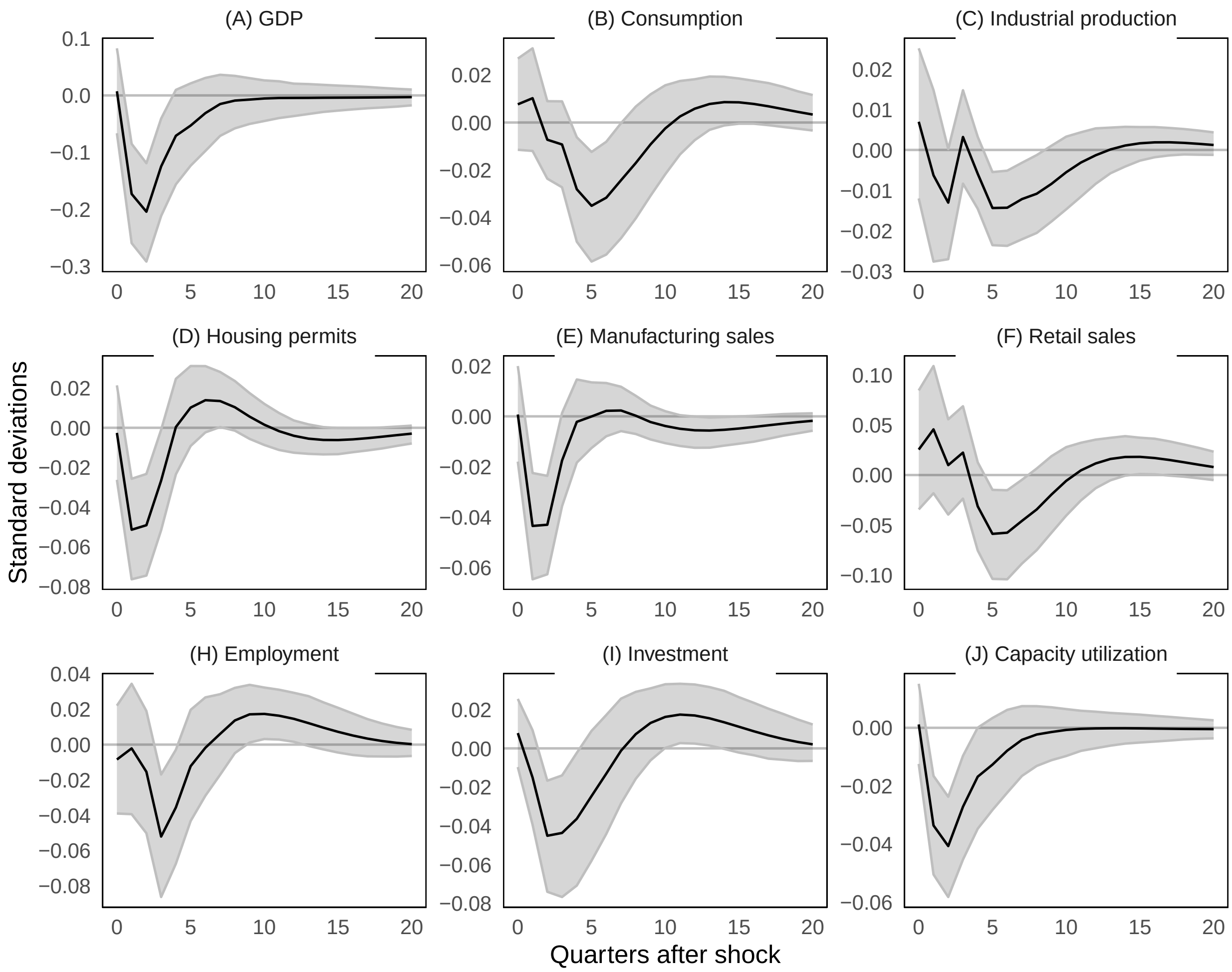
I summarize the economy with four latent states, F^M, chosen to balance parsimony with explanatory power. A four factor model explains approximately 52 percent of variance within the collection of observable variables, while the marginal variance explained by an additional factor falls below four percent.[37]

[36] 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.

