Bank Risk Sentiment*

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Abstract

This paper studies the financial and macroeconomic effects of sentiment in the U.S commercial bank lending market. I first create an empirical measure of Bank Risk Sentiment (BRS) using bank-level data and a novel semi-structural identification strategy. Aggregate BRS is pessimistic during financial crises and optimistic during financial asset booms, but is heterogeneous at the bank-level. I then show, at the macro level, a pessimistic aggregate BRS shock acts like a negative credit supply shock and causes a persistent deterioration in activity and prices, inducing a monetary policy easing. BRS is also equally or more important in explaining macroeconomic outcomes than bond market sentiment, aggregate demand, supply and monetary policy shocks. At the micro level, a pessimistic bank-level sentiment shock tightens firm-level earnings-based borrowing constraints.

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

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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 has long been of interest to academics as a source of amplification in business cycle fluctuations and policymakers as a transmission channel of monetary policy.

There has likewise been a long standing interest in understanding how sentiments, or animal spirits in the language of Keynes, influences economic cycles. An emerging literature has attempted to study this question through the lens of financial risk sentiment —agents' fear regarding future states of the economy reflected in their demanded compensation for holding risk. Financial risk sentiment has been identified as a key factor in determining prices and quantities across several financial markets, such as the corporate bond and equity. 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 risk sentiment literature has been limited in its ability to measure true animal spirits, instead largely relying on reduced form measures of excess asset returns as proxies for sentiment.

This paper measures animal spirits in the U.S. commercial bank lending market and evaluates their effects on macroeconomic outcomes. I first use a semi-structural estimation approach to identify and measure bank-level risk sentiment shocks from public regulatory data. I then find that 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 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 bank pessimism tightens borrowers' earnings-based borrowing constraints.

I first create an empirical measure of BRS. I will study *bank risk sentiment* as an animal spirits shock to a bank's expectations of loan losses, or more concretely, as the difference between a bank's forecast of loan defaults and haircuts and its rational expectations forecast of these losses.

However, sentiments are not observable, thus not easily measured. I overcome this challenge by developing a semi-structural estimation strategy. I start by writing an analytical heterogeneous macro-banking model rich enough to take to the data but tractable enough to yield a closed form solution to a bank's loan pricing problem. In the context of this 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 estimated with standard econometric methods. Using this approach, I estimate bank-level risk sentiments at a quarterly frequency for the universe of U.S. commercial banks from 1992 to 2024 using regulatory Call Reports.

Aggregate BRS (the loan-weighted average of bank-level sentiments) spikes during financial crises or potential financial crises, such as the Dot-com crash, the Global Financial Crisis (GFC), the European Debt Crisis, and the COVID-19 pandemic. Conversely, it tends to be optimistic during debt-fueled asset booms, 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. Moreover, 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 sentiments.

I then empirically test that BRS behaves like an animal spirits shock with two exercises. First, I show that bank-level sentiments are systematically uninformative for forecasting loan losses, thus are irrational to include in the bank's forecasts. Second, I show that aggregate BRS is statistically independent of generic macroeconomic shocks, such as demand, supply, and monetary policy shocks. Therefore aggregate BRS can be interpreted as an exogenous shock in the context of macroeconomic models driven by these particular structural shocks, such as the canonical three-equation New Keynesian DSGE model.

Having measured and characterized BRS, I next turn to asking the question: do bank sentiment shocks 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

[1] The analysis is extended to also consider the role of aggregate uncertainty and a bank's time-varying risk aversion in Appendix C. 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.

a variety of lending market characteristics and outcomes in a flexible and theoretically agnostic Jordà (2005) style local projection framework.

A pessimistic aggregate BRS shock 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 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 —tightening credit limits imposed on borrowers— thus tightening the intensive 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 borrowers seeking new loans, 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 financial 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 recent empirical examples), but, as I will show, this is not necessarily the most important source of sentiments driving macroeconomic outcomes.

Pessimistic BRS shocks lead to a 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.

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 to 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 this paper's contributions, 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 contributes to the broad literatures on market sentiments, the macroeconomic role of banks, and the real outcomes of credit supply shocks, while being most closely related to works on the macroeconomic effects sentiment shocks. I will discuss this project's relationship with and contribution to each broad topic in turn.

The macroeconomic effects of market sentiments. There has been a long history of studying how market sentiments may dictate credit and real business cycles alike, see for example Minsky (1977) and Kindleberger (1978) for summaries of the topic from Keynes through the beginnings of the rational expectations revolution of the 1970's and 80's. However, the debate has been reinvigorated in the wake of the GFC. 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), 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).[2] These works find investor risk sentiment to empirically matter for explaining fluctuations in macroeconomic outcomes, such as activity and prices, as well as the credit cycle. However, most of these works have to stop short of describing their measures as true sentiment shocks given the reduced form nature of their measurement strategies, with one exception being Boeck and Zörner (2023) which pursues a structural estimation strategy.

A second strand of literature has focused on explaining the sentiment formation process through a theoretical lens. For example, sentiments as animal spirit shocks are micro-founded as noisy signal and dispersed information problems in works such as Angeletos and La'o (2010, 2013) and further surveyed in Angeletos and Lian (2016). While on the other hand, sentiments arising from diagnostic expectations are micro-founded as agents over-extrapolating forecast errors, and were introduced by Bordalo et al. (2018). Diagnostic expectations have since been used by Bordalo et al. (2019), Krishnamurthy and Li (2021), Bianchi et al. (2022), and Maxted (2023), among others, to explain boom and bust credit cycles. The concept of sentiments studied in this work follows the animal spirits literature.[3] 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 identifying model. 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 two-fold: a measure of agent-level sentiment shocks in an overlooked credit market, the commercial bank lending market, and an assessment of how bank sentiment impacts macroeconomic outcomes. Moreover, while I am not the first to study the im-

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

[3] A separate type of financial market sentiments, namely optimism and pessimism vis-à-vis future liquidity, has also recently emerged in the international finance literature, and has been used to explain recessions and financial crisis, see for example Perri and Quadrini (2018) or Schmitt-Grohé and Uribe (2021). This is not the style of investor sentiment this project considers.

pact of sentiment shocks on macroeconomic outcomes —for example, López-Salido et al. (2017) evaluates the effect of investor risk sentiment shocks in the corporate bond and stock markets on real outcomes, while Lagerborg et al. (2023) study the impact of consumer sentiment on aggregate activity— this project is the first to jointly compare the relative empirical importance of risk sentiment, real, and monetary policy shocks in explaining business cycle and steady state variation in macroeconomic activity, prices, and policy.

A third strand of literature has studied the impact of bank-level deviations from rationality, but with a focus on micro-level financial outcomes. This paper compliments these works, such as Ma et al. (2021) and Falato and Xiao (2023), by focusing on the real macroeconomic impacts of bank-level deviations from rationality.

The macroeconomic effects of banks and credit supply shocks. Both the theoretical and empirical macro-banking literature has expanded rapidly since the GFC. Early (theoretical) entries focused on more explicitly incorporating financial intermediaries into DSGE models, resulting in a Handbook chapter, Gertler and Kiyotaki (2010), as well as 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 (2024) 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. This paper 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 GFC. 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). However, studies in this literature pinpoint the source of credit supply or demand shocks by either 1) using externally identified shocks, as in Khwaja and Mian (2008), 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 allows for a clear interpretation of the responses of interest, but it requires the researcher to obtain 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 a semi-structural approach to decomposing loan prices into credit supply and demand factors. 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. While the resulting ability to relate fluctuations in supply or demand to specific factors in a bank's loan pricing problem allows for a level of structural interpretation that is inaccessible in the purely reduced form supply and demand decomposition approach.

3 A model of sentiments in bank lending 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.

My analytical model takes the canonical Gertler and Kiyotaki (2010) as a foundation. Risk neutral banks raise capital each period to form one-period loan portfolios, face (indirect) net worth constraints, and operate as monopolistic creditors within a segmented market. However, the analytical model will diverge from Gertler and Kiyotaki (2010) in two key respects: aggregation and regulation. First, banks operate as the sole creditor within their own Lucas (1973) style island, which in this setting may be interpreted as representing markets for differentiated credit products (e.g. commercial and industrial loans versus mortgages) or geographic regions (e.g. U.S. counties or states). However, unlike Gertler and Kiyotaki (2010), I stop short of aggregating financial intermediaries across islands.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 its 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.[4]

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.[5] When loans default, they yield a gross return of zero. That is, the entire principal 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:

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

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

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:

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

[4]Note that the Broker is not necessary for the results derived in this analytical setting, but its presence makes examining aggregate loan rates and quantities more tractable.

[5]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).

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 $\alpha \in (0,1]$.

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.[6]

3.5 Specialized banks

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

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

[6] This assumption is key in maintaining the tractability of the 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.

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

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.[7]

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, such as Drechsler et al. (2017).

Specialists also pay a regulatory cost based on their funding gap, $L_{i,t} - N_{i,t}$.[8] 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 increasing, weakly convex, and zero at the origin. More formally, I assume $\Phi'(X) \geq 0$ and $\Phi''(X) \geq 0$ for all $X \in \mathbb{R}$, and $\Phi(0) = 0$. Although, I will later assume a (quadratic) functional form when deriving a concrete econometric strategy for measuring BRS. The 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:

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

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

[8] 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 (2024) 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.

so that as the expected default rate, $E\lambda_{i,t}$, market power, $\theta_{i,t}$, cost of capital $C_{i,t}$, 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 in the empirically estimation.

3.6 Default rates and bank risk sentiment

I define a bank's risk sentiment as a shock differentiating a 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.[9] 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).[10] As a Specialist's portfolio ex-post return fluctuates according to the loan default rate, I will adopt the literature's standard approach and postulate a reduced form law of motion for risk in the economy.

In the spirit of Bellifemine et al. (2022) and Jamilov and Monacelli (2023) I will assume that a bank's specific level of default risk is a function of idiosyncratic risk (reflecting a bank's innate ability to manage and perceive risk) and aggregate risk (reflecting uninsurable shocks to the entire economy).[11] Additionally, in keeping with evidence presented in Falato and Xiao (2023), 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.

[9] 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.

[10] See Brunnermeier and Sannikov (2014) for an example in continuous time or Gertler and Kiyotaki (2010) in discrete time.

[11] Alternative laws of motion for risk are tested and discussed in Appendix B.

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. With the postulated law of motion for default risk, one can further expand the Specialist's loan pricing equation to explicitly reflect the presence of the bank's rational expectations and risk sentiment:

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

which in turn makes the relationship between bank risk sentiment and bank lending clear. 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.

