Banks, Sentiments, and Business Cycles*

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Abstract

This paper measures the "animal spirits" of U.S. banks and asks whether they are an important determinant of credit conditions and source of business cycle fluctuations. I first construct a novel semi-structural measure of bank-level sentiment, revealing heterogeneous animal spirits across banks and common dynamics marked by surges in pessimism during crises and excessive optimism during periods of elevated asset prices. I then jointly estimate the contribution of shocks to bank and household sentiment, aggregate demand and supply, financial risk, and monetary policy to fluctuations in macroeconomic conditions using a structural BVAR framework. Bank sentiment shocks explain 38% of the business cycle variation in credit conditions, 10% in output, 22% in prices, and 26% in the policy rate.

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1 Introduction

Economic sentiments, or animal spirits in the language of Keynes, have long been hypothesized to shape investors' willingness to supply credit and play a central role in driving business cycle fluctuations. This is because the potential effects of *animal spirits* —an economic agent's irrational optimism or pessimism about the current and future state of the world— on the economy are quite clear.[1] When banks become excessively pessimistic, they forecast greater losses in their loan portfolios and, in turn, increase loan rates to compensate for the expected losses. As loan rates rise, firms and households are priced out of debt markets, leading to a subsequent decline in economic activity that reinforces the precipitating fear, making the credit crunch self-enforcing. A similar mechanism may also explain how banks' excessive optimism can lead to a credit boom.

However, economic sentiments are unobservable and difficult to measure, which has limited empirical evidence of their impacts on the supply of credit and the economy more broadly. Two leading empirical strategies for studying sentiments have emerged. The first relies on risk premia in asset markets to infer how investors feel about the current and future state of the economy.[2] While this approach yields plausible proxies for sentiments, it cannot disentangle whether those sentiments originate from the demand or supply side of the market. As a result, these measures cannot directly confront the Keynesian hypothesis that animal spirits drive business cycles through their effects on investors' willingness to supply credit. A second approach extracts sentiments from surveys of households or firms about their economic outlook.[3] However, because these surveys capture demand-side sentiments, they remain silent on how animal spirits shape the credit supply.

This paper measures the animal spirits of U.S. banks and asks whether they are an important determinant of investors' willingness to supply credit and a source of business cycle fluctuations. The answer is yes. To reach this conclusion, I first construct a novel measure of bank-level sentiments and find that they are characterized by sharp increases in pessimism during periods of crisis, excessive optimism during periods of elevated asset prices, and with substantial heterogeneity across banks. I then use this new measure as an instrument for bank sentiment shocks in a standard vector-autoregression framework and find that banks' animal spirits are an important source of business cycle fluctuations in credit conditions, activity, prices, and the monetary policy rate —even relative to aggregate demand, supply, monetary policy, financial risk, and household sentiment shocks.

[1] I will use the terms sentiments and animal spirits interchangeably. This particular definition of animal spirits may be micro-founded as shocks in a noisy signal and dispersed information problem, as in Angeletos & La'o 2013.

[2] See Akerlof & Shiller 2010 or López-Salido *et al.* 2017 for a recent review.

[3] See Lagerborg *et al.* 2023 for a recent example and review of the literature taking this approach to measuring sentiments.

I will study animal spirits through the lens of *bank risk sentiment* (BRS), a bank's expectation of future loan losses in excess of the rational expectations forecast of those losses. However, a bank's forecast of loan losses, let alone its rational expectations benchmark, is not observable. I overcome this challenge by developing a semi-structural estimation strategy that closely mirrors the revenue residual approach commonly used in the firm dynamics literature to estimate non-financial firm-level productivity, a similarly unobservable object of economic interest (see Blackwood *et al.* 2021 for a recent detailed discussion on measuring productivity).

I start by developing a structural model of the U.S. banking sector. The theoretical framework embeds animal spirits shocks à la Angeletos & La'o 2013 into a heterogeneous banking model similar in spirit to Jamilov & Monacelli 2025. The resulting model is rich enough to take to the data but tractable enough to yield a closed form solution to a bank's loan rate schedule. To summarize the setting: Banks pay capital funding and regulatory costs to issue risky loans in an oligopolistic lending market, satisfying borrower's CES demand for credit products, but are subject to noisy sentiment shocks when trying to assess loan default risk. A bank's loan rate equation is then shown to be a function of the bank's market power, capital costs, regulatory costs, and expected loan default rate. Importantly, a bank's risk sentiment —as the difference between the bank's forecast of its loan losses and its rational expectations forecast of these losses— is therefore embedded in, and identifiable through, the lens of the structural loan rate equation.

I estimate the bank-level pricing schedule in three steps: 1) log-linearize the structural loan rate equation; 2) create observable proxies for loan markups, capital costs, regulatory costs, and expected loan losses; and 3) estimate the linearized loan rate equation using standard panel-data methods. The resulting estimated pricing schedule can be used to decompose loan rates into observable pricing factors and unobservable bank risk sentiments.

Bank risk sentiments are then recovered from the estimated bank-level loan rate decomposition. Bank-level sentiments are identified as the residualized loan rate, and account for as much as 10 percent of loan rate fluctuations. Then, with estimated bank-level sentiments in hand, creating the micro-to-macro measure of aggregate sentiments is straightforward: aggregate bank risk sentiment is the quarterly, loan-weighted, average bank-level sentiment index. This is directly implied by the CES preferences of the generic borrower representing the demand side of the theoretical framework and the estimated elasticity of intermediate loan substitution. Using this approach, I estimate bank-level risk sentiments at a quarterly frequency for the universe of U.S. commercial banks from 1984 through 2023 using regulatory Call Reports.

Aggregate bank risk sentiment is broadly acyclical, but characterized by sharp increases in times of financial stress and uncertainty in the United States. For example, BRS increases during the Savings and Loans (S&L) Crisis, Dot-com bust, Global Financial Crisis (GFC), and COVID-19 pandemic. Conversely, banks appear to be excessively optimistic during the mid-2000s housing boom, among other asset bubbles. It is important to clarify that while uncertainty and financial stress may lead to a rational increase in forecasted loan losses, the rise in bank sentiment indicates that banks become even more pessimistic about future states of the economy than is necessarily implied by a rational expectations view of the world. That is, BRS indicates banks become *excessively* pessimistic in times of uncertainty and financial stress.

However, focusing on the common movements in banking sector sentiments obscures a large degree of heterogeneity at the bank-level. There is significant dispersion in bank-level sentiments, although the extent of the dispersion varies over time. Disagreement in sentiments is both countercyclical, spiking during recessions, as well as in secular decline. These differences in bank-level sentiments may occur because banks are either hit with different sentiment shocks or they have different biases and persistence in sentiments. I show it is a combination of both, although banks are on average unbiased and experience relatively small, short-lived, sentiment shocks.

Before turning to use the estimated bank risk sentiments to proxy for sentiment shocks in my macroeconomic analysis, I verify that they may indeed be interpreted as animal spirit shocks. I first show that bank-level risk sentiments do not contain systematically useful information for forecasting bank-level default rates. That is, bank risk sentiments are noise and should not be used in a rational expectations forecast of loan losses. I then show that bank-level risk sentiments are not forecastable with bank characteristics. That is, bank risk sentiments are unanticipated, noisy signals and may be interpreted as animal spirits.

With a measure of bank sentiment in hand, I turn to evaluating the relative importance and transmission of sentiment shocks for business cycle fluctuations in credit conditions, prices, activity, and monetary policy. To do so, I study the economy through the lens of a traditional macroeconometric tool, the structural Bayesian vector-autoregression (BVAR). A BVAR is the ideal tool in this case because, as a generative model, it can be used to both estimate a collection of structural shocks as well as evaluate their impact on the macroeconomy. I will jointly estimate and compare the effects of six structural shocks of interest: bank sentiment, household sentiment, aggregate demand, aggregate supply, monetary policy, and financial risk. The two sentiment shocks will be identified with an instrumental variables approach (bank sentiment using my measure of BRS and household sentiment using mass shootings in the U.S. as in Lagerborg *et al.* 2023) while the remaining shocks will be identified with theoretically motivated sign restrictions as in Uhlig 2005.

Bank sentiment is the dominant force driving credit conditions and is important as aggregate demand and aggregate supply shocks in determining policy rate fluctuations. In comparison, bank sentiment is less impactful on inflation in the short term but grows to be the most influential force in the medium term. More concretely: bank sentiment shocks account for 38 percent of business cycle variation in credit conditions, 10 percent of variation in activity, 22 percent of variation in prices, and 26 percent of variation in the monetary policy rate.

While bank sentiment is an important source of business cycle fluctuations on average, its actual contribution to the economy varies over time. Most notably, bank sentiment helped set the stage for, amplified, and then slowed the recovery from the GFC. Moreover, bank sentiment is shown to slow economic recovery after most U.S. recessions, not just the GFC.

Having found bank sentiments to be an important determinant of credit conditions and source of business cycle fluctuations, I lastly turn to understanding the impact and transmission of sentiment shocks through bank lending to the broader economy.