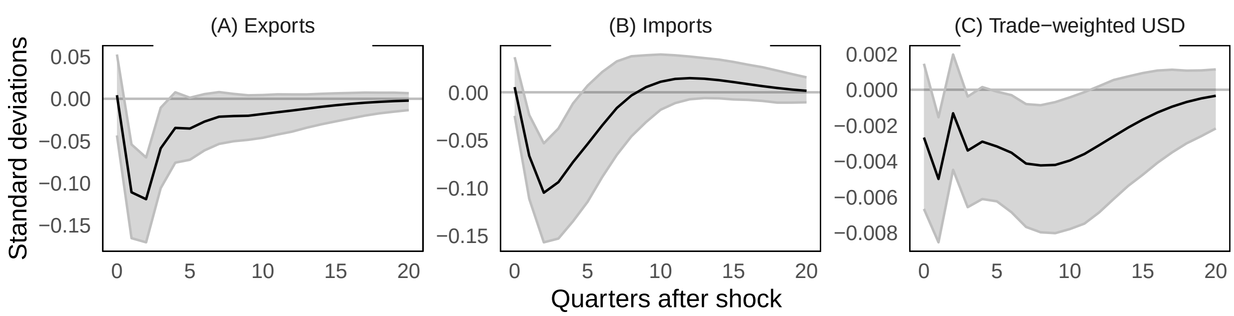
[37] The choice of four factors can be motivated by appealing to McCracken and Ng (2020), which similarly models the dataset with four factors. Although the Bai and Ng (2002) information criterion would select a one factor model for the data at hand. Since my goal is to trace the impact of a BRS shock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