Equilibrium and lending outcomes. Having fully specified the banks' loan pricing equation, I leave completing the model with a description of the competitive equilibrium and a series of predictions for how bank sentiment may impact aggregate lending outcomes to Appendix A.

4 Measuring and characterizing Bank Risk Sentiment

I next turn to estimating and describing bank risk sentiment. The measurement strategy, data, and sentiments are discussed in order.

4.1 Measurement strategy

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

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

Equation 8, becomes:

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

and the log-linear pricing equation is then:

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

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

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

Therefore, if I estimate the linear regression:

$$r_{i,t} = \gamma_i + b_1 log\left(\frac{\theta_{i,t}}{\theta_{i,t} - 1}\right) + b_3 c_{i,t} + b_4 2r(L_{i,t} - N_{i,t}) + b_4 \rho_1 \lambda_{i,t-1} + b_5 \rho_2 \lambda_{t-1} + \varepsilon_{i,t} \tag{9}$$

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 $\varepsilon_{i,t}$ will equal the unobservable risk sentiment, $\psi_{i,t}$.

Estimation. Equation 9 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.

4.2 Sentiment in a credit supply and demand decomposition

My measurement strategy is related to the credit supply and demand decomposition framework developed in Greenstone et al. (2020) and used by 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:

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

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.

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 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, thus, 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 then 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 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:

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

where $\mathbf{D}$ is the vector of observable proxies for credit demand, leaving $\varepsilon_{j,t}$ 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:

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

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.

Table 1: Summary statistics of BRS measurement equation data

	Mean	SD	p(5)	p(25)	p(50)	p(75)	p(95)
Bank characteristics							
Δ Loan rates	-0.051	0.203	-0.388	-0.149	-0.041	0.052	0.256
Capital funds cost	0.517	0.328	0.056	0.196	0.526	0.792	1.023
Leverage ratio	10.383	2.936	5.892	8.463	10.244	12.057	15.100
Δ Charge-off / loan ratio	-0.005	0.436	-0.542	-0.063	0.000	0.052	0.517
Macroeconomic conditions							
Sate-level loan HHI	0.004	0.011	0.000	0.000	0.001	0.003	0.016
Demand for business loans	0.120	26.383	-51.200	-18.600	4.200	18.300	35.400
Demand for household loans	-1.721	25.889	-44.800	-20.200	-1.500	17.900	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. Loan demand is measured as the coincidence indicator of banks reporting an increase in demand for a given loan category, as reported by the Senior Loan Officer Opinion Survey put out by the Federal Reserve. The sample is made up of 946.3 thousand observations, 14569 unique banks represented in the sample and dates ranging from 1992 to 2024.

4.3 Data

Equation 9 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).[12] Regulatory costs are proxied by the bank's leverage ratio, assets divided by equity.[13] Marginal cost of capital is proxied by the bank-level interest expenses divided by total assets, that is, the average interest paid to maintain a dollar of the bank's capital assets. Realizations of bank-level risk are measured by the bank's charge-off ratio, total charge-offs divided by total loans.[14] Realizations of aggregate risk are the quarterly loan weighted average of bank-level loan charge-offs. Bank-level

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

[13] 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.

[14] 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.

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.[15]

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's Senior Loan Officer Opinion Survey (SLOOS).

Table 8 summarizes the sample used to estimate the BRS panel regression. The sample includes 946.3 thousand bank-quarter observations, running from 1992 to 2024. The average bank-level loan rate 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 loan rates in my econometric model to ensure the dependent variable follows a stationary process. The average change in the loan rates is slightly negative, but close to zero, at approximately negative 5.1 basis points. However the distribution of changes indicates a large dispersion in potential outcomes across banks, with a fifth percentile near negative 39 percent and a 95th percentile near 26 percent. Meanwhile, the bank-level co-variates display large variation across the sample while aggregate series are more symmetric across the sample. The further description and construction details for each variable in the BRS measurement equation are presented in Appendix H.

4.4 Characterizing bank risk sentiment

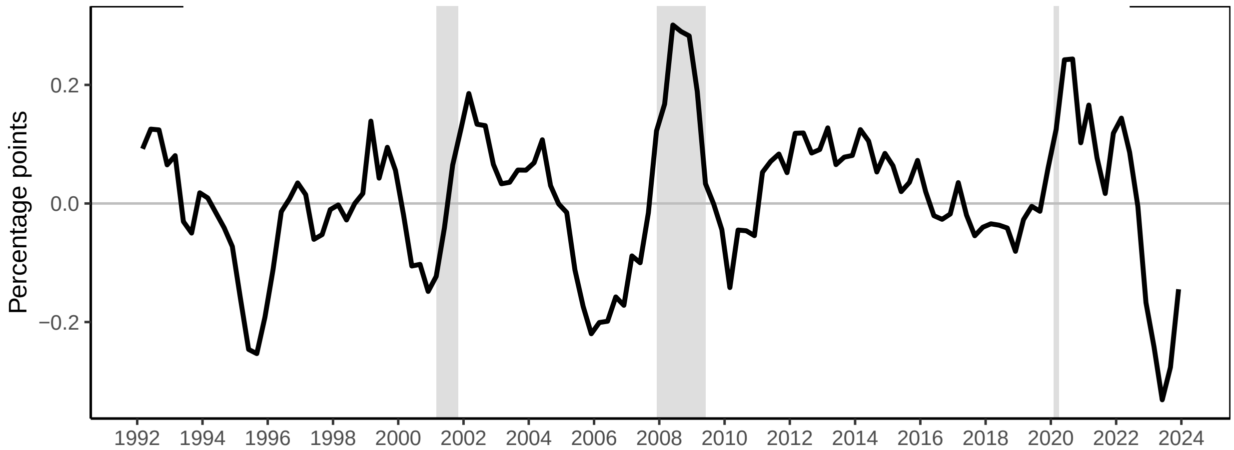
I next turn to presenting the aggregate measure of BRS, the underlying bank-level risk sentiment processes, and the validity of interpreting bank risk sentiment as an exogenous shock.

Aggregate bank risk sentiment. Aggregate bank risk sentiment —the loan-weighted average bank-level sentiment— is characterized by sharp increases in times of financial stress and uncertainty in the United States. 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 GFC, and COVID-19 pandemic.[16] Moreover, periods of deteriorating sentiments are often precipitated by events elevating 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 optimism include the Dot-com bubble of the late 1990s and the 2000s housing boom.

[15]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.

[16]Figure 12 in Appendix D additionally shows BRS plotted against financial crises and other major economic events.

Figure 1: Bank risk sentiment



Notes: This plot depicts the quarterly loan-weighted average bank-level risk sentiment. Sentiments increase as banks forecast an increase in future loan losses, that is, a deterioration in economic conditions. NBER dated recessions are marked in gray. Data are quarterly from 1992 to 2024.

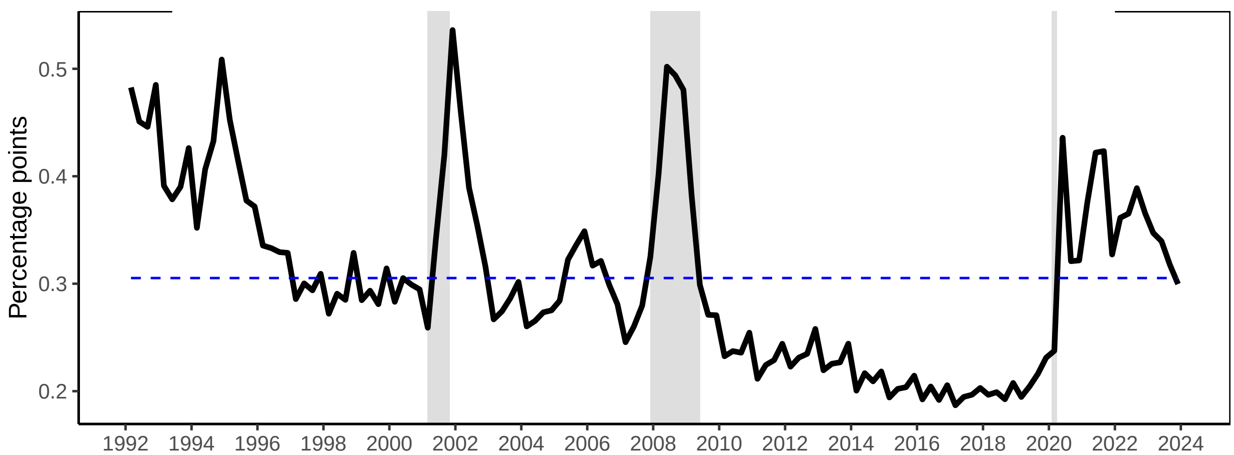
While there are common movements in sentiments across banks, there is also a wide range of sentiments across banks in any given quarter. Figure 2 shows the dispersion of bank risk sentiments from 1992 through 2020. There is a large degree of heterogeneity across bank-level risk sentiments through the 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. However, a notable disruption to this cylicality occurs in the post-COVID era, when the dispersion in sentiments dramatically rises and remains elevated for the remainder of the sample.[17]

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

[17]The following empirical analysis will use 1992 through 2020 as a baseline sample period because 2021 is when the dispersion in sentiments first increases dramatically outside of a recession, perhaps indicating a structural change in the underlying data generating process. However, I do not observe enough data points yet to formally test for a structural break in the time series.

Figure 2: Dispersion in bank risk sentiment



Notes: This plot 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. Data are quarterly from 1992 to 2024.

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.