First, a pessimistic bank sentiment shock increases the loan rate premium (the loan rate in excess of the prevailing policy rate) while decreasing bank 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. The deterioration in bank lending market conditions then spills over to other financial markets, resulting in an increase in the corporate bond rate, decline in stock prices, and decrease in Treasury rates along the yield curve as a general flight to safety takes place.

The tightening financial conditions then affect economic activity, prices, and policy. The pessimistic bank sentiment shock acts like a negative demand shock, slowing activity and inflation, while inducing a monetary policy easing. The shock is felt broadly throughout the domestic economy, but most acutely in sectors where consumers purchase goods and services on credit. For example, durable consumption (e.g. car purchases) declines more than nondurable consumption (e.g. groceries). As well as across the global economy, with both import and export growth declining by more than one percent within a year after the shock. The severity of the decline in gross trade may additionally highlight the international transmission of U.S. financial sector sentiment shocks.

Contributions and related literature. This paper contributes to the broad literatures on sentiments and the macroeconomic impacts of non-rational decision making, the sources business cycle fluctuations, and the macroeconomic effects of bank lending. The first contribution is the semi-structural measure of animal spirits in the U.S. bank lending market, and is twofold. First, there is no other measure of animal spirits in the bank lending market, despite its importance to the U.S. financial system as a primary source of credit for small businesses and households. Second, the measurement strategy is a methodological contribution that bridges the gap between the two most common methods for measuring sentiments and ameliorates their respective shortcomings.

The first common measurement strategy attempts to quantify economic confidence based on surveys of households and businesses' outlooks on the current and future state of the economy. For example, Barsky & Sims 2012, Mian *et al.* 2015, and Lagerborg *et al.* 2023 use the University of Michigan Survey of Consumers, while Faccini & Melosi 2022 and Bianchi *et al.* 2022 use the Survey of Professional Forecasters. The strength of this approach is that it can be specific about what type of economic agent is being studied and the horizon they are concerned with, or even more specifically, track individual agents over time. The agent specificity accessible in this strategy is useful when controlling for individual bias or institutional details that may otherwise confound the decomposition of forecasts into sentiments. However, its weakness is that it relies on survey responses, and is therefore subject to all the caveats associated with survey data (see Stantcheva 2023 for a description of potential errors and biases in survey data).

The second common measurement strategy focuses on extracting measures of sentiment by decomposing risk premia found in various financial asset markets, such as the corporate bond market, Gilchrist & Zakrajšek 2012, Leiva-Leon *et al.* 2022, and Boeck & Zörner 2023, equity markets, Baron & Xiong 2017 and Pflueger *et al.* 2020, and the syndicated loan market, Saunders *et al.* 2021 and Kwak 2022.[4] This approach has the credibility of a revealed preference measurement strategy, but it is also limited in its ability to identify whose sentiment is actually being studied, thus limited in its ability to account for the institutional details and potential confounders of those agents when measuring sentiment.

[4] 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 measure 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.

I take advantage of banks' unique position in the economy to construct a measure of economic sentiments. Commercial banks' core function is maturity transformation, that is, to transform short-term loans (e.g. deposits) into long-term loans (e.g. business loans and household mortgages). This activity, however, introduces risk in the form of long-term loans defaulting and banks being left to pay back short-term loans out of their own net worth. As a result, banks are constantly evaluating the future state of the economy, what those future states mean for the probability of borrowers defaulting, and embedding those expectations into the loan rates they offer borrowers as compensation for holding that default risk. Therefore, a bank's sentiment about the economy may be recovered through a decomposition of its loan rates. By extracting sentiment from bank-specific loan rates, I achieve the agent specificity of the survey approach —thus can properly account for the institutional details of the subjects being studied— as well as the quantitative precision and revealed preference credibility of the risk premium approach.

The paper's second contribution is its empirical evaluation of sentiments as a source of credit conditions and business cycle fluctuations. In other words, a modern assessment of the Keynesian hypothesis that animal spirits work through credit markets and drive business cycles.

This is certainly not the first work to study the impact of financial market sentiments on macroeconomic outcomes. For example, Minsky 1977 and Kindleberger 1978 discuss the topic from Keynes through the beginnings of the rational expectations revolution of the 1970s and 1980s, while more recently Bordalo *et al.* 2018, Bordalo *et al.* 2019, Bianchi *et al.* 2022, Maxted 2023, and Krishnamurthy & Li 2025 take a quantitative approach to studying the extent that sentiments arising from diagnostic expectations drive boom and bust credit cycles as well as their subsequent effects on business cycle fluctuations.

However, this paper is the first to empirically estimate the macroeconomic impact of sentiment shocks in the bank lending market. As a result, this work most closely complements empirical studies of sentiment shocks originating in the corporate bond market, such as López-Salido *et al.* 2017, Leiva-Leon *et al.* 2022, and Boeck & Zörner 2023. Since the bank lending market is a primary source of credit for agents that cannot access the corporate bond market, these papers together create a comprehensive empirical assessment of how sentiment shocks originating in credit markets may impact macroeconomic activity.[5]

[5] I exclude corporate bond market sentiments because I lack a valid instrumental variable to proxy for bond market sentiment shocks. This is necessary for inclusion alongside the instruments for bank and household sentiment shocks.

This paper additionally complements the large literature studying the macroeconomic impact of sentiment shocks originating among households. For example, Lagerborg *et al.* 2023 empirically estimates the impact and importance of household sentiment shocks on business cycle fluctuations and finds they account for a substantial amount of fluctuations in activity but do not affect credit conditions. In comparison, I estimate that bank sentiment shocks are a primary driver of fluctuations in credit conditions over the cycle but are less impactful for activity. These findings together suggest that sentiment shocks play a meaningful role in driving business cycles, but how they move business cycles depends on which agents' sentiments are shocked.

This paper's third contribution is the behavioral banking model, which builds on the canonical Gertler & Karadi 2011 macro-banking framework and is related to the recent work on heterogeneous banks and their effects on the macroeconomy. However, this model is best seen as complementary to current heterogeneous banking models for two reasons. First, it introduces a distinct form of heterogeneity—behavioral sentiment shocks—rather than relying on heterogeneous capital costs, reduced-form income shocks, or value-at-risk constraints, as in Corbae & D'Erasmo 2021, Jamilov & Monacelli 2025, and Coimbra & Rey 2024, respectively. Second, the model yields an analytical loan rate schedule that can be directly estimated using standard, linear, econometric methods, avoiding the non-linear dynamics and indirect inference techniques typically required in fully quantitative heterogeneous-agent models.

Roadmap. The remainder of the paper is organized as follows: Section 2 details the measurement strategy and estimation, Section 3 introduces and describes the empirical measure of bank risk sentiment, Section 4 evaluates the macroeconomic importance of sentiments, Section 5 traces the transmission of bank sentiment shocks across the broader economy, and Section 6 concludes.

2 Measuring bank risk sentiment

I begin by constructing a measure of banks' animal spirits. This section first describes the theoretical framework necessary to define bank risk sentiment and derive a structural loan pricing equation. The subsequent subsections detail the resulting measurement strategy, required data, and estimated measurement equations.

2.1 Theoretical framework: A model of sentiments in bank lending markets

The theoretical framework begins with the canonical Gertler & Kiyotaki 2010 macro-banking model as a foundation: Risk neutral banks raise capital each period to form one-period loan portfolios, face (indirect) net worth constraints, and satisfy a generic CES loan demand. However, this model will diverge from the canonical macro-banking model in three key aspects.

First, banks are subject to animal spirit shocks, which act as a wedge between their rational expectations forecast of loan losses and their actual forecast of loan losses, following Angeletos & La'o 2013.[6] I choose this particular approach to defining sentiments for two reasons. First, this approach is easily and flexibly 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.

Second, banks operate in a (Cournot) competitive credit market. The oligopolistic market structure has two distinct advantages over the monopolistically competitive environment common in the macro-banking literature. First, oligopolistic competition allows for a tractable representation of both time- and firm-varying markups, which have recently been observed among banks in works such as Corbae & D'Erasmo 2021 and Jamilov & Monacelli 2025. Second, oligopolistic competition falls more in line with the competitive market structure studied in the industrial organization literature of the U.S. banking system, such as in the canonical Monte-Klein banking model or more recently Wang *et al.* 2022, and incorporates competitive pressures on loan pricing into the model.

Third, I impose regulatory costs based on a bank's leverage ratio, similar to Gabaix & Maggiori 2015, rather than a moral hazard friction on raising funds as in Gertler & Kiyotaki 2010. While both frictions incorporate a bank's net worth into its lending decisions and restrict the size of loan portfolios, the regulatory cost reflects real costs and can be extended to nest a tractable mean-variance investor's problem.

2.1.1 Details of the model

Loans. Banks issue one period, uncollateralized, risky loans. Loans are risky because borrowers will default with an exogenous time-varying and bank-specific probability. When loans default, they yield a gross return of zero and the principal is lost.