Figure 17: Macroeconomic response to a bank risk sentiment shock

(A) Economic activity



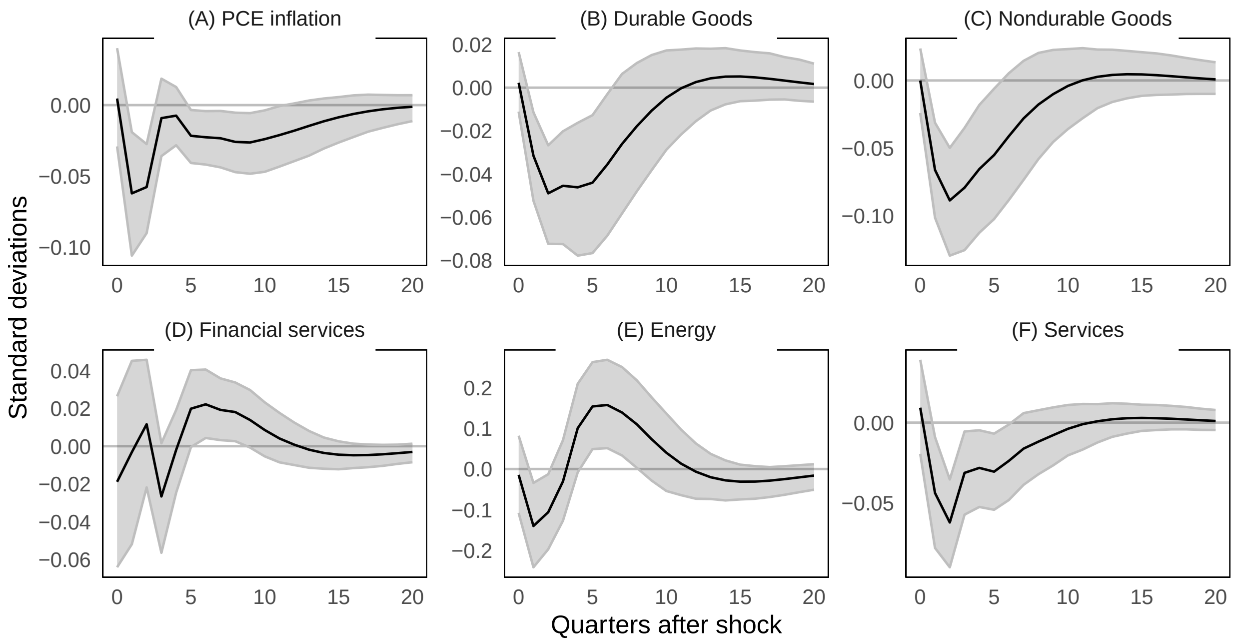
(B) Trade



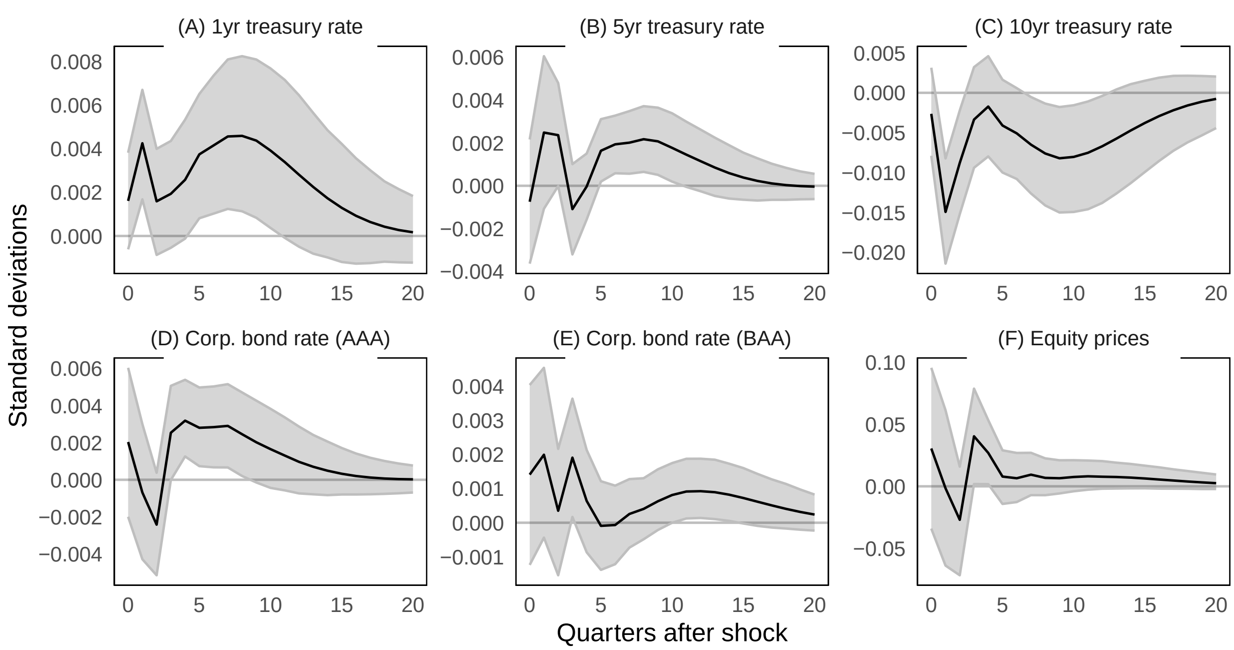
Notes: This figure reports the impulse response functions of select macroeconomic and trade variables to an unanticipated one percentage point increase in aggregate BRS. Solid black lines represent the responses to the equally weighted aggregate BRS, dotted blue lines represent responses to loan weighted aggregate BRS. Gray bands represent the 90 percent confidence intervals around the response to changes in the loan-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 17: Macroeconomic response to a bank risk sentiment shock (continued)

(C) Prices



(D) Financial assets



Notes: This figure reports the impulse response functions of select macroeconomic and trade 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 loan-weighted aggregate BRS, based on 1000 bootstrapped samples which account for both state and measurement equation uncertainty. Data is quarterly from 1992 to 2021.

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

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

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 **??**.

G.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.[38] 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).

G.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 relative than short term assets. BRS shocks are also shown to spill over into the international economy

[38] 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.

via declines in imports, exports, and an appreciating U.S. dollar.

Economic activity deteriorates. Figure 17 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 0.2 standard deviations within two quarters of impact, and only recovers after three years (although the response becomes statistically indistinguishable from zero a year after impact). 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 0.05 standard deviations within a year after impact, which does not fully recover for two 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 0.05 standard deviations and recover within a year after impact— with the deeper and more long lived fall in retail sales —which falls as much as 0.07 standard deviations before recovering only two and a half 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. 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.

Gross trade declines and the dollar modestly depreciates in the medium term. Panel B shows that as the economy broadly shrinks, so do gross trade flows. Both import and export growth declines a statistically significant 0.1 standard deviations within a year of the BRS shock. While at the same time, movements in the U.S. dollar are imprecisely estimated until a modest depreciation against a trade-weighted basket of global currencies emerges approximately two to three years after impact. These results suggest that news of the sentiment induced recession spreads globally in the medium term, and in response global investors divest from deteriorating U.S. assets, leading to a decrease in demand for the dollar and bidding down the price of the currency.

Overall price levels decrease. Panel C shows that going hand-in-hand with the broad based slow down in economic activity, prices decline upon a one percentage point increase in BRS. Moreover, the deterioration in prices appears to be similarly broad based. Headline PCE inflation decreases by almost 0.06 standard deviations within a year after impact. At the same time, prices fall in unison across almost all sectors, including durable and nondurable goods, and services. The exceptions to the pattern are financial services and energy prices, which appears to slightly decrease, before increasing a little over a year after the shock.