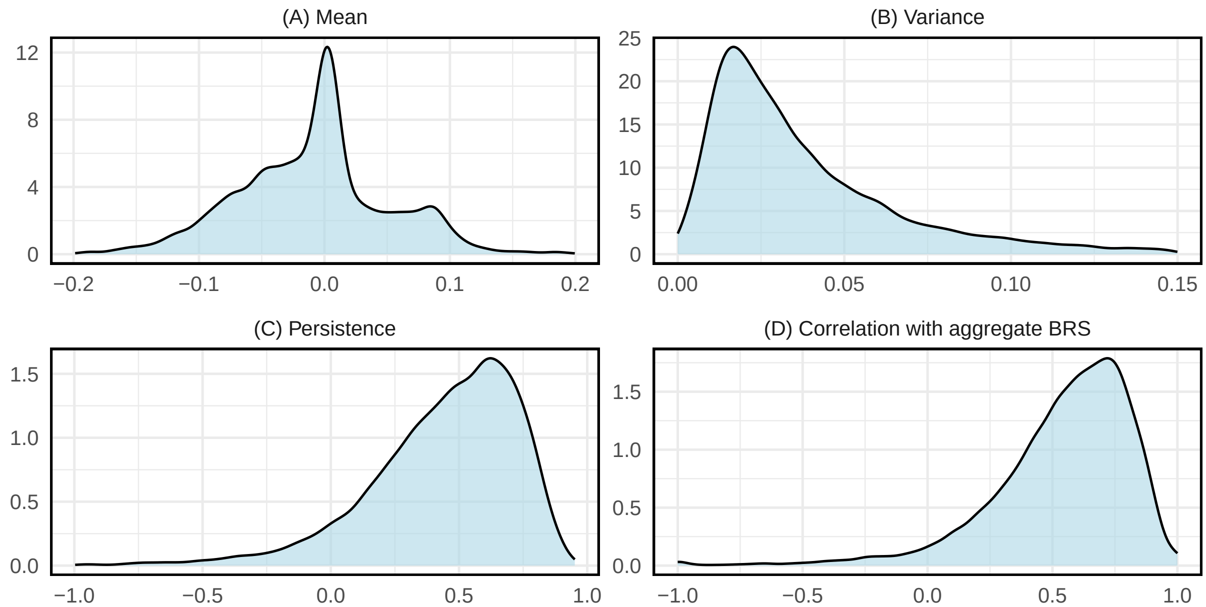
The persistence of bank-specific risk sentiment processes (panel C) is measured as its AR(1) coefficient, and is on average approximately 0.433 —suggesting a relatively transient sentiment process, with a half-life of only two quarters.[18] However, by inspection, it is clear that the modal AR(1) coefficient is approximately 0.6 and the distribution is heavily skewed to the right.

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.

[18] One lag is almost universally the BIC and AIC minimizing lag order for bank-level sentiment processes.

Figure 3: Bank-level sentiment processes



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 to 2024.

In summary, most banks experience weakly persistent and low variance risk sentiment series that are only moderately, but positively, correlated with aggregate BRS. 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.

4.5 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 statis-

Table 2: (In-sample) Bank-level loan losses forecasting information content of bank sentiment

Bank risk sentiment	−0.007	−0.009	−0.007	0.001
	(0.005)	(0.006)	(0.006)	(0.001)
Bank FE		✓		✓
Date FE			✓	✓
Obs. (thousands)	862.01	862.01	862.01	862.01
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. Data are quarterly from 1992 through 2020.

tically independent of macroeconomic shocks, thus may be themselves considered an exogenous shock for the purposes of my subsequent macro-level empirical analysis.

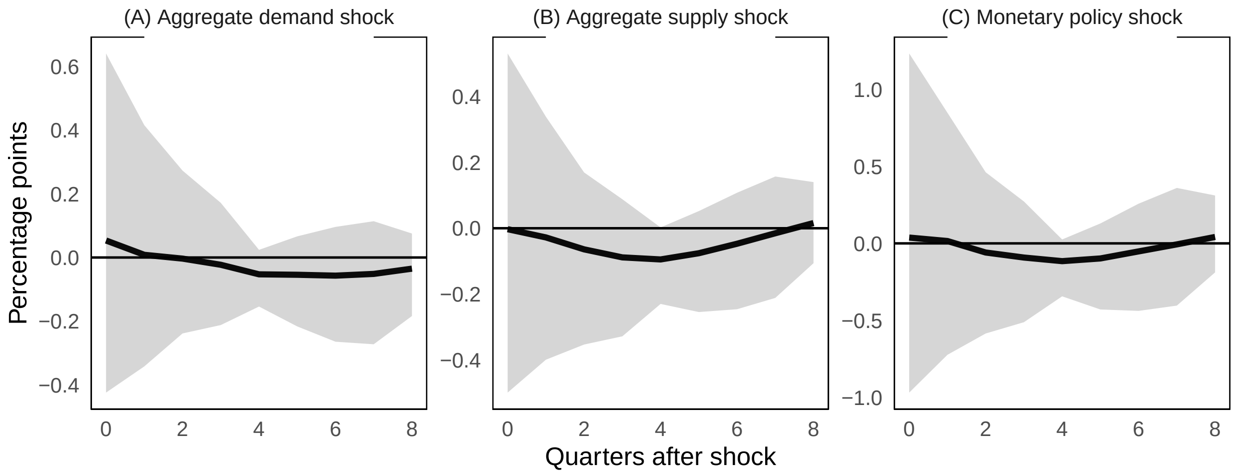
First, to test that bank-level risk sentiment does not contain any systematically useful loan default information, I conduct a simple in-sample forecasting exercise: I project the next quarter's realized loan portfolio losses onto the current period's bank-level risk sentiment.[19] If the coefficient 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 2 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 losses). That is, BRS does not contain systematically useful information for forecasting loan losses, thus is not a part of the rational expectations forecast of loan losses 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, which models the joint evolution of four (potentially) endogenous macro-variables: BRS, core PCE inflation, real GDP growth, and the

[19] 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 4: 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 Minnesotta priors and a Gibbs sampler with 50 thousand draws after a 50 thousand burn-in period. Data is quarterly from 1992 through 2020.

one year Treasury rate as a proxy for the policy rate. The BVAR contains four lags of each variable and is based on standard Minnesota priors, while shocks are identified with standard, theoretically motivated, sign restrictions (detailed in Section 6, while leaving the impact on BRS unrestricted).

Figure 4 shows that BRS does not respond to any of these three standard macroeconomic 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, I can conclude that (aggregate) bank risk sentiment is itself an exogenous economic phenomenon, or at least it may be treat 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 shock.

Alternative definitions and sources of bank risk sentiment. There are two alternative definitions (i.e. sources) of bank risk sentiment found in the macro-finance literature: time-varying risk aversion and uncertainty. I document the relationship between these two sources of sentiment and BRS in more detail in Appendix C. I first show that time-varying risk aversion is already controlled for in the measurement of BRS. I then show that BRS is qualitatively robust to controlling for the effects of aggregate uncertainty, although with modest attenuation during select crises.

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:

$$\Delta^h(Y_{t-1}) = \alpha^h + \theta^h BRS_t + \beta^h X_{t-1} + \varepsilon_{t+h} \tag{10}$$

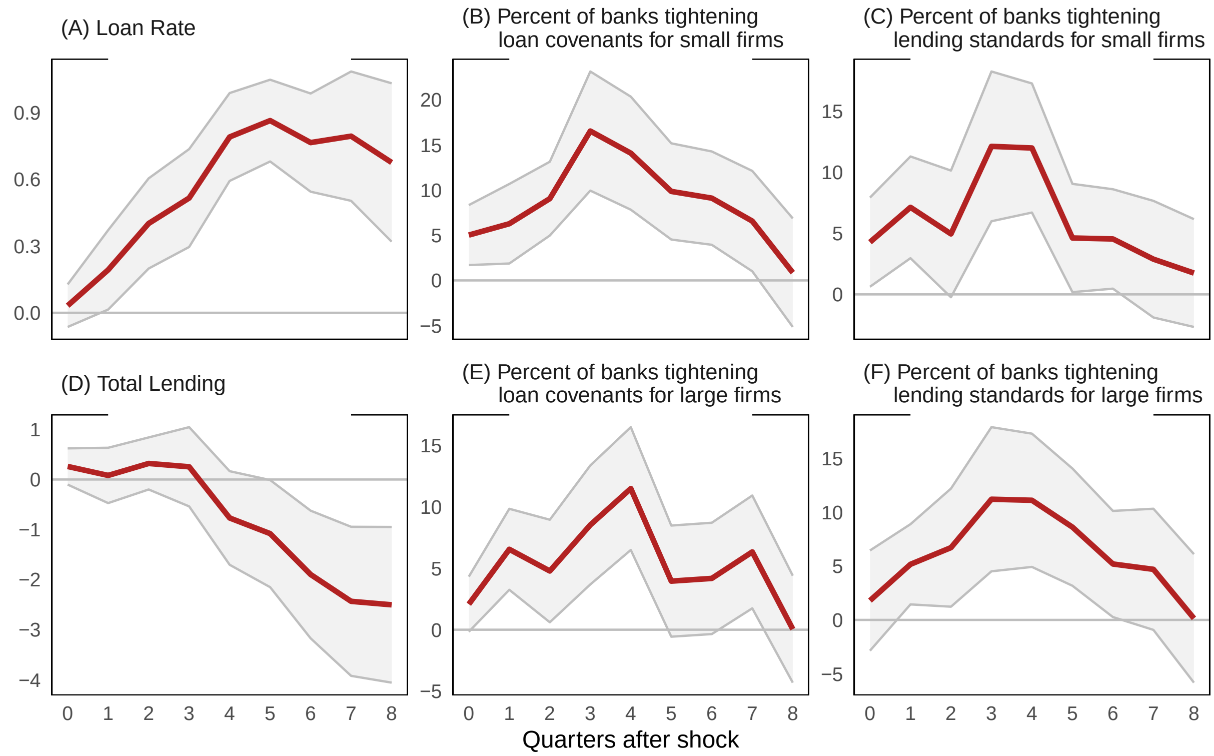
where $\Delta^h(Y_{t-1})$ is the change in the economic outcome of interest h quarters from $t-1$, BRS_t is the aggregate measure of bank sentiment, and X_t is the vector of four auto-regressive lags of the dependent variable Y, as well as lagged controls representing the state of the business cycle, 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 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 restrictive bor-

[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 size) from U.S. Call Reports. The percent of banks tightening standards and covenants are collected from the SLOOS. Data runs from 1992 through 2020.

Figure 5: 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 gray band marks the Newey-West adjusted 90-percent confidence interval. Data is quarterly from 1992 through 2020.

rowing 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 4.5) bank risk sentiments act as bank-level animal spirit shocks, estimating the causal impact of common 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 (see Ramey (2016) for a thorough discussion of this literature, as well as a broader overview on identification strategies in local projection models). 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.

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 5 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 5 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 5 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 5 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 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 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) and empirical study (e.g. Bernanke et al. 1996, 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 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 5 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. (2021), highlight that earnings-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 earnings-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

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

cycle fluctuations to sentiment shocks in other credit markets, real demand shocks, real supply shocks, 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 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:

$$Y_t = \nu + \mathbf{A}Y_{t-1} + \mathbf{B}\varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(\mathbf{0}, I_K) \tag{11}$$

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. 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— to fully identify the structural impact matrix, B.

Bank risk sentiment 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]

[23] The standard *relevance* and *exclusion* conditions necessary for valid instrumental variable research designs are satisfied in this exercise. First, the relevance condition is self-evident theoretically —bank sentiment acts as a loan rate shock, thus is relevant for the equilibrium quantity of loans— and empirically —evidence in Section 5 clearly shows aggregate sentiment shocks effect aggregate lending. Second, the exclusion restriction is satisfied given Appendix 4.5, which shows that BRS acts like an animal spirit shock, and more specifically, aggregate BRS is statistically independent of structural aggregate demand, supply, and monetary policy shocks, thus of all other macroeconomic

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.