Demand. A continuum of entrepreneurs require bank loans to fund projects. These entrepreneurs behave as if a representative borrower demands loans to maximizes a CES utility preference over

[6] An alternative approach would have been to define a sentiment formation process explicitly, for example with diagnostic expectations, which have been used to describe banks in structural settings before (see specifically Maxted 2023 or Krishnamurthy & Li 2025). However, this approach is restrictive when taken to the data because it only allows for one type of sentiment to emerge. I take a more structurally agnostic approach.

bank-specific credit products.[7] Thus, loan demand for bank i at time t is standard and given as:

$$L_{i,t} = \psi_{i,t}\left(\frac{R_t}{R_{i,t}}\right)^{\theta_t} L_t \tag{1}$$

where $L_{i,t}$ is bank i's loans, L_t are total banking sector loans, $R_{i,t}$ is bank i's portfolio average loan rate, R_t is the sector-wide loan rate, $\psi_{i,t}$ is the bank-specific appeal (i.e. the CES preference weight), and $\theta_t \geq 1$ is the time-varying elasticity of intermediate loan substitution.[8] The bank's product appeal $\psi_{i,t}$ may subsume aggregate and bank-specific demand shocks, as well as account for non-pecuniary differences that create persistent differences in bank-specific demand (such as the strictness of loan terms and branch locations).[9] Bank appeal will not be used to measure bank risk sentiment, but it will be used later to verify estimated sentiments behave like animal spirits.

Supply. Banks operate in a Cournot competitive loan market with the goal of maximizing their expected present discounted franchise value (i.e. net worth). Bank i's dynamic programming problem is:

$$\max_{L_{i,t}} \mathbf{V}(N_{i,t}, C_{i,t}; L_t, R_t) = \left[\mathbb{E}\Pi_{i,t} + N_{i,t}\right] + \beta_i \mathbb{E}\mathbf{V}(N_{i,t+1}, C_{i,t+1}; L_{t+1}, R_{t+1}) \quad \text{s.t.} \tag{2}$$

$$\Pi_{i,t} = R^*_{i,t} L_{i,t} - (L_{i,t} - N_{i,t})C_{i,t} - \Gamma(L_{i,t}/N_{i,t}) \qquad \text{(Profit function)}$$

$$R^*_{i,t} = (1-\lambda_{i,t})R_{i,t} \qquad \text{(Realized gross return)}$$

$$N_{i,t} = N_{i,t-1} + \Pi_{i,t-1} \qquad \text{(Net worth)}$$

where the bank maximizes profits, and in turn net worth, by issuing $L_{i,t}$ loans. The gross realized portfolio return on loans, $R^*_{i,t}$, is realized at the beginning of period $t+1$ after $\lambda_{i,t}$ percent of borrowers default at the end of period t. Thus, profits $\Pi_{i,t}$ are known at the beginning of period $t+1$.

[7] To be concrete, take the representative borrower as having CES preferences as: $U_t = \left(\int_{i\in\mathscr{B}} \psi_{i,t} L_{i,t}^{\frac{\theta_t-1}{\theta_t}} d_i\right)^{\frac{\theta_t}{\theta_t-1}}$, where the banking sector is the set of banks $\mathscr{B}$, which implies the corresponding aggregate loan rate: $R_t = \left(\int_{i\in\mathscr{B}} \psi_{i,t}^{\theta_t} R_{i,t}^{1-\theta_t} d_i\right)^{\frac{1}{1-\theta_t}}$ Solving the standard cost minimization problem then yields the demand schedule for bank-specific loans.

[8] Note that demand is homothetic across the size of total loans demanded, L_t. The CES demand structure is key in maintaining the tractability of the measurement equation. Non-homothetic preferences over bank-specific loans may allow for the demand ratios for 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.

[9] See Hottman *et al.* 2016 or Eslava *et al.* 2024 for a more thorough description of firm-specific appeal in a similar oligopolistic competition and CES demand setting, but in a non-financial firm application.

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. Future net worth is discounted at rate $\beta_i < 1$. I will make the simplifying assumption that banks are sufficiently well funded to cover loan losses so that I may abstract from the possibility of bank failures.[10]

Banks 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 of bank-specific capital costs is motivated by recent work on banking market power in deposit markets, such as Drechsler *et al.* 2017, and deliberate spatial sorting into markets with cheap deposits, such as Oberfield *et al.* 2024.

Banks also pay a regulatory cost based on their leverage ratio, $L_{i,t}/N_{i,t}$.[11] The regulatory cost function, $\Gamma(\cdot)$, is 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 $\Gamma'(X) \geq 0$ and $\Gamma''(X) \geq 0$ for all $X \in \mathbb{R}$, and $\Gamma(0) = 0$. The convex regulatory cost acknowledges the real presence of such costs borne by banks, as well as establishes a connection between a bank's net worth, $N_{i,t}$, and ability to make loans.

Loan Rates. Bank i solves its loan quantity problem and in turn charges the loan rate:

$$R_{i,t} = \frac{1}{\beta_i} \cdot \underbrace{\frac{\theta_t}{\theta_t - 1} \frac{1}{1 - s_{i,t}}}_{\text{markups}} \cdot \underbrace{\frac{1}{1 - E\lambda_{i,t}}}_{\text{risk compensation}} \cdot \underbrace{(C_{i,t} + \Gamma'(L_{i,t}/N_{i,t}))}_{\text{marginal cost}} \tag{3}$$

so that as the expected default rate, loan market share $s_{i,t}$, cost of capital, or marginal regulatory cost increases, so does the loan rate. Conversely, as the size of the bank increases, $N_{i,t}$, the loan rate decreases and the quantity supplied increases. See Appendix B.3 for the formal proof.

Sentiments. I define a bank's risk sentiment as a shock differentiating the bank's rational expectations benchmark and actual forecast of loan losses. Therefore, I must postulate a law of motion for loan losses in the economy that will provide an analytical forecast to benchmark a bank's expectations against.[12]

[10]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.

[11]Various authors take up a similar object of interest when formulating regulatory costs and constraints. For example, Gabaix & Maggiori 2015 focus on a liquidity ratio while Coimbra & Rey 2024 employ a leverage ratio.

[12]One may take a more agnostic approach to estimating a rational expectations forecast by combining machine learning and large datasets, as in Bianchi *et al.* 2023 or McCarthy & Hillenbrand 2021. However, these approaches threaten to predict the behavioral sentiment of interest in addition to the fundamental risk of interest. Such an over-

In the spirit of Jamilov & Monacelli 2025 I will assume that a bank's loan losses are 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). Additionally, in keeping with evidence presented in Falato & Xiao 2023, the law of motion for loan losses will take on an AR(1) process. Thus, I will postulate that $\lambda_{i,t}$ follows a stochastic process with an idiosyncratic and aggregate component:

$$\lambda_{i,t} = \gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} + \omega_{i,t} \tag{4}$$

where $\lambda_{i,t}$ is a bank's loan default rate in time t, λ_t is the aggregate default rate, and $\omega_{i,t}$ is a mean zero, idiosyncratic, and exogenous shock.

The rational expectations forecast of loan default rates is then:

$$E_{RE}(\lambda_{i,t}) = \gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} \tag{5}$$

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

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

where $\varepsilon_{i,t}$ is the bank's risk sentiment, the bank-level deviation from the rational expectations forecast of loan default rates. With the postulated law of motion for default rates, one can further expand the Bank's loan pricing equation to explicitly reflect the presence of the bank's rational expectations and risk sentiment:

$$R_{i,t} = \frac{1}{\beta} \cdot \frac{\theta_t}{\theta_t - 1} \frac{1}{1 - s_{i,t}} \cdot \frac{1}{1 - (\gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} + \varepsilon_{i,t})} \cdot (C_{i,t} + \Gamma'(L_{i,t}/N_{i,t})) \tag{6}$$

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, $\varepsilon_{i,t}$, leads to an increase in the bank loan rate.

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

prediction problem becomes an identification problem when attempting to isolate sentiment shocks. For this reason I do not adopt these agnostic approaches.

2.2 Measurement strategy

The theoretical framework yields a closed-form solution for a bank's loan pricing equation, which I can in turn use to measure bank-level sentiments in observed data.