Risky asset prices are largely unaffected while the yield curve steepens. Panel D shows that a BRS shock has a limited impact on corporate bond market and equity prices, but does spills into the Treasury market. Investors' risk appetite decline in tandem with the economic deterioration set off by a BRS shock. For example, corporate bond yields (both investment grade and high yield) increase. However, the increase in yields (i.e. a decrease in bond prices) is not statistically significant for high yield bonds, while it is delayed for a year after impact for investment grade bonds. Equity prices on the other hand appear to remain relatively unchanged by the BRS shock. Although bank sentiments' relative lack of impact on corporate bond and equity markets may simply be a symptom of the fact that U.S. commercial banks largely do not participate in corporate bond and equity markets, unlike investment banks. In contrast, 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.

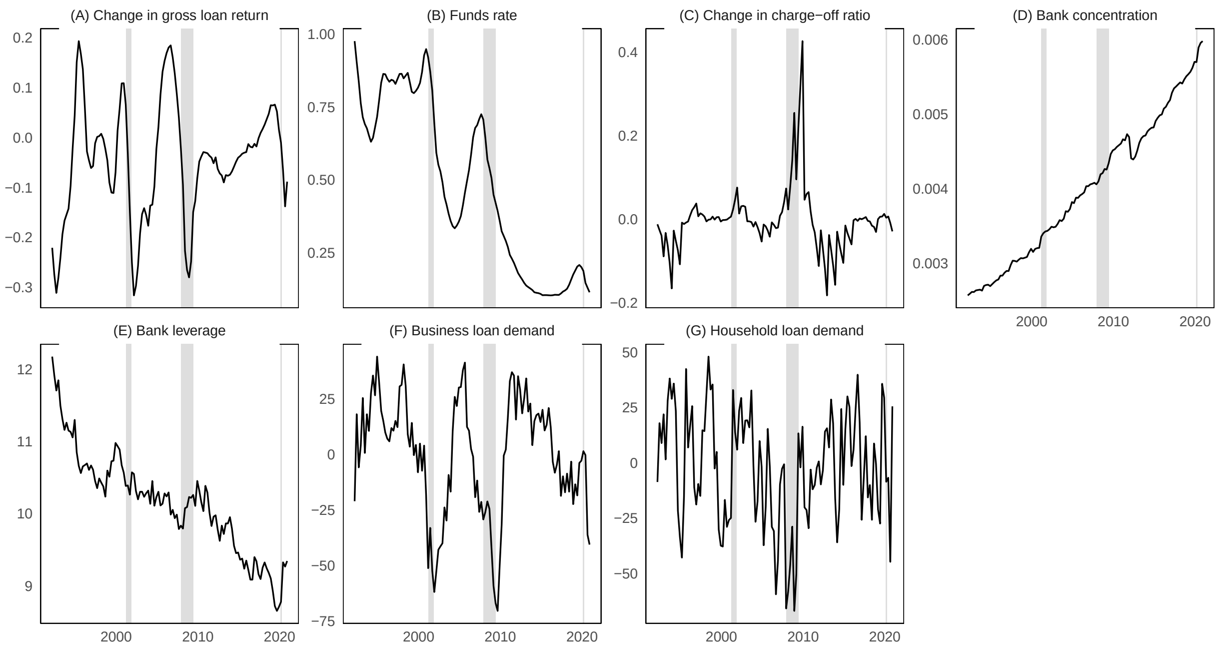
Robustness. These results are robust to using 3 to 6 latent states (i.e. factors), as well as using a loan-weighted measure of aggregate BRS rather than an unweighted average. Results are also robust to using 1 to 4 quarterly lags.

H Data Appendix

I provide additional data definitions, summary statistics, and visualizations.