Table 3: 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).

shocks that may be subsumed by these generic shocks. Moreover, by construction, BRS is independent of fluctuations in credit demand, and in turn any macroeconomic shocks that may manifest through the credit demand channel, such as consumer sentiment shocks.

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 identified, dynamic, empirical model with real, financial, and sentiment 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 with 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.

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

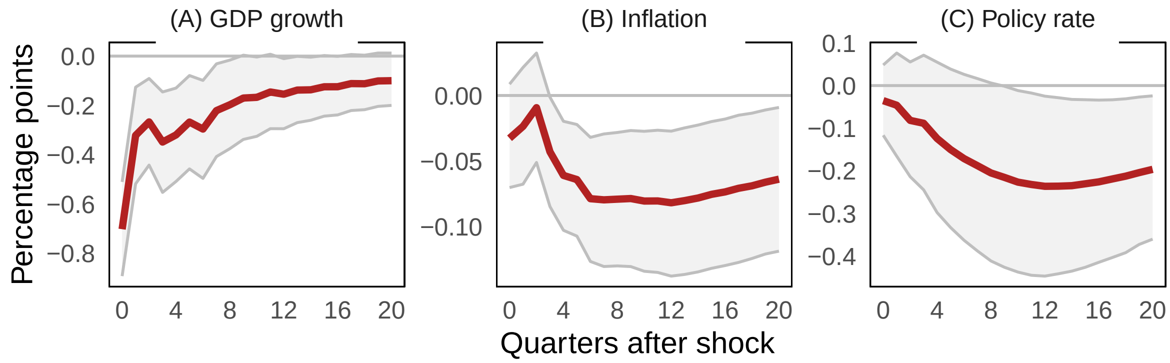
6.2 Examining the effects and relative importance of bank sentiment shocks

Pessimistic bank sentiment shocks induce a significant and long-lived deterioration in economic activity, slowing inflation, and sharp monetary policy easing. Figure 6 (top panel) 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 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).

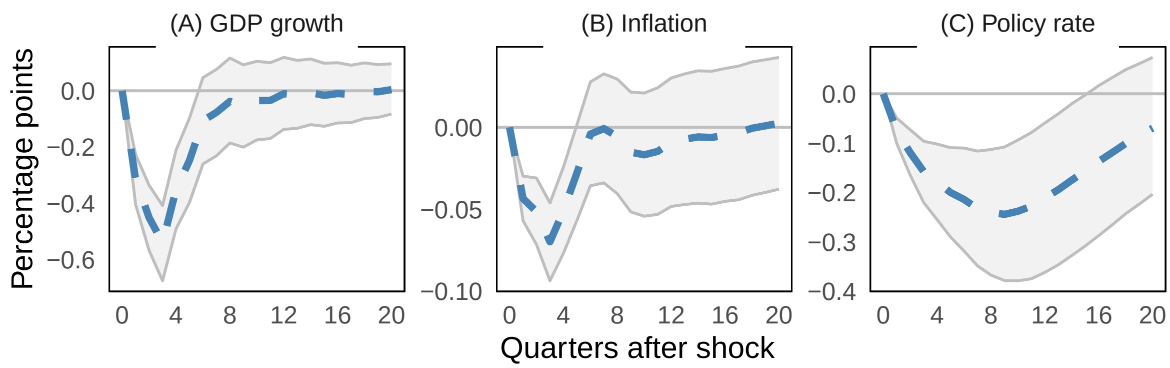
Given bank sentiment's sizable impact on GDP growth and the policy rate, it is not surprising that

Figure 6: Macroeconomic response to financial sentiment shocks

(A) Bank sentiment shocks



(B) Bond sentiment shocks

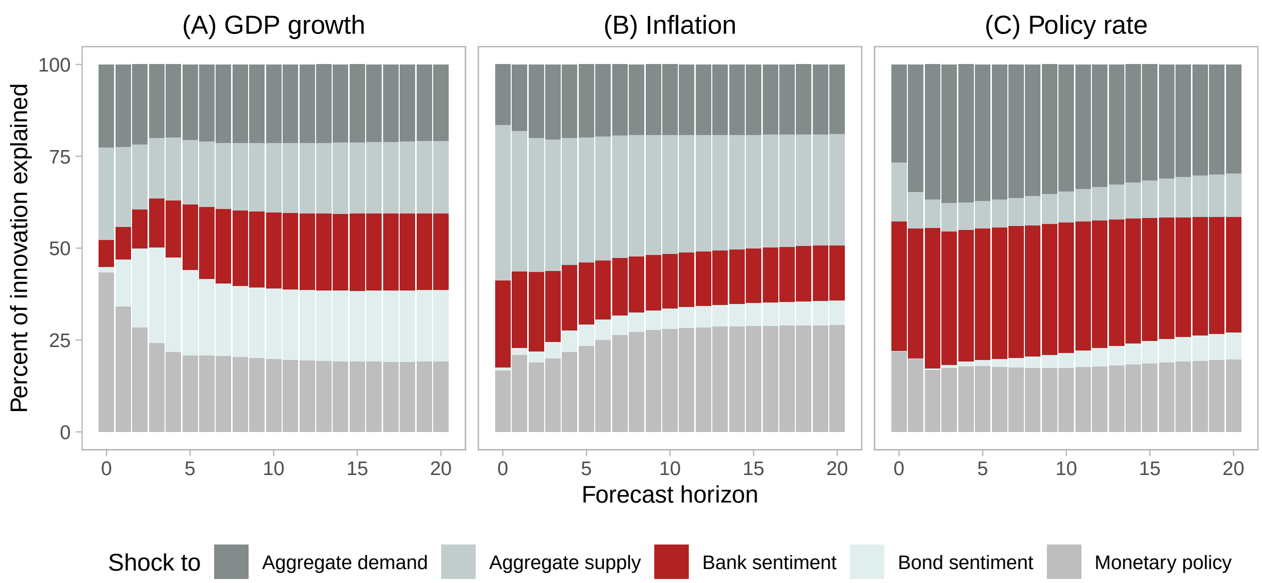


Notes: This plot shows the impulse response functions of macroeconomic activity, prices, and policy rates to financial sentiment shocks. The solid red line represents the mean response to a one standard deviation pessimistic BRS shock. The dashed blue line represents the mean response to a one standard 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 2020.

it also accounts for large portions of variation in these phenomena over the business cycle. Figure 7 shows the percent of business cycle variation in GDP growth, inflation, and the policy rate explained by the five structural shocks that drive this empirical economy, while Table 4 presents the analogous steady state variance decomposition.

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 falling to 28.6 percent in steady state. In comparison, real and policy shocks account for less but still substantial

Figure 7: Business cycle 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 2020.

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.

Table 4: Steady state decomposition of macroeconomic activity and prices

	Percent of innovation explained by:				
Endogenous Variable	Bank Sentiment	Bond Sentiment	Aggregate Demand	Aggregate Supply	Monetary Policy
GDP growth	20.5	18.7	20.2	21.6	18.9
Inflation	16.6	7.31	19.4	27.9	28.8
Policy rate	28.6	7.89	28.0	14.4	21.1
Corp. Bond Premium	16.3	44.4	14.6	13.9	10.9
Bank Lending	20.9	17.5	20.3	21.0	20.3

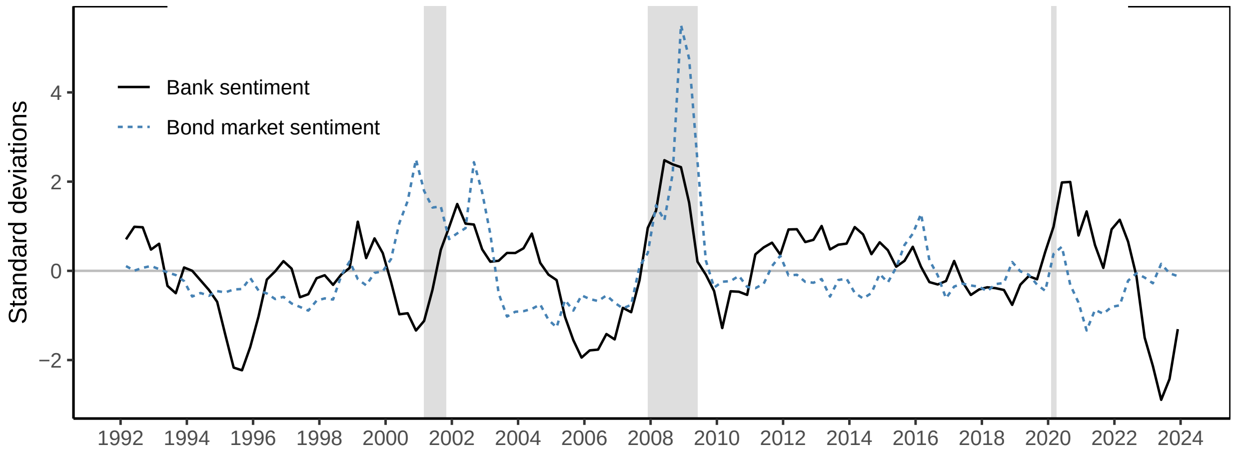
Notes: This table shows the variance decomposition of activity and prices in steady state. Each shock's marginal contribution is calculated as the mean draw from the Gibbs sampling chain, then rows are normalized to sum to one hundred percent. Steady state is approximated by the 100 quarters ahead forecast error. 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 2020.

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

Figure 8: 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 2024. Gray shaded regions denote NBER dated recessions.

activity, trade, prices, and financial assets. However, 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. 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 two key reasons. First, the corporate bond market is the asset market most often analyzed in studies of investor risk sentiment. 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 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.

Before comparing the effects of bank and bond market sentiment shocks, I will first discuss the differences in the sentiments themselves. Figure 8 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 GFC 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.