The bank's log-linearized loan rate schedule is:

$$r_{i,t} = \gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} + \varepsilon_{i,t} + \log\left(\frac{1}{\beta_i}\right) + \log\left(\frac{\theta_t}{\theta_t - 1}\frac{1}{1 - s_{i,t}}\right) + c_{i,t} + \Gamma'(L_{i,t}/N_{i,t}) \tag{7}$$

assuming small enough marginal capital costs, and marginal regulatory costs. The pricing schedule can then be further written as the linear equation:

$$r_{i,t} = a_i + BX_{i,t} + \varepsilon_{i,t} \tag{8}$$

$$a_i = \gamma_i + \log \beta_i^{-1} \qquad X_{i,t} = \begin{bmatrix} \lambda_{i,t-1} \\ \lambda_{t-1} \\ \log\left(\frac{\theta_t}{\theta_t - 1}\frac{1}{1 - s_{i,t}}\right) \\ c_{i,t} \\ \Gamma'(L_{i,t}/N_{i,t}) \end{bmatrix} \qquad B' = \begin{bmatrix} \rho_1 \\ \rho_2 \\ 1 \\ 1 \\ 1 \end{bmatrix}$$

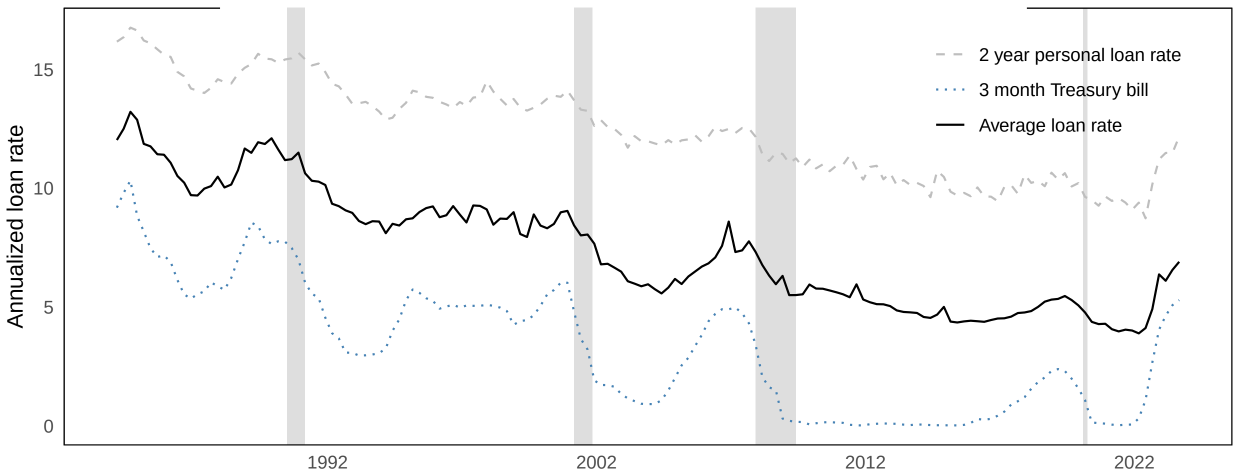
which is easily recognizable as a linear fixed effects panel model that can be estimated with standard econometric techniques given observable proxies for the covariates $X_{i,t}$.

Sentiments are easily recovered from the estimated Equation 8. First, bank-level sentiment is isolated as the unobservable component of the net loan rate, and is captured by the residual of the resulting loan rate decomposition. Then, with estimated bank-level sentiments in hand, measuring aggregate sentiments is straightforward: aggregate bank sentiment is the quarter-by-quarter loan-weighted average bank-level sentiment index. This is directly implied by the CES aggregator used by the generic borrower presented in the theoretical framework, since when $\theta = 1$ (as will be shown to be the case here) the CES aggregator is effectively the activity-weighted linear aggregator.

Relationship with other measurement problems. Conceptually, this approach parallels strategies in the productivity measurement literature, where unobservables are inferred from structural residuals. In particular, the measurement strategy taken here mirrors the revenue residual approach to estimating firm-level productivity.[13] When measuring productivity, the econometrician derives

[13] See Foster *et al.* 2016 and Blackwood *et al.* 2021 for detailed discussions of productivity measurement strategies.

Figure 1: Commercial bank loan rates



Notes: This plot compares the sample implied loan-weighted loan rate to published risk free and consumer loan rates. The bank-level sample loan rate is calculated as the reported quarterly loan income divided by total loans, scaled by the inverse one minus net charge-off ratio. The average loan rate is then the loan-weighted average of bank-level loan rates over the cross-section of banks in the given quarter. The risk-free rate is proxied by the US 3-month T-bill. The consumer loan rate is the Finance Rate on Personal Loans at Commercial Banks, 24 Month Loan, reported by the Federal Reserve Board's G.19 Consumer Credit. Data is quarterly from 1984:Q1 through 2023:Q3.

a firm's revenue function from its theoretical profit maximization problem, yielding a structural equation that decomposes revenues into inputs and productivity. The log-linearized revenue function is then estimated with observable proxies for input quantities and costs, identifying productivity as the residual revenue. My approach to measuring sentiment follows a similar path, but uses the structural loan rate equation to identify sentiments rather than revenue to identify productivity.

2.3 Data

The measurement strategy requires six ingredients: loan rates, markups, regulatory costs, capital costs, bank-level default rates, and aggregate default rates. Several ingredients are easily 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 and income statement.[14] Realized returns are measured as the bank-level loan interest income, divided by total loans. Marginal cost of capital is proxied by the bank-level interest expenses divided by total loans, that is, the average interest paid to maintain a dollar of the bank's loan portfolio. Realizations of bank-level loan losses are measured by the

[14]Standard micro-data cleaning procedures are applied. Bank-level data are winsorized at the 1st and 99th percentiles, observations with negative capital costs, loan rates, and loans are removed.

bank's charge-off ratio, defined as net charge-offs divided by total loans.[15] Aggregate loan losses are the quarterly loan-weighted average of bank-level charge-off ratios.

However, Call Reports do not have information on loan rates, $R_{i,t}$. Instead, one might infer loan rates from the realized returns and charge-offs, which are observable in Call Reports. Note that given $R^* = (1-\lambda)R + \lambda \cdot 0$, then, $R = \frac{R^*}{1-\lambda}$.[16] Therefore, with R^* and λ, two observable bank-level characteristics, one can infer the bank-level portfolio average R.

Figure 1 shows the industry-wide (loan-weighted) average loan rate, and compares it to the risk-free rate proxied by three month Treasury Bill yield, and the Federal Reserve reported two year personal loan rate. Notably, loan rates have been in secular decline since the beginning of the sample. In response, I will augment Equation 8 with a linear time trend to account for the secular decline in the estimation and further take the year-over-year difference in the resulting residualized loan rate to remove the residual trend.

Lastly, banks' markups and regulatory costs are neither directly observable nor easily inferred from Call Report data, so I create quarter-by-quarter estimates of these two bank-level objects. However, I leave a full description of their estimation to Appendix A.1.

Table 1 summarizes the sample used to estimate bank risk sentiment. The dataset comprises 690,084 bank-quarter observations from 18,525 unique U.S. banks over the period 1984:Q1 to 2023:Q3 and captures substantial heterogeneity in bank balance sheets and behavior. Median net worth is modest at \$1.32 billion, with a highly skewed distribution reflected in a 95th percentile of \$20.2 billion. Capital costs and loan rates are low on average, at 1.10% and 1.97% respectively, and exhibit tight interquartile ranges, indicating limited variation in bank funding and lending costs across most institutions. Default rates are generally low, with a median of 4.3 basis points but a right tail extending above 79 basis points, consistent with episodic stress among a small subset of banks. The regulatory cost proxy, constructed as the marginal cost of leverage $\Gamma'(L_{i,t}/N_{i,t})$, is similarly skewed, with a 95th percentile of 1.33%. Lastly, markups are tightly clustered around one, indicating minimal dispersion in price-setting power among banks. The further description and construction details for each variable are presented in Appendix A.1.

[15] 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.

[16] Recall that λ is the portfolio average loan-level haircut, net recoveries, and so incorporates the average level of recoverable collateral. This implies that in an empirical setting one can assume a loan yields $R = 0$ if $\lambda = 1$, because the actual collateral recovery rate is incorporated into the average non-default yield via λ.

Table 1: Bank-level quarterly summary statistics

Variable	Symbol	Units	Mean	P(5)	P(25)	P(50)	P(75)	P(95)
Net worth	$N_{i,t}$	\$ Bn	19.6	0.187	0.623	1.320	3.01	20.2
Capital costs	$c_{i,t}$	%	1.10	0.107	0.359	0.878	1.54	2.87
Loan rate	$r_{i,t}$	%	1.97	1.160	1.490	1.900	2.39	3.01
Default rate	$\lambda_{i,t}$	%	0.18	0.000	0.007	0.043	0.150	0.792
Regulatory cost	$\Gamma'(L_{i,t}/N_{i,t})$	p.p.	0.42	0.015	0.107	0.261	0.535	1.33
Markups	$\frac{\theta_t}{\theta_t-1}\frac{1}{1-s_{i,t}}$		1.00	0.995	1.000	1.00	1.01	1.01

Notes: This table shows the bank-level quarterly summary statistics for the sample used to estimate bank risk sentiments. The column $P(X)$ presents the x-th percentile of observations in the sample. Observations are at the bank-quarter level. The sample includes 690,084 bank-quarter observations with 18525 unique banks and quarterly data from 1984:Q1 through 2023:Q3.

2.4 Estimated loan rate decomposition and measurement equation

I estimate the loan pricing schedule, Equation 8, to decompose loan rates between observable pricing factors and unobservable bank sentiments. Table 2 reports the resulting price schedules. Columns (1) and (2) are distinguished by whether or not the linear fixed effects model is estimated with quarter-loan-share-weighted observations. Since the ultimate goal is to understand sentiments in the bank lending market, the loan-weighted model will be the baseline estimation used in subsequent analysis. However, key features of the two loan rate decompositions are similar.

Unobservable bank-level sentiments account for a non-trivial portion of loan rates. Table 2 reports that sentiments explain approximately 10 percent of loan rate variation. The proportion of loan rate variation explained by sentiments increases to approximately 12 percent in the unweighted loan rate decomposition. While it is unlikely that sentiments account for the full 10 or 12 percent of loan rate variation due to measurement error from the imperfect proxies for regulatory costs and the law of motion for defaults, these estimates nonetheless establish a high ceiling for how much loan rate variation might be accounted for by sentiments.