H.1 BRS measurement data

Figure 18: Bank risk sentiment information set



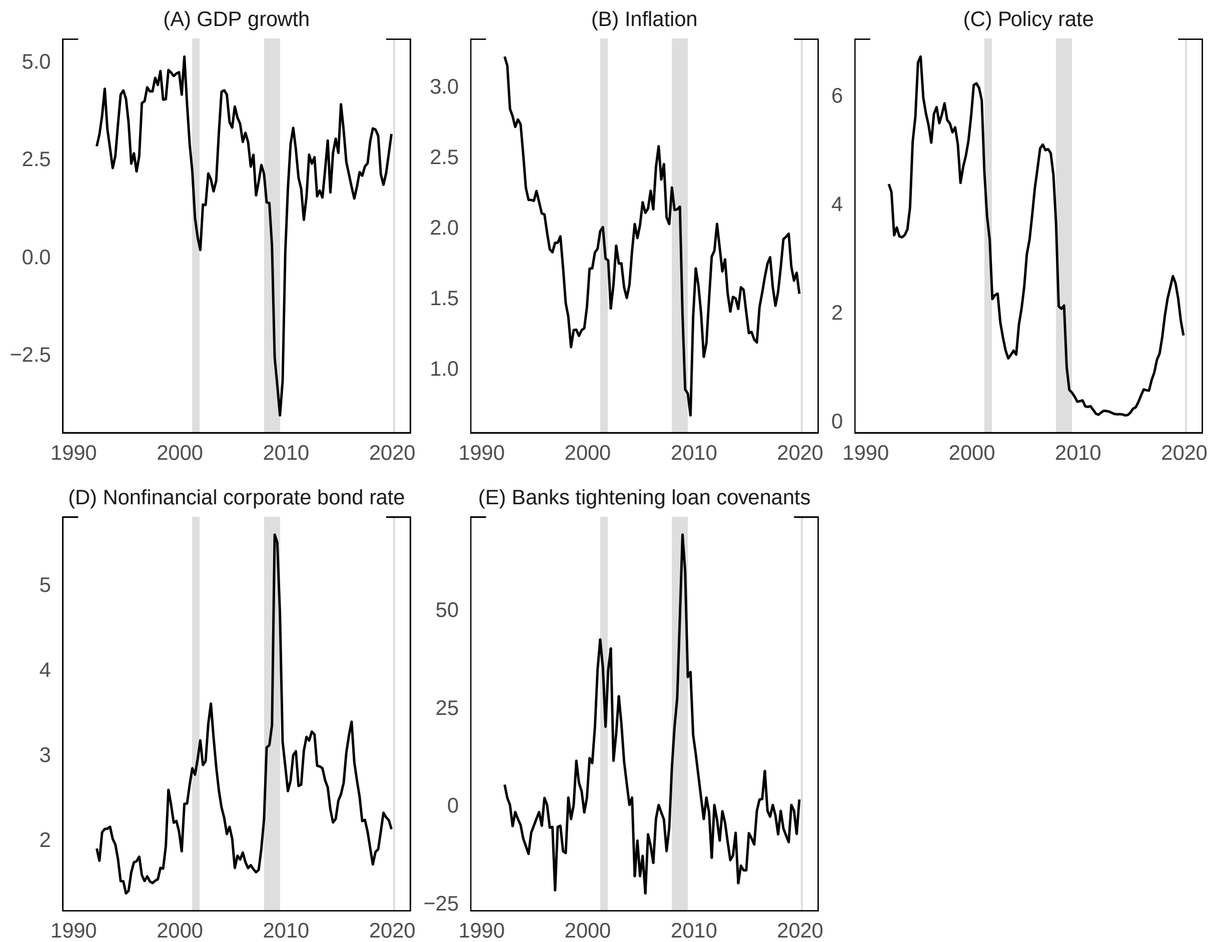
Notes: This plot shows that quarterly average values of the covariates and dependent variables used in the bank-level risk sentiments measurement equation. Gray shaded regions denote NBER dated recessions. Data is quarterly from 1992 to 2021.

Table 7: Bank-level variable details

Variable	Formula	Call Report variables
Δ Realized gross return on loans	$\frac{\text{loan interest income}_t}{\text{total loans}_t} - \frac{\text{loan interest income}_{t-4}}{\text{total loans}_{t-4}}$	RIAD4010, RCON2122
Leverage ratio	total assets / net worth	RCON2170, RCON3210
Capital funding costs	total interest expense / total assets	RIAD4073, RCON2170
Δ Charge off / loan ratio	$\frac{\text{charge offs}_t}{\text{total loans}_t} - \frac{\text{charge offs}_{t-4}}{\text{total loans}_{t-4}}$	RIAD4635, RCON2122

H.2 Macro-level analysis data

Figure 19: Endogenous variables in the Proxy BVAR



Notes: These plots show the six covariates that make up the endogenous variables in the structural BVAR used to compare financial market sentiments in Section 6. Data is quarterly from 1992 through 2019. Gray shaded regions denote NBER dated recessions. All variable are presented in percent.

H.3 Loan-level analysis data

Table 8: 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 U.S.D. 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 U.S. 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.

The sample covers a large range of loan, borrower, and lender sizes. Table 8 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.