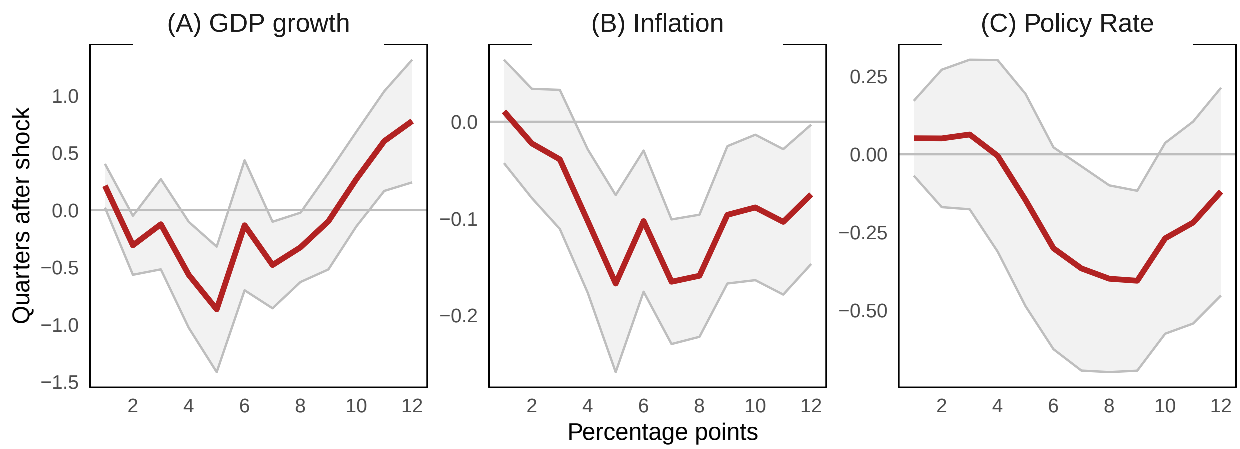
Turning to comparing the effects of sentiment shocks, bank sentiment shocks induce longer lived recessions in economic activity and prices and monetary policy easings than analogous bond market sentiment shocks. Figure 6 shows that a one standard deviation bond market sentiment shock actually induces 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 4, 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.

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 10, but now focus on an alternative set of outcomes of interest: activity, prices, and monetary pol-

Figure 9: 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 bank 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 2020.

icy. 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 9 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 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. 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 should be 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.

7.1 Micro-econometric model and identification strategy

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

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

where $y_{l,f,b,t}$ is the loan-level outcome of interest, such as loan rate, amount, and covenant requirements, indexed by loan l, firm f, bank b, and date t; $\gamma_{f,t}$ denotes a firm-quarter fixed effect, and $\gamma_{f,b}$ a borrower-lender fixed effect; $BRS_{b,t}$ is the bank risk sentiment of bank b at date t; Θ_t collects the vector of loan and firm characteristics.

My elasticity of interest when evaluating Equation 12 is δ, the response of loan outcome $y_{l,f,b,t}$ to a one percentage point change in a bank's risk sentiment. I will study four loan outcomes in particular: the loan rate, log loan amount, maximum debt to EBITDA covenant, and the presence of covenants more generally. That is, I am interested in how a bank-level risk sentiment shock impact the price, quantity, and quality of loans.[24]

[24] 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

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.[25] These three steps 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.

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

Data. The loans studied in this analysis are in fact individual facilities, also known as tranches, of syndicated loans from the LPC DealScan database.[26] 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.[27] 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

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.

[25] 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.

[26] 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.

[27] 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.

Table 5: 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

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.

BRS.[28] 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

[28]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 6: 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

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.

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 to distribution pipeline, see Fleckenstein et al. (2020) and Buchak et al. (2024a,b).

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 effects are not precisely estimated.

On the one hand, Table 5 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 amortization (EBITDA) ratio declines by 0.558 ratio points. The average ratio in the sample is 3.403, meaning the shock produces a 16.4 percent tightening from the average. As discussed in works such as Lian and Ma (2021), Drechsel (2023), and Caglio et al. (2021) these earnings-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 6 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 re-negotiated 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 5 and 6 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.

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 and a semi-structural approach I construct an empirical measure of BRS. I find that aggregate BRS is counter-cyclical with spikes during 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 tightening earnings-based borrowing constraints.

These findings have important implications for both academics and policymakers. For academics, my findings suggest that risk sentiments should be considered as a factor in models of 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. Although a normative analysis of policy responses to sentiment shocks is left open to future research.

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A Analytical model equilibrium and aggregate effects of BRS

I present the competitive equilibrium of the analytical model, a series of predictions for how bank sentiment may impact aggregate lending outcomes, and highlight how credit demand may influence loan rates.

A.1 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 $\{R_t, R_{i,t}, C_{i,t}\}_{t=0,i=1}^{\infty,N}$, 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 $N_{i,t}$, $C_{i,t}$, and $\psi_{i,t}$ that satisfies its profit maximization problem, Equation (4)
- The Broker sources specialized loans $\{L_{i,t}\}_{i=1}^{N}$ to create consumer loan L_t such that its profit maximization problem, Equation (2), is satisfied
- Households and Firms take out loans L_t^D according to the demand schedule, Equation (1)
- The aggregate loan markets clear, $L_t^D = L_t$, as well as the market for each specialist loan

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

A.2 Bank risk sentiment and aggregate outcomes

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

A.2.1 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:

$$R_t = \sum_i^B R_{i,t} \left(\frac{L_{i,t}}{L_t} \right) \tag{13}$$

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:

$$R_t = \frac{1}{\beta} \sum_i^B \frac{\theta_{i,t}}{\theta_{i,t} - 1} \frac{1}{1 - E\lambda_{i,t+1}} \frac{L_{i,t}}{L_t} (C_{i,t} + \Phi'(L_{i,t} - N_{i,t})) \tag{14}$$

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.

A.2.2 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:

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

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:

$$L_t^D = P - AR_t + \pi_t \implies R_t = \frac{P - L_t - \pi_t}{A} \tag{15}$$

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

B 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:

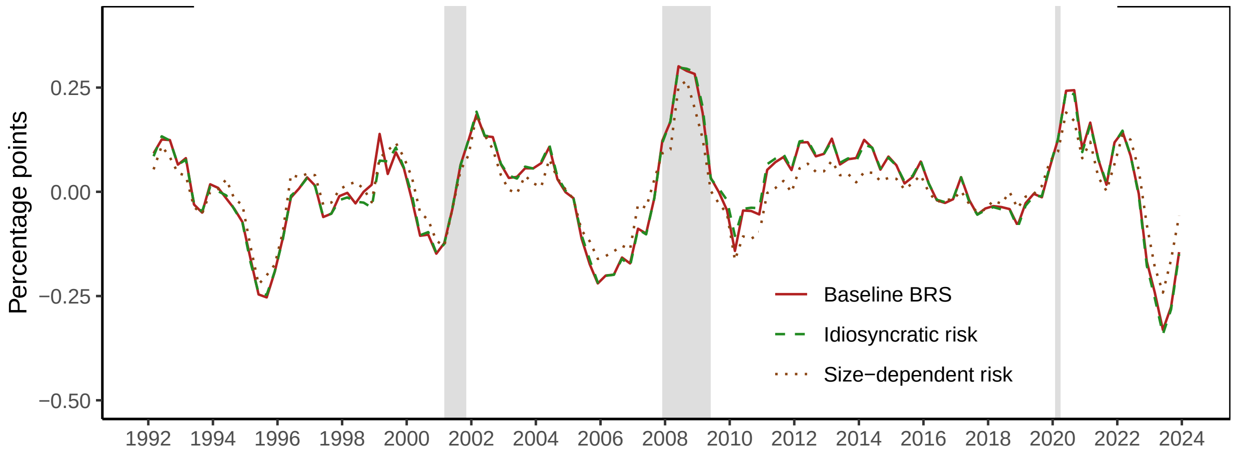
$$E_{RE}(\lambda_{i,t}|s_{i,t-1}) = E_{RE}(\lambda_{i,t}|\lambda_{i,t-1}) = \rho \lambda_{i,t-1}$$

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

Figure 10: 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 2024.

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 10 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).

C Alternative definitions and potential sources of BRS

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.

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 examine these two alternative definitions of bank risk sentiment as potential sources of my measures of bank risk sentiment. 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.

C.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.[29] 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.

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

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

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

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

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

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

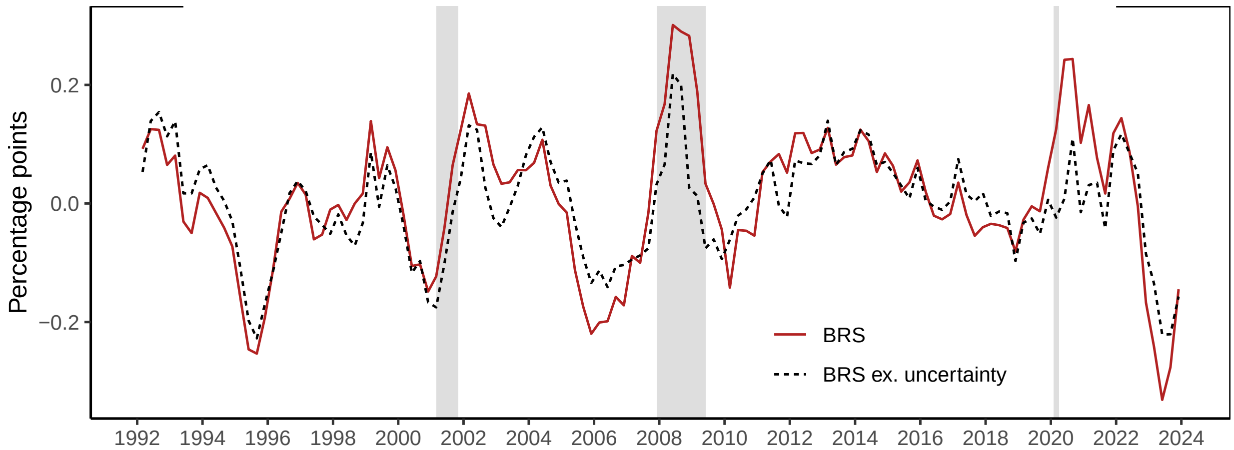
$$\begin{aligned} N_{i,t} &= N_{i,t-1} + \Pi_{i,t-1} \\ L_{i,t} &= \frac{1}{\alpha}\frac{R_t^{\theta-1}}{R_{i,t}^{\theta}}L_t \\ E(R^p_{i,t}) &= (1-E\lambda_{i,t+1})R_{i,t} \end{aligned}$$

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

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

where $\alpha \in [0,1]$ is assumed to be decreasing in risk-aversion, γ_t, so that as risk

Figure 11: 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 2024.

aversion increases the loan rate increases.[30] That is, as the Household becomes more risk averse, its demanded compensation for holding risk increases.

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

C.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

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

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.