Observable bank-level characteristics and fixed effects account for a large portion of loan rate variation, approximately 88 and 90 percent. This follows from a similarity in how both models attribute variation to the pricing factors. First, an increase in capital funding costs increases loan rates in a statistically significant manner. However, after controlling for both bank fixed effects and the time trend in loan rates, the capital funding cost pass-through rate is less than one-for-one. The weighted model only shows a 50 percent pass-through, which falls to only 25 percent in the

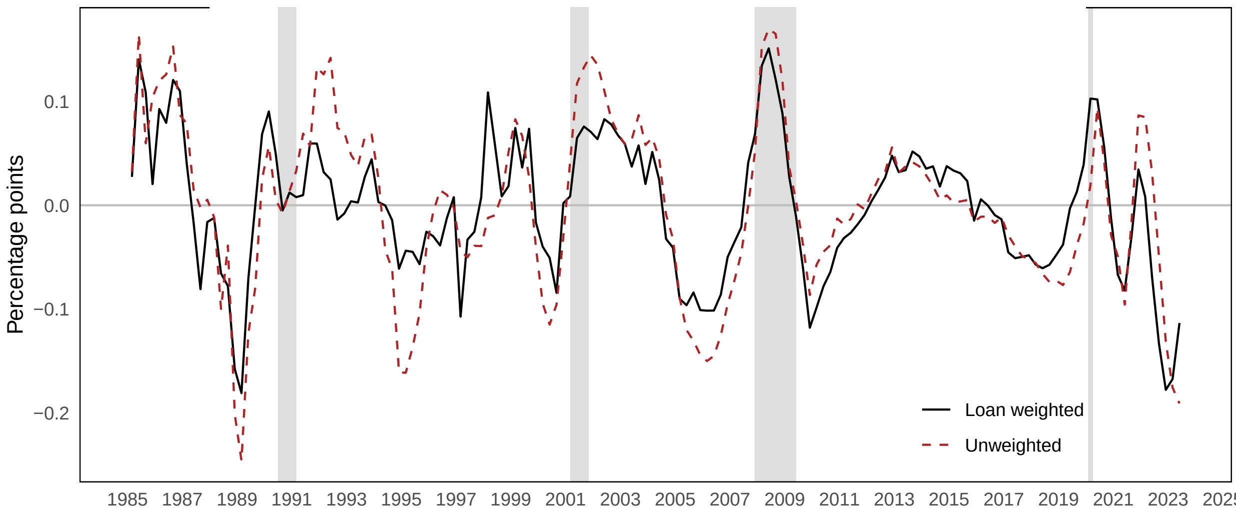
Table 2: Estimated bank loan rate pricing schedules

	(1)	(2)
capital cost: $c_{i,t}$	0.250^{***}	0.487^{***}
	(0.021)	(0.024)
regulatory cost: $\Gamma'_{i,t}$	-0.023	0.049^{*}
	(0.014)	(0.029)
markups: $\log(\frac{\sigma_t}{\sigma_t-1}\frac{1}{1-s_{i,t}})$	-0.007	0.001
	(0.010)	(0.010)
idio. defaults: $\lambda_{i,t-1}$	-0.007^{**}	-0.008
	(0.003)	(0.011)
agg. defaults: λ_{t-1}	-0.233^{***}	-0.141^{*}
	(0.043)	(0.078)
Loan share weighted		✓
Time trend	✓	✓
Bank FE	✓	✓
Observations	690,084	690,084
Total R^2	0.879	0.901
Within R^2	0.781	0.800

Notes: This table presents the sentiment measurement equations. Column (1) is the unweighted model and Column (2) is the quarterly-loan-share-weighted model. Both models include a linear time trend and bank fixed effects. Both models are estimated as within-group fixed effect linear panel models. The quarterly, unbalanced, panel includes 19.5 thousand banks from 1984:Q1 through 2023:Q3. Parentheses wrap the robust standard errors, which are clustered at the bank level, and * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

unweighted model. Further, regulatory costs only appear to be positive and statistically significant in the weighted model, suggesting a difference in the regulatory burden bornee by large and small banks. Markups are neither economically nor statistically significant contributors to loan rates in either model. Lastly, the most notable difference between the weighted and unweighted decomposition comes from the role of loan losses. In the unweighted model both bank-level and aggregate defaults contribute to loan rates while in the weighted model only aggregate defaults matter. This may reflect the fact that large banks dominate the weighted model, and also dominate aggregate defaults (which are loan-weighted), thus the bank-level defaults of the small banks do not matter.

Figure 2: Aggregate bank risk sentiment



Notes: This plot shows the quarterly aggregate bank risk sentiment of U.S. commercial banks. The solid black line presents the loan-weighted sentiment index and the dashed red line presents the unweighted sentiment index. Gray shaded regions mark NBER dated recessions. Data is from 1985:Q1 through 2023:Q3.

Measurement robustness. I present evidence that aggregate bank risk sentiment is robust to 1) the postulated law of motion for bank-level loan losses, 2) portfolio composition effects, including the average loan maturity and underlying borrower risk, 3) estimation under full sample or expanding window information sets, and 4) excluding prominent historical events, in Appendix C.

3 Describing Sentiments

I next describe the estimated bank risk sentiments, starting with the aggregate index before moving to summarize the bank-level heterogeneity and verifying that bank risk sentiments may be interpreted as animal spirits shocks.

3.1 Aggregate Sentiments

Bank risk sentiment is characterized by sharp increases in times of financial stress and uncertainty in the United States. Figure 2 shows that, for example, BRS spikes during the beginning of the S&L Crisis in the mid-1980s, the Dot-com stock bubble burst and the sudden collapse of Enron and WorldCom in the early 2000s, the GFC, and COVID-19 pandemic. Moreover, BRS also appears to be sensitive to news of foreign crises and uncertainty, with pessimistic sentiment spiking during the East Asian Financial and Ruble crises (1997-1998), and Europe's "double-dip" recession. Periods of deteriorating sentiments are often precipitated by events elevating uncertainty, such as the September 11 terrorist attacks and beginning of the Fed's quantitative tightening in 2018 (and subsequent yield curve inversion in 2019). Conversely, marked periods of bank optimism include the S&L crisis recovery, Dot-com bubble of the late 1990s, and the mid-2000s housing boom.

It is important to clarify that while uncertainty and financial stress may lead to a rational increase in forecasted loan defaults, the rise in bank sentiment indicates that banks become even more pessimistic about future states of the economy than is necessarily implied by a rational expectations view of the world. That is, BRS indicates banks become *excessively* pessimistic in times of uncertainty and financial stress. The fact that banks appear to become excessively pessimistic during periods of bad news falls in line with similar behavior documented among households in Lagerborg *et al.* 2023, which shows that households become pessimistic about economic outcomes when mass shootings are in the news.

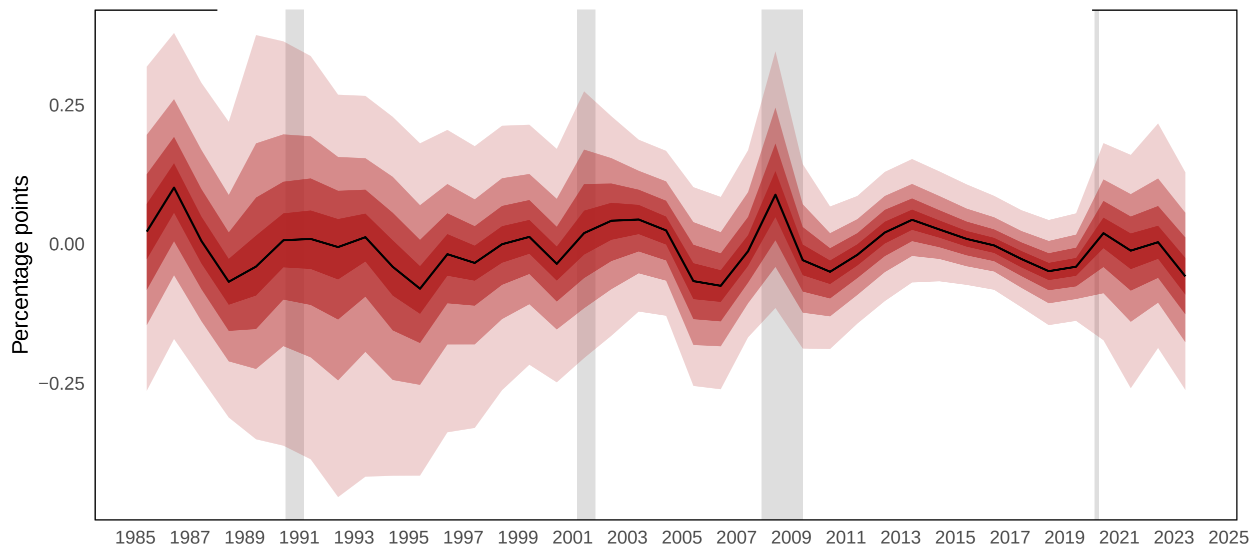
3.2 Bank-level Sentiments

However, focusing on the common movements in banking sector sentiments obscures a large degree of heterogeneity at the bank-level.

There is a wide and time-varying distribution of bank-level sentiments. Figure 3 summarizes the quarterly cross-section of bank-level sentiments, showing bank sentiments are neither optimistically nor pessimistically biased over time, but the dispersion among bank-level sentiment is both countercyclical and in secular decline. Figure 4 more succinctly summarizes the evolution of the sentiment dispersion by plotting the interquartile range of sentiments through time. First, the dispersion in bank-level sentiments is generally countercyclical, increasing during the Dot-com recession, GFC, and COVID. In fact, the dispersion in sentiments more than triples during the COVID-19 pandemic, reaching levels higher than during the GFC. Second, the dispersion of bank-level sentiments has been in secular decline since 1990. The interquartile range of bank-level sentiments has fallen from 26.5 basis points in 1990 to approximately 7 basis points in 2019. There may be a number of reasons for the growing coordination in bank sentiments, for example the consolidation in the U.S. banking sector or the gradual increase in the use of hard information to approve loan applications.[17] Although it is beyond the scope of this paper to determine why

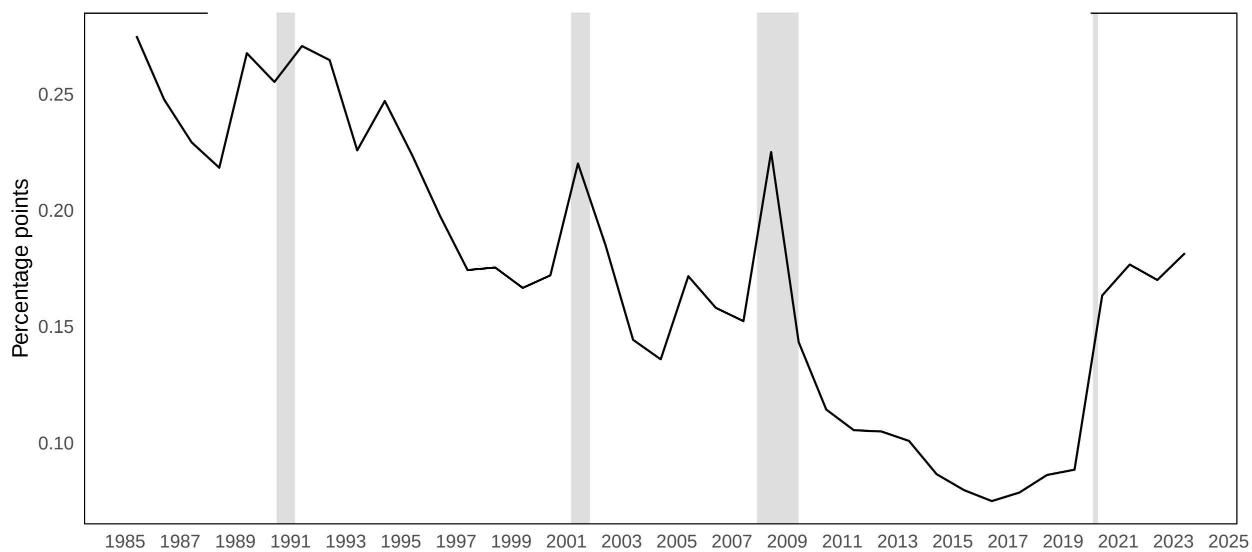
[17] *Hard information* is quantifiable and portable, such as accounting information used to evaluate potential loan offers. Banks are gradually relying more on hard information when making decisions about extending loans. Conversely, human loan officers' own sentiments are being gradually removed from the loan application process, which in turn

Figure 3: Distribution of bank-level sentiments



Notes: This plot shows the distribution of bank-level sentiments through time. The solid black line presents the median bank-level sentiment, and the red bands mark the first through ninth deciles of bank-level sentiments in a given year. Gray shaded regions mark NBER dated recessions. Data is annual from 1985 through 2023.

Figure 4: Dispersion of bank-level sentiments



Notes: This plot shows the dispersion of bank-level sentiments through time. The solid black line presents the annual average inter-quartile range of bank-level sentiments. Gray shaded regions mark NBER dated recessions. Data is annual from 1985 through 2023.

removes them as a source of bank risk sentiment. Fewer sources of variation in sentiments over time may explain the secular convergence in sentiments. See Liberti & Petersen 2019 for further discussion of hard information in banking.

there has been a secular convergence in bank sentiments.

The time-varying dispersion in bank-level sentiments may be due to heterogeneity in bank-level sentiment processes, differences in realized sentiment shocks, or a combination of both. That is, if one considers bank-level sentiments to follow an AR(1) process, such as

$$\varepsilon_{i,t} = \alpha_i^{\varepsilon} + \rho_i^{\varepsilon} \cdot \varepsilon_{i,t-1} + \eta_{i,t} \tag{9}$$

then differences can arise from differences in the average α_i^{ε}, persistence ρ_i^{ε}, or shocks $\eta_{i,t}$.[18]

Differences in bank-level sentiment are driven by differences in both sentiment processes and realized shocks. Figure 5 shows the distributions of bank-level average sentiment, persistence, and variance. Panel (A) shows that the average bank sentiment is centered around zero, but with a large mass of optimistic and pessimistic banks. In fact, there is a small group of banks that on average decrease (increase) loan rates by 10 basis points due to excessive optimism (pessimism). Panel (B) and (C) show that the bank-level variance and persistence in sentiments are also heterogeneous. Though most banks have relatively stable sentiments that slowly decay (in fact the mean persistence near 0.6 suggests the effects of a sentiment shock will take more than a year to decay to less than 10 percent of its initial impact).

Bank size. Lastly, bank size is not a source of heterogeneity in bank risk sentiments. This can be inferred from the qualitatively similar dynamics of the loan-weighted and unweighted measures of aggregate BRS. The loan-weighted measurement equation, thus the loan-weighted BRS, is dominated by the dynamics of the largest banks, while the unweighted measurement equation and bank-level aggregate is dominated by the dynamics of small banks.[19] Therefore, the similarity across the two indexes reflects a similarity across the dynamics of small and large bank sentiments.[20]

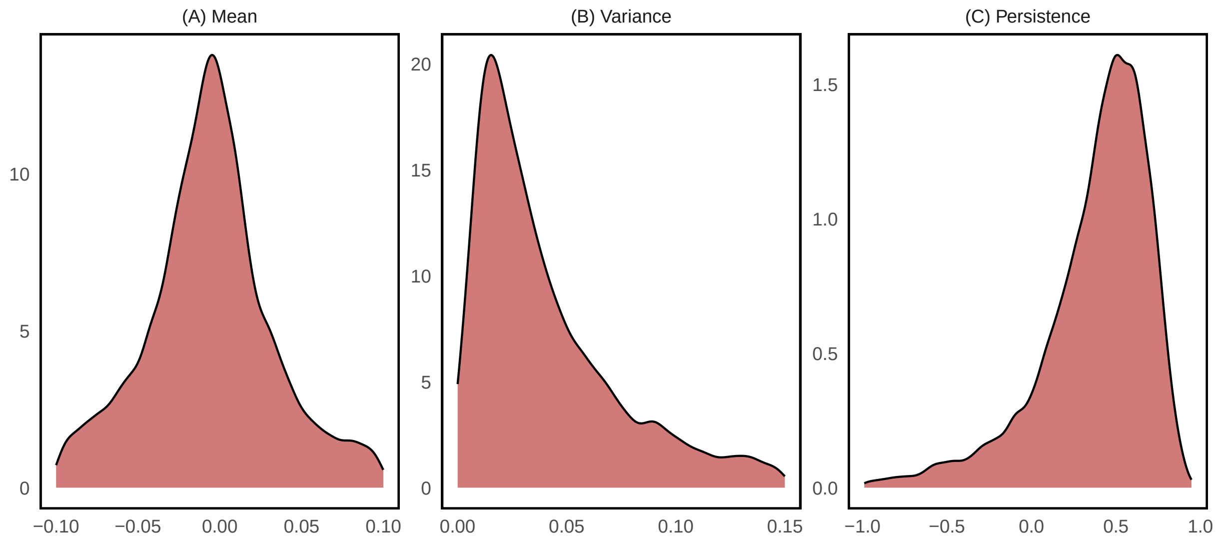
In summary, industry-wide sentiments are generally acyclical, though with pessimism spiking during times of crisis and excessive optimism during commonly labeled asset bubbles. However, these

[18]The BIC minimizing lag order for autoregressive representations of the bank-level sentiment process is one in both the pooled sample estimation and when estimating the series bank-by-bank.

[19]Loans are highly concentrated among a few large banks in the U.S. (Corbae & D'Erasmo 2021 show the top ten bank holding companies account for approximately 60 percent of bank assets), although there are several thousand banks actually operating in the United States (see Figure 14 in the Data Appendix A.1).

[20]A more direct test might be to compare sentiments among the largest banks to the aggregate BRS series, however, since there are fewer than 20 large banks that dominate U.S. lending markets, this instead would be a study of granular sentiment shocks to the largest banks, rather than the systematic influence of bank size on sentiment formations.