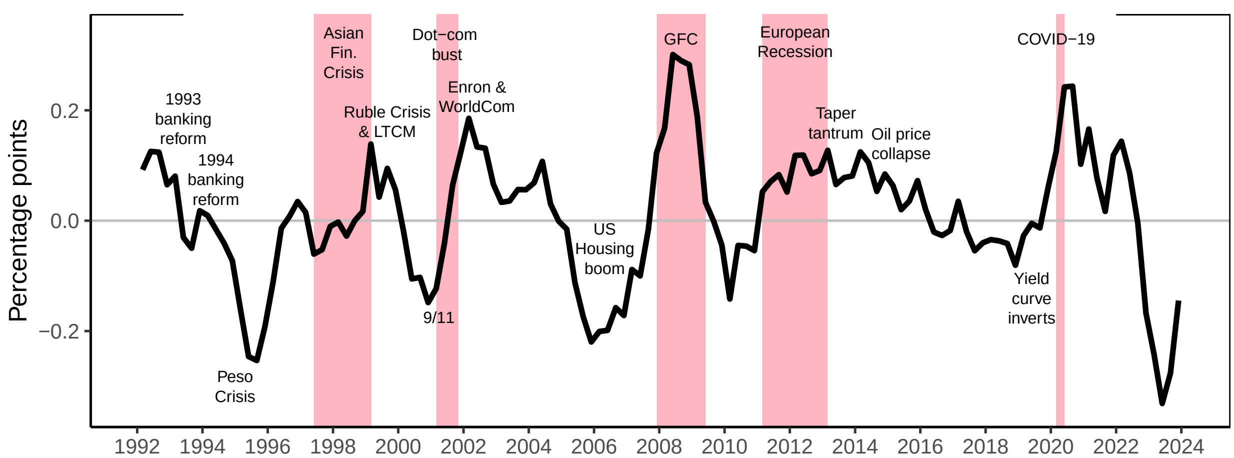
Figure 11 compares the baseline BRS and sentiment removing the effect of aggregate uncertainty. BRS appears qualitatively unchanged by removing aggregate uncertainty. However, select crisis periods appear to be significantly driven by uncertainty. For example, BRS is attenuated during both the Ruble crisis and COVID-19 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.

D Additional aggregate BRS robustness checks

Measuring aggregate BRS is robust to a number of modifications and across various sub-samples. 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.

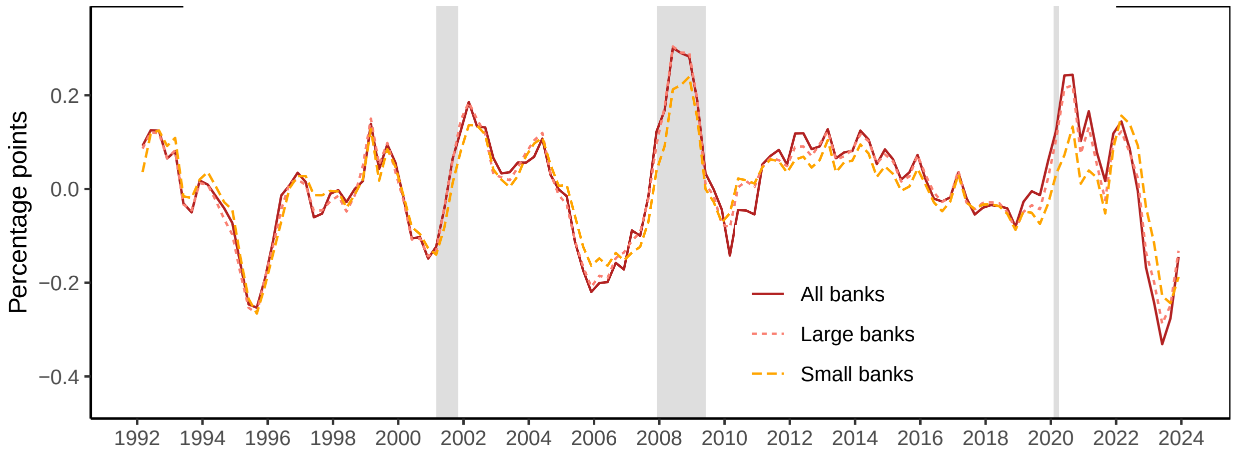
First, there is little difference in the aggregate BRS when comparing sentiments across large banks and small banks. Figure 13 shows the quarterly loan-weighted average bank-level risk sentiments for large banks (those in the top 15 percent of banks, in a quarter, by total assets), small banks (those 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

Figure 12: 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 losses, 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 2024.

Figure 13: Bank risk sentiment by bank size

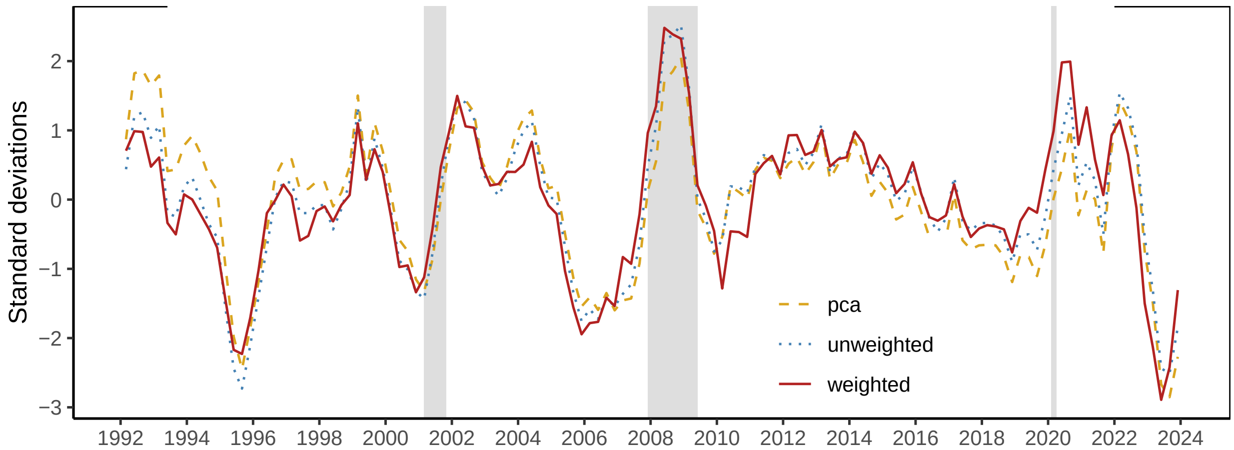


Notes: Solid red line depicts the loan-weighted average bank-level risk sentiments. The pink dashed line depicts the loan-weighted average bank-level risk sentiments of the top 15% of banks by net worth in a given quarter, while the orange long-dashed line depicts the loan-weighted average bank-level 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 2024.

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.

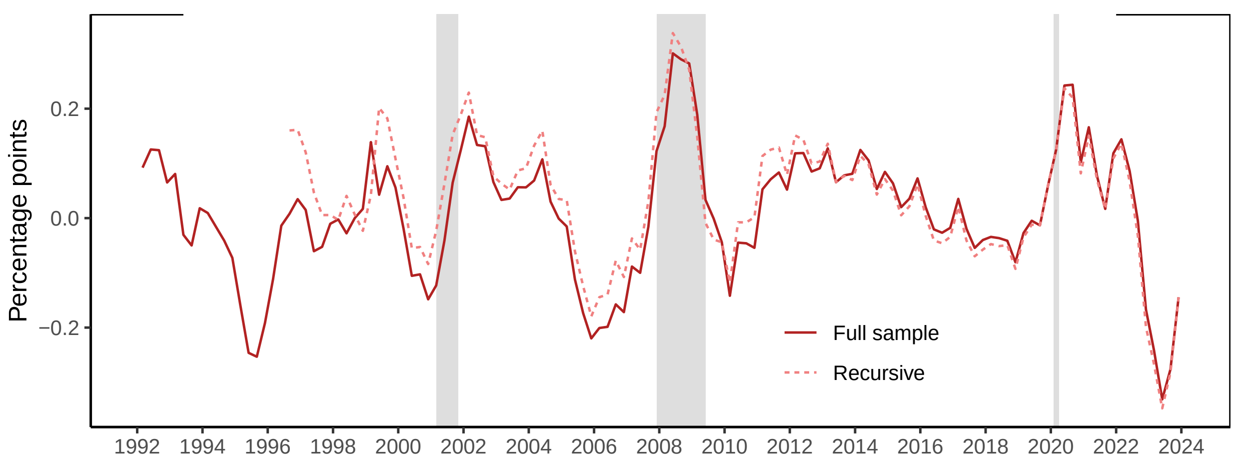
Second, there is little difference in aggregate BRS when using different weighting schemes to average over bank-level sentiments. Figure 14 shows the quarterly quarterly loan-weighted average, unweighted average, and first principal component weighted, bank-level risk sentiments. The loan-weighted measure 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)

Figure 14: 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 2024.

Figure 15: 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 2024.

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 15 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.

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.

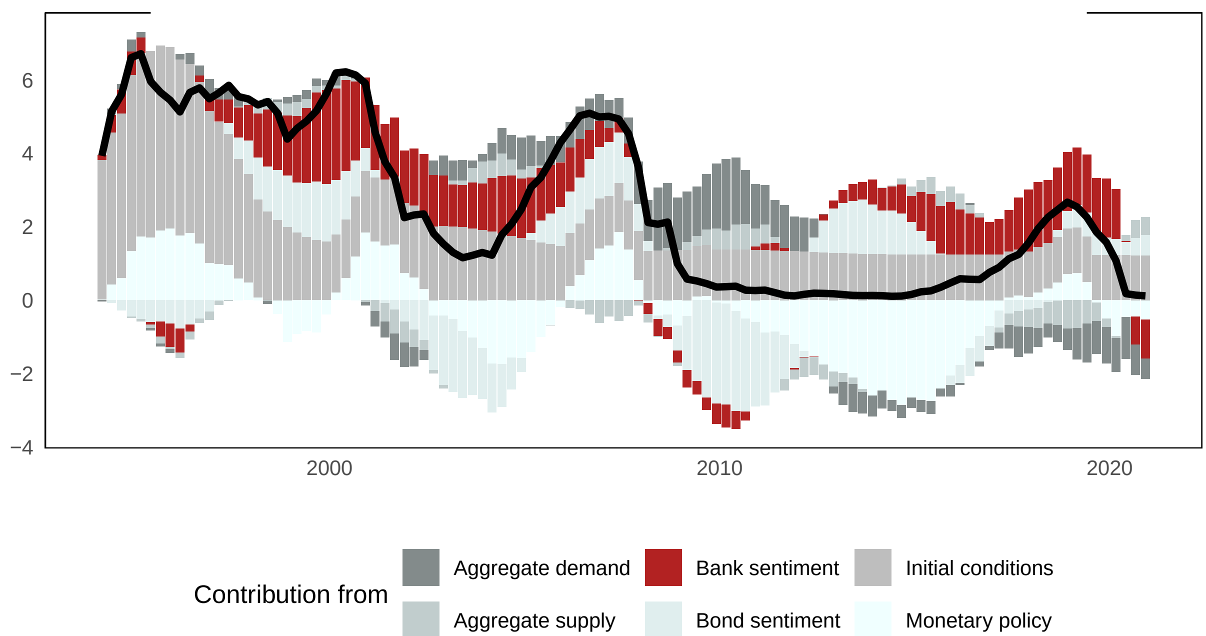
Note that, by construction, the linear mapping between structural shocks and reduced form errors is preserved such that: $BB' = CQQ'C' = CC' = \Sigma$.