Figure 5: Bank-level sentiment processes



Notes: red shaded regions show the empirical density functions of bank-specific (A) mean risk sentiments, (B) variance of risk sentiments, and (C) AR(1) coefficient of risk sentiments. Data is an unbalanced panel of 18,525 banks, quarterly from 1985:Q1 to 2023:Q3.

common movements mask a large degree of heterogeneity at the bank-level, which is in secular decline but with cyclical increases during crises.

3.3 Interpreting as animal spirits

Before using my measure of bank risk sentiments to evaluate the macroeconomic importance of sentiments, I first verify that they may indeed be interpreted as animal spirit shocks. While I cannot observe a bank's rational expectations forecast of its future loan losses, I can test that bank risk sentiments 1) do not contain systematically useful information for forecasting loan defaults, and 2) are forecastable beyond their autoregressive dynamics. The former condition tests that bank risk sentiments are systematically uninformative, thus irrational to include in a bank's forecast of loan defaults. The latter condition tests that bank risk sentiments are unanticipated fluctuations and statistically independent of fundamental lending supply and demand factors, thus reasonably considered an exogenous shock.[21]

First, I test the (lack of) information in sentiments with an in-sample forecasting exercise. If sentiments can forecast bank-level loan losses, then they must contain useful information about

[21] Aggregate bank risk sentiment is additionally shown to be statistically independent of common aggregate shocks of interest in Appendix E.

Table 3: (In-sample) Forecasting bank-level loan losses with sentiments

	1-quarter ahead forecast			1-year ahead forecast		
	(1)	(2)	(3)	(4)	(5)	(6)
sentiment: $\varepsilon_{i,t}$	0.664	-0.380	-0.389	1.762***	0.529	0.523
	(0.570)	(0.647)	(0.652)	(0.777)	(0.595)	(0.598)
Bank characteristics			✓			✓
Bank & Date FE		✓	✓		✓	✓
Loan-share weighted	✓	✓	✓	✓	✓	✓
Bank Clustered SE	✓	✓	✓	✓	✓	✓
Observations	547,533	547,533	547,533	510,358	510,358	510,358
R^2	0.000	0.134	0.135	0.001	0.127	0.128

Notes: This table presents the coefficients from in-sample forecasting regressions predicting the bank-level charge off ratios with bank-level risk sentiments. Columns (1)-(3) present the estimated one-quarter ahead forecasting models, while Columns (4)-(6) present the one-year ahead forecasting model. Columns (3) and (6) present models including a vector of observable bank characteristics containing the bank's net worth, leverage ratio, and quarterly loan share. Observations are loan-share weighted across all models. Parentheses wrap bank-level clustered standard errors, and * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

future states of the world and should necessarily be included in the rational expectations forecast of defaults. If sentiment cannot systematically forecast loan losses, then they represent deviations from the rational expectations forecast and are properly interpreted as animal spirits. The in-sample forecasting model will follow a simple linear form:

$$\lambda_{i,t+h} = \eta_i + \eta_t + \beta \varepsilon_{i,t} + \theta x_{i,t} + e_{i,t+h}$$

which forecasts bank-level default rates $\lambda_{i,t+h}$ either one quarter (h=1) or one year (h=4) ahead with bank-level sentiments $\varepsilon_{i,t}$ and, in some configurations, with time fixed effects η_t (to account for the possible influence of aggregate shocks), bank fixed effects η_i (to account for the bank-specific bias in default rates), and additional bank-level covariates, $x_{i,t}$, including the bank's net worth, leverage ratio, and market share, with forecast errors $e_{i,t+h}$.

Sentiments do not contain systematically useful information for forecasting loan defaults. Table 3 reports the loading on bank-level sentiment (i.e. the regression coefficient) in the estimated forecasting models. Columns (1) through (3) more specifically show that there is no systematically useful information in bank-level sentiments for forecasting one-quarter ahead loan losses in any of

Table 4: (In-sample) Forecasting bank-level sentiments

	One-quarter ahead forecast			One-year ahead forecast		
	(1)	(2)	(3)	(4)	(5)	(6)
$(1000) \cdot \text{leverage}_{i,t-1}$	-0.27		-0.24	-0.12		-0.17
	(0.31)		(0.32)	(0.78)		(0.78)
$(100000) \cdot \text{appeal}_{i,t-1}$		-0.141	-0.134		0.185	0.190
		(0.241)	(0.243)		(0.357)	(0.357)
Bank FE	✓	✓	✓	✓	✓	✓
Loan-share weighted	✓	✓	✓	✓	✓	✓
Bank Clustered SE	✓	✓	✓	✓	✓	✓
Observations	560,984	560,984	560,984	522,339	522,339	522,339
R^2	0.292	0.292	0.292	0.122	0.123	0.123

Notes: This table presents the coefficients from in-sample forecasting regressions predicting bank-level sentiments with observable bank characteristics. Columns (1) - (3) present the estimated one-quarter ahead forecasting models, while Columns (4) - (6) present the one-year ahead forecasting model. Models include a bank-fixed effect, four lags of the bank-level sentiment, and/or bank-level appeal and leverage. Observations are loan-share weighted across all models. Parentheses wrap bank-level clustered standard errors, and * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

the forecasting models tested. That is, bank-level sentiments do not enter any forecasting model with a loading statistically distinguishable from zero at any standard confidence level. Columns (5) and (6) show a similar result when forecasting one-year ahead loan losses and accounting for additional information from fixed effects and bank-level characteristics. Meanwhile column (4) indicates sentiments are systematically useful in forecasting loan losses one-year ahead when accounting for no other information. However, this forecasting model accounts for almost no variation in loan losses, yielding an R-squared of 0.001.

Second, to test if BRS is unforecastable and statistically independent of credit demand and supply shocks, thus reasonably interpreted as an exogenous shock, I turn to another in-sample forecasting exercise. I will forecast sentiment with two bank-level characteristics in particular, bank-specific appeal and leverage ratio. First, a bank's appeal captures aggregate and bank-specific demand shocks (see Hottman *et al.* 2016 and Eslava *et al.* 2024 for a more detailed discussion of firm-specific appeal).[22] Second, changes in a bank's leverage ratio reflect changes in its willingness to supply credit for idiosyncratic reasons, such as changes in its risk aversion or uncertainty (as in

[22]See Appendix A.1 for details on estimating bank-specific appeal.

He & Krishnamurthy 2013 and Brunnermeier & Sannikov 2014), or for macroeconomic reasons, such as aggregate shocks deteriorating collateral values (as in Gertler & Kiyotaki 2010). Thus the two bank-level characteristics provide a holistic summary of bank-level and aggregate factors affecting the demand and supply of bank credit. If there are exogenous forces driving bank risk sentiment, then these two characteristics should reasonably subsume these forces and indicate their importance in the forecasting exercise.

The in-sample forecasting model will follow a similar form to the previous exercise:

$$\varepsilon_{i,t+h} = \eta_i + \beta_1 \left(\frac{L_{i,t}}{N_{i,t}} \right) + \beta_2 \psi_{i,t} + \theta x_{i,t} + e_{i,t+h}$$

where one is forecasting bank-level sentiments $\varepsilon_{i,t+h}$ either one quarter (h=1) or one year (h=4) ahead with a vector of four autoregressive lags of sentiment, $x_{i,t}$, the bank's leverage ratio $\frac{L_{i,t}}{N_{i,t}}$, and appeal $\psi_{i,t}$, with forecast errors $e_{i,t+h}$.

Bank risk sentiment is not forecastable with bank-level supply and demand factors. Table 4 reports the loading of the bank leverage ratio and appeal in the estimated forecasting models. The bank characteristics are not informative about future sentiments in any estimated model. However, this is not simply because the relationships are imprecisely estimated, but rather, the loadings are precisely estimated around zero. Moreover, the inability to forecast bank-level sentiments is robust. I additionally tested in-sample forecasting models without loan-weighting observations, in various sub-samples (for example, with and without the COVID-19 pandemic period), with time fixed effects, and with polynomial terms, but without any discernible increase in the ability to forecast bank-level sentiments. These exercises are omitted for brevity.

4 Evaluating sentiments as a source of business cycles

I next evaluate the effects of bank sentiment shocks on macroeconomic dynamics —fluctuations in prices, activity, monetary policy, and credit conditions— and compare their importance in explaining business cycle fluctuations relative to a host of other macroeconomic shocks.

4.1 Econometric framework

I begin with a parsimonious representation of the economy. More specifically, I summarize the economy through the lens of six endogenous variables: activity, prices, monetary policy rate, credit conditions, consumer sentiment, and the loan rate premium. The first four variables build on a standard parsimonious empirical representation of the economy, see for example Gertler & Karadi 2015 and Caldara & Herbst 2019. The latter two variables are included as observable indicators for household and bank sentiments respectively.