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.

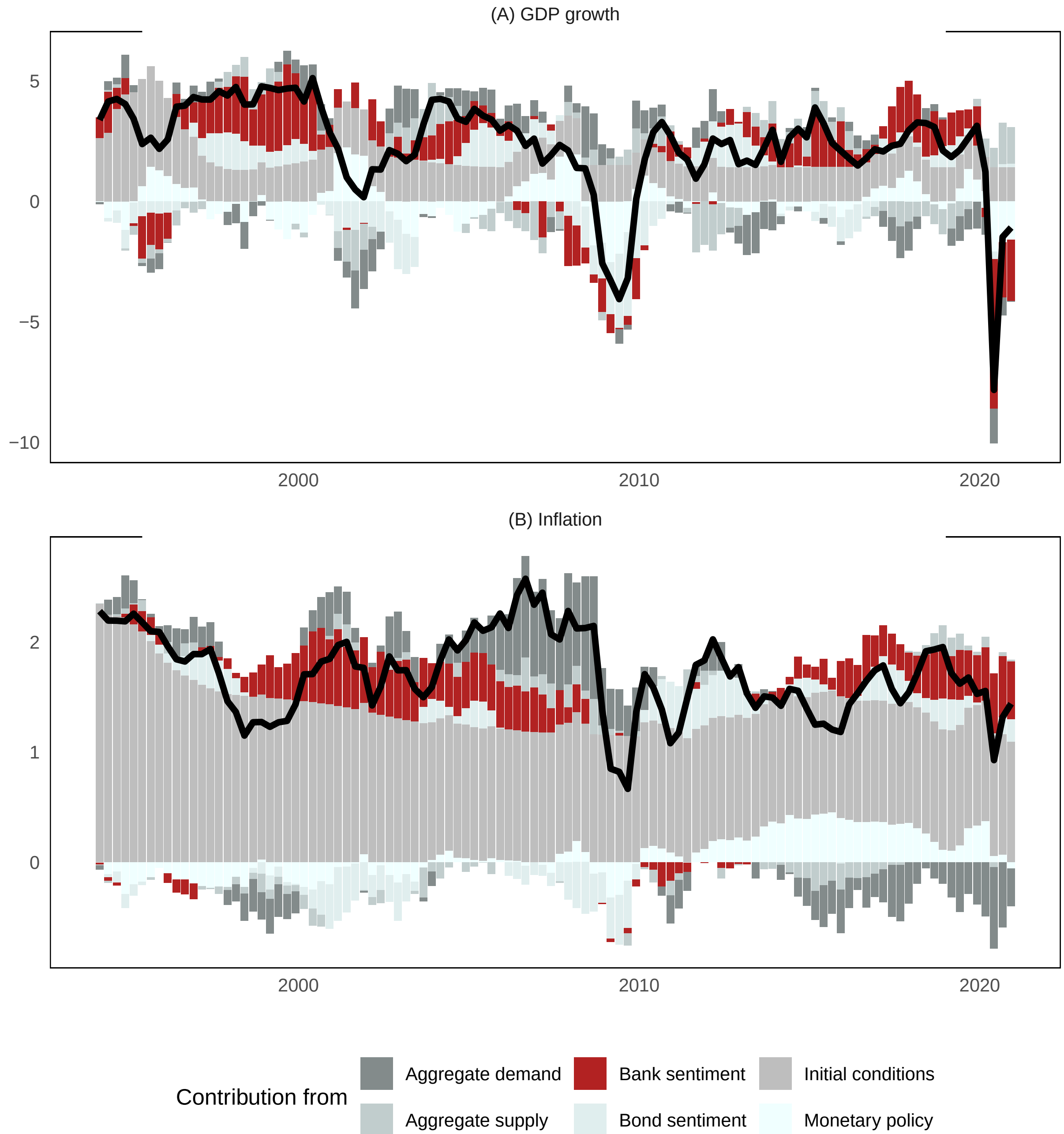
BRS plays a prominent role in determining the policy rate. Figure 16 shows the historical decomposition of the one year Treasury rate into contributions from initial conditions, aggregate demand, supply, monetary policy, bond market sentiment, and bank risk sentiment shocks. The policy rate appears to be actively lean-

Figure 16: 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 2020.

Figure 17: 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 2020.

ing 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-19 pandemic, then it was pushing the policy rate rate towards a more accomodative level. The policy rate 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:

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

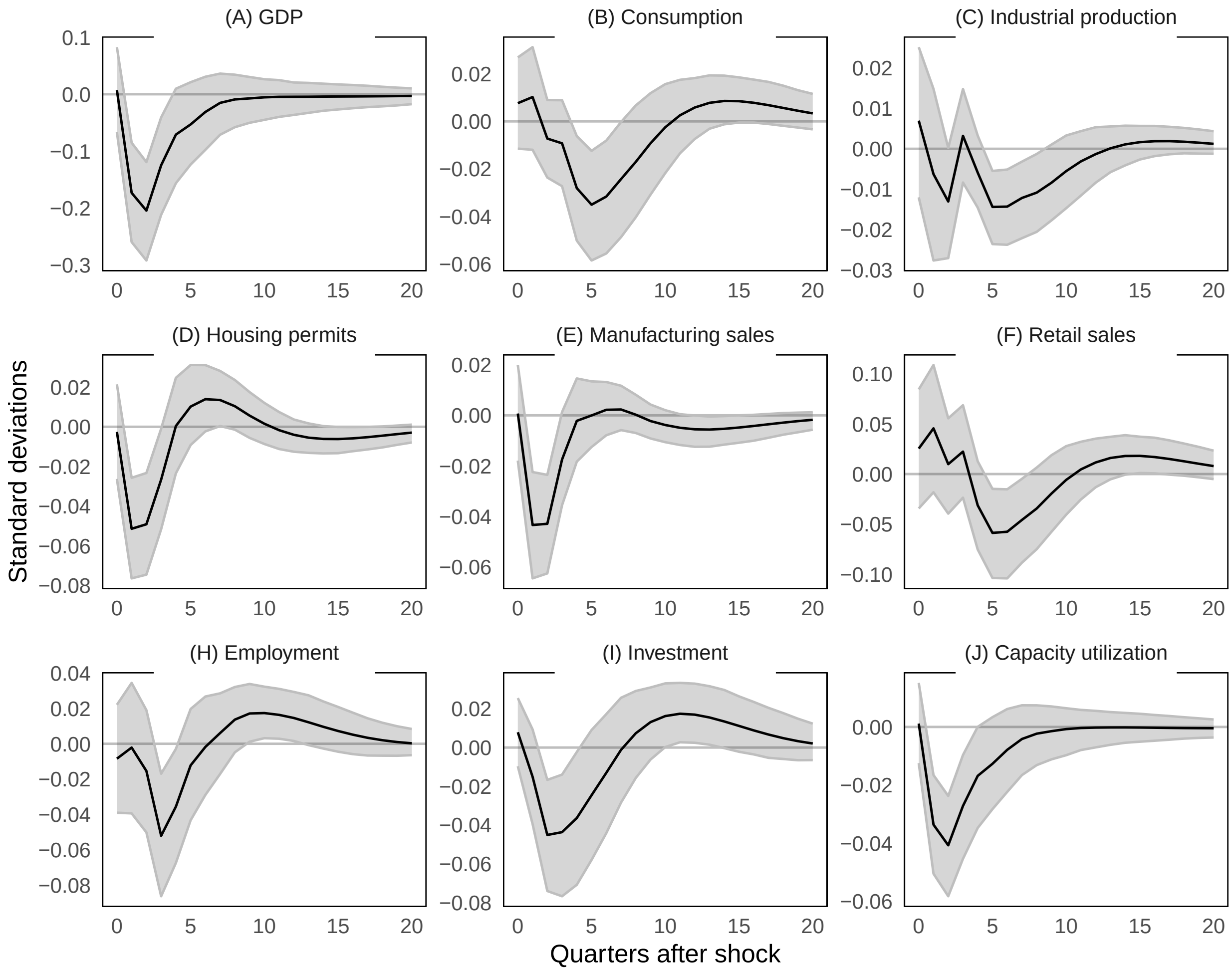
$$X_t = A X_{t-1} + \varepsilon_t, \quad \varepsilon_t \sim N(0, \Sigma_\varepsilon) \tag{19}$$

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.[31] Reduced form disturbances vectors, η_t

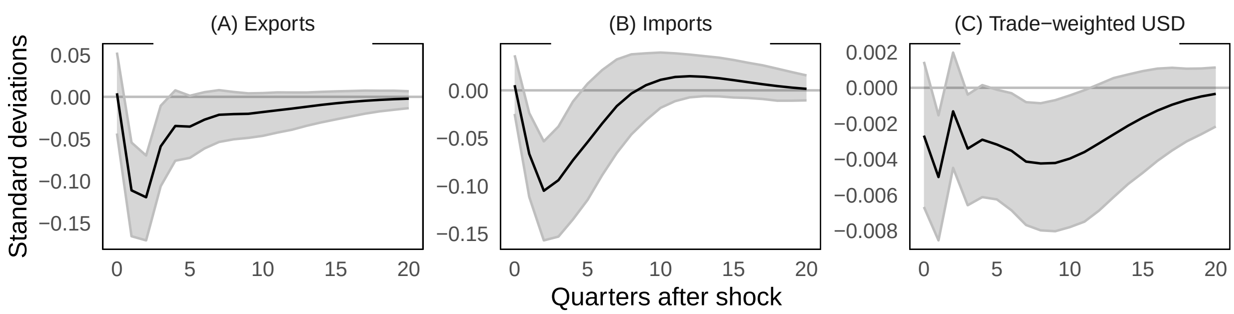
[31] Two lags are chosen by both AIC and BIC criterion for the full sample, as well as in the bootstrapping algorithm

Figure 18: Macroeconomic response to a bank risk sentiment shock

(A) Economic activity



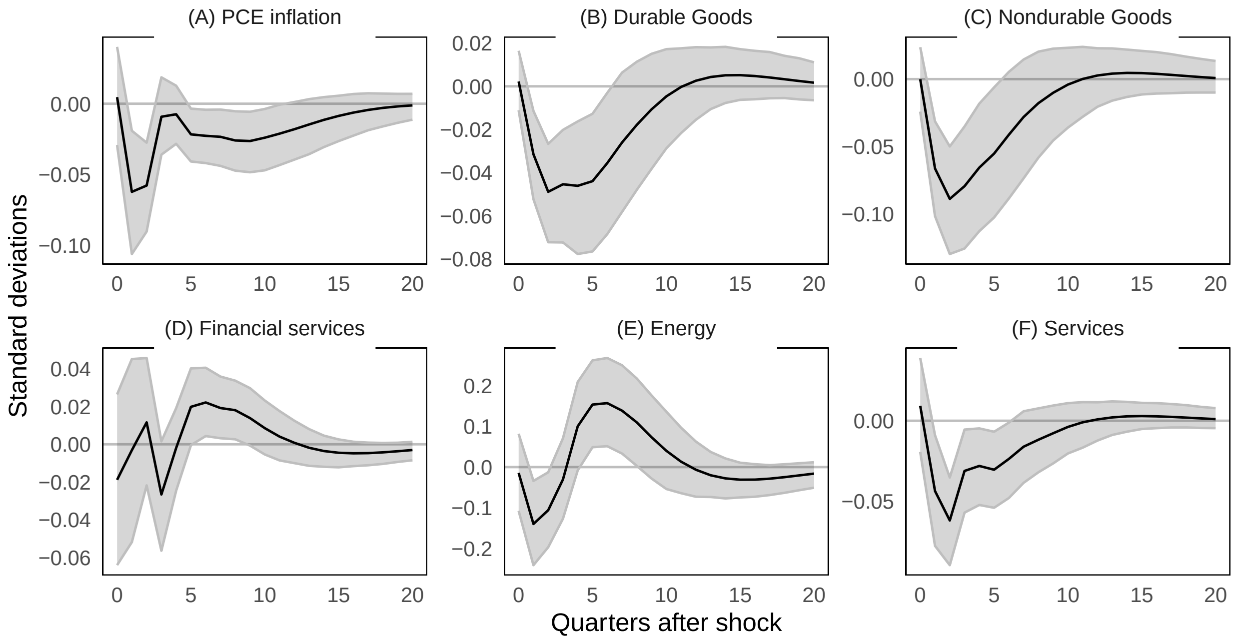
(B) Trade



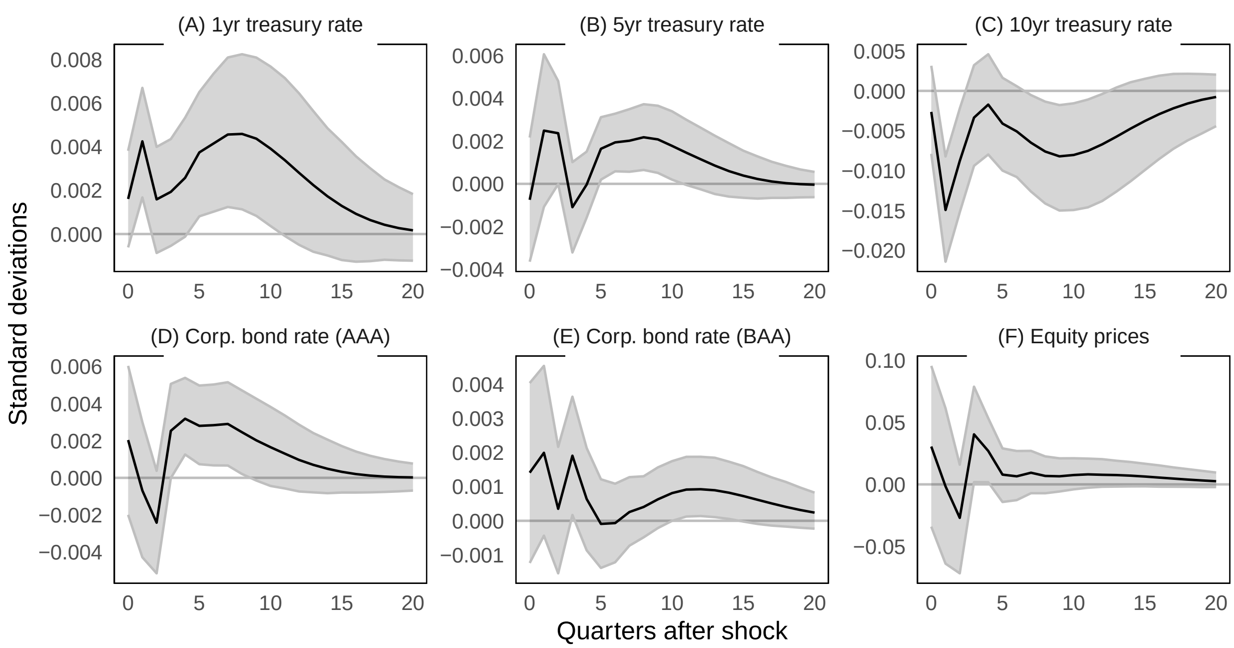
Notes: This figure reports the impulse response functions of select macroeconomic and trade variables to an unanticipated one percentage point increase in aggregate BRS. Solid black lines represent the responses to the equally weighted aggregate BRS, dotted blue lines represent responses to loan weighted 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 18: 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.

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.[32]

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.

used to calculate confidence intervals. The results presented are robust to using four lags.

[32] 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.

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

Economic activity deteriorates. Figure 18 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

[33] 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.

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

Table 1 summarizes the sample used to estimate the BRS panel regression. The sample includes 946.3 thousand bank-quarter observations, running from 1992 to 2024. The average bank-level loan rates 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 loan rates in my econometric model to ensure a the dependent variable follows a stationary process. The average change in the loan rates is slightly negative, but close to zero, at approximately negative 5.1 basis points. However the distribution of changes indicates a large dispersion in potential outcomes across banks, with a fifth percentile near negative 39 percent and a 95th percentile near 26 percent. Bank-level characteristics also display large variation across the sample; state-level loan HHI are highly skewed, with a mean of 0.004, median of 0.001 and 95th percentile near 0.0016. 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.

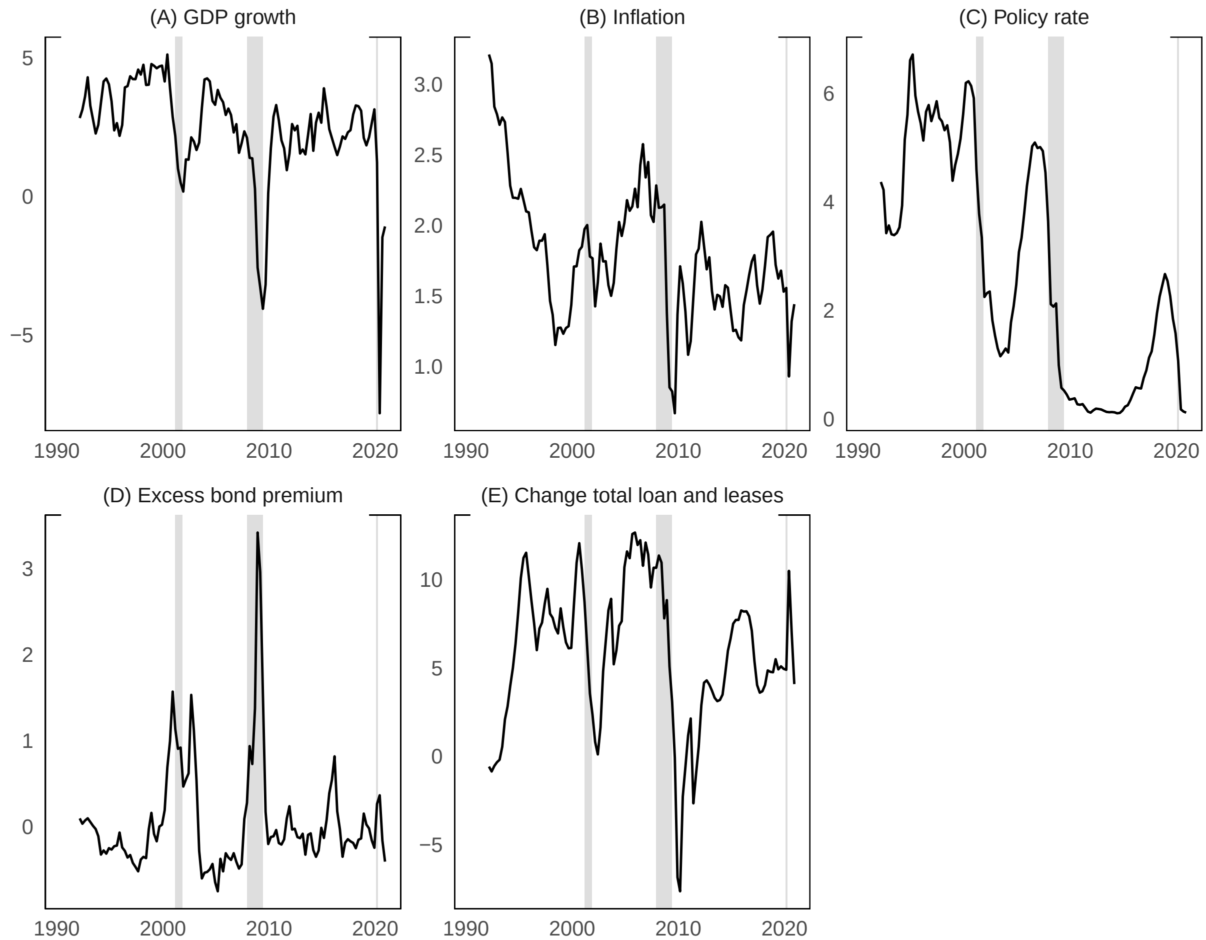
Table 7: Bank-level variable details

Variable	Formula	Call Report variables
Δ Loan rates	$\frac{\text{loan interest income}_t}{\text{total loans}_t} - \frac{\text{loan interest income}_{t-4}}{\text{total loans}_{t-4}}$	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

Macroeconomic variables are standard. GDP growth is the four quarter percent change in real GDP, published by the U.S. Bureau of Economic Analysis (BEA). Inflation is core PCE inflation, published by the BEA. The policy rate is the one year Treasury yield, reported in the Federal Reserve Board's H.15 Selected Interest Rates statistical form. The Excess Bond Premium is detailed in Gilchrist and Zakrajšek (2012). Change in total loan and leases is the four quarter percent change in total loan and leases in bank credit, for all commercial banks in the U.S., reported by the Federal Reserve Board's H.8 Assets and Liabilities of Commercial Banks in the United States statistical form.

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 2020. Gray shaded regions denote NBER dated recessions. All variable are presented in percent.

H.3 Loan-level analysis data

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

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.

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.