I then postulate that the economy can be well summarized by the joint evolution of these six variables following a standard linear vector-autoregressive law of motion:

$$A_0 Y_t = \sum_{l=1}^{P} A_l Y_{t-l} + \varepsilon_t, \quad \varepsilon_t \sim \mathcal{N}(0_K, I_K) \tag{10}$$

where Y_t is the vector of $K = 6$ endogenous variables observed at time t, A_0, A_l $\forall l \geq 1$ are conformable coefficient matrices (including a constant intercept for each endogenous variable), $P = 4$ is the lag order of the autoregressive system, and ε_t is the vector of K white noise structural shocks.[23]

The structural law of motion can be mapped to its reduced form representation by multiplying each side of the equation by A_0^{-1}, yielding:

$$Y_t = \sum_{l=1}^{P} B_l Y_{t-l} + u_t, \quad u_t = S\varepsilon_t \tag{11}$$

where $B_l = A_0^{-1} C_l$ and $A_0^{-1} = S$. The reduced form and structural shocks therefore mutually satisfy the condition:

$$E[u_t u_t'] = E[SS'] = \Sigma \tag{12}$$

where u_t is the reduced form shock, S is the linear function mapping structural to reduced form shocks, and Σ is the variance-covariance matrix of the reduced form shocks. That is, structural shocks are each a linear combination of the reduced form shocks that preserve the variance-covariance matrix of the reduced form model. The classic macroeconometric question is then how one statistically identifies the columns of S.

Identifying structural shocks. I use a combination of instrumental variables and sign restrictions to jointly identify six structural shocks —bank sentiment, household sentiment, aggregate demand, supply, financial risk, and monetary policy.

The two sentiment shocks will be identified with instrumental variables. First, I follow Lagerborg

[23] The structural shocks, by definition, satisfy the conditions: $E[\varepsilon_t] = 0, \quad E[\varepsilon_t \varepsilon_t'] = I_K, \quad E[\varepsilon_t \varepsilon_s'] = 0 \;\; \forall s \neq t$, where I_K is the K dimensional identity matrix.

et al. 2023 and instrument household sentiment shocks with the number of mass shooting events in the United States in a given quarter. I leave further discussion of the data and validity of the relevance and exclusion restrictions to Lagerborg *et al.* 2023.

Second, I instrument bank sentiment shocks with the impact of bank risk sentiment on the bank loan rate premium. Bank risk sentiment satisfies both the standard relevance condition and exclusion restriction *theoretically*, following from its definition in Section 2.1, as well as *empirically*. The first stage F-statistic is greater than 200, indicating a relevant instrument, and bank risk sentiments are statistically independent of the five other aggregate structural shocks that drive endogenous outcomes in the BVAR (when not orthogonal to BRS by construction), satisfying the exclusion restriction. I leave the full discussion of the instrument validity tests to Appendix E.

Given bank risk sentiment is a valid instrument for bank sentiment shocks, the procedure for estimating the corresponding column of S is standard and follows Gertler & Karadi 2015 in three steps.[24] 1) Estimate the reduced form VAR and calculate the matrix of reduced form residuals $\mathbf{u}_t$. Let u_t^b be the vector of reduced form residuals from the equation for the loan rate premium (the bank sentiment indicator) and let $\mathbf{u}_t^{-b}$ be the reduced form residuals from the equations for all other endogenous variables. Let S^{-b} be the response of $\mathbf{u}_t^{-b}$ to a unit increase in the sentiment shock ε_t^b. The next two steps will then use a standard two stage least squares procedure to estimate the ratio s^{-b}/s^b. 2) In the first stage, project u_t^b onto the instrument vector Z_t to form the fitted value $\widehat{u_t^b}$. The resulting predicted value isolates the variation in the reduced form residual for the loan rate premium that is due to the structural bank sentiment shock. 3) In the second stage, regress u_t^{-b} on $\widehat{u_t^b}$. Given the variation in $\widehat{u_t^b}$ is due only to ε_t^b, the second stage regression yields a consistent estimate of s^{-b}/s^b, so that:

$$u_t^{-b} = \left(\frac{s^{-b}}{s^b}\right)\widehat{u_t^b} + o_t \tag{13}$$

where $\widehat{u_t^b}$ is orthogonal to the error term o_t, given the exclusion restriction. An estimate for s^b is then derived from the reduced form variance-covariance matrix, Equation 12, and Equation 13.

The remainder of the structural shocks are jointly identified by theoretically-motivated sign restrictions following Uhlig 2005, Rubio-Ramirez *et al.* 2010, Fry & Pagan 2011, among others. Using GDP growth as activity and inflation as prices the restrictions are as follows:

- A positive demand shock will increase both activity and prices. It then follows from a standard Taylor rule that monetary policy will unambiguously tighten in response to a positive

[24] I sketch the process for estimating bank sentiment shocks here because it is the focus of this study, although I refer to Mertens & Ravn 2013 and Gertler & Karadi 2015 for a more detailed description of the procedure.

Table 5: Sign restrictions identifying structural shocks

	GDP growth	Inflation	Policy Rate	Credit Conditions
Demand shock	+	+	+	?
Supply shock	+	-	?	?
Monetary policy shock	-	-	+	?
Risk shock	-	-	-	+

demand shock, thus the policy rate will increase to prevent the economy from overheating.

- A positive supply shock increases activity and decreases prices. However, the monetary policy response to a supply shock is ambiguous as policymakers need to weigh the cost-benefit trade-off of leaning against the increasing activity at the cost of further pushing inflation below its target rate.

- The tightening monetary policy shock will be identified as an increase in the policy rate, and a decrease in activity and inflation in the economy. See Galí 2015 for a New Keynesian textbook model motivation of these restrictions.

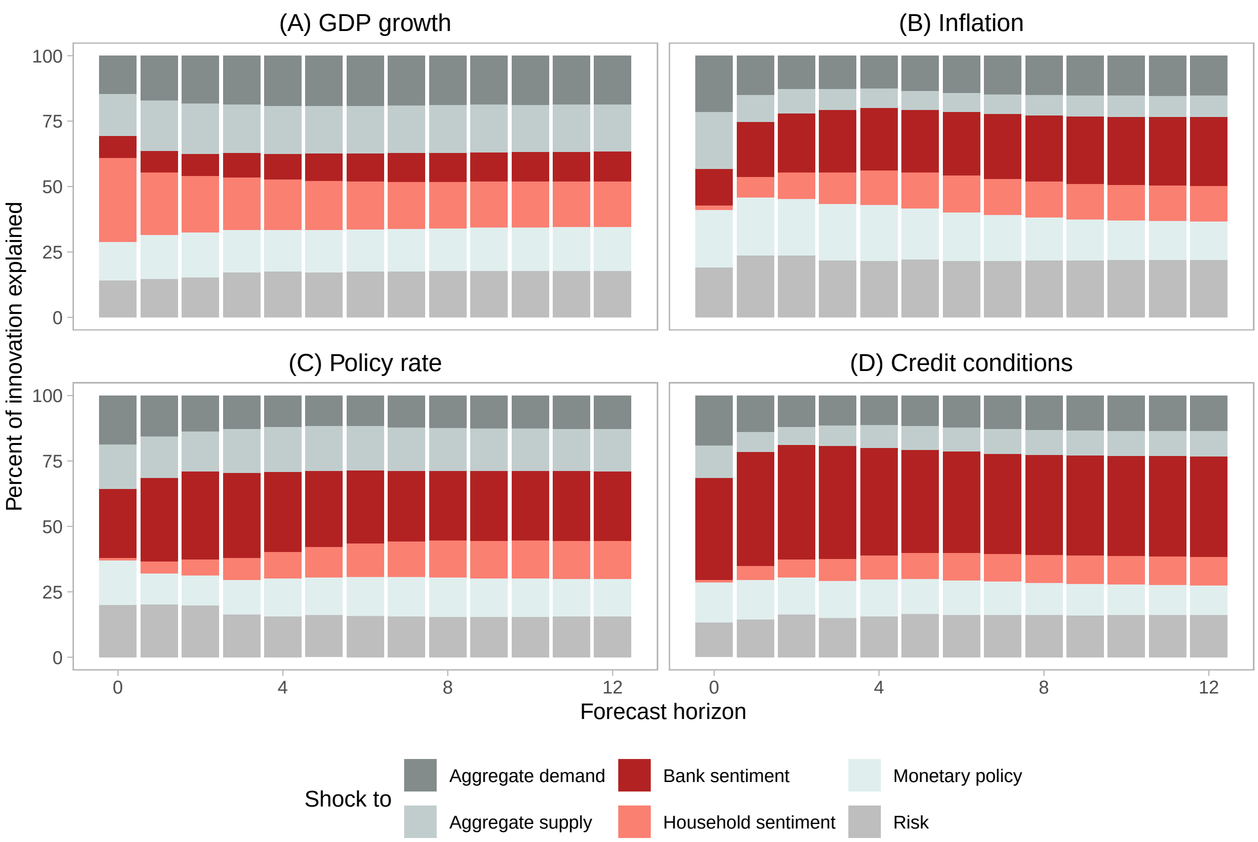
- The financial risk shock is defined by following Christiano *et al.* 2014, where an increase in financial risk restricts creditors' ability to lend, leading to tightening financial conditions as well as a deterioration in activity and prices, prompting a monetary policy easing.

See Uhlig 2017 for further intuition regarding the standard supply and demand shock identification schemes, as well as a discussion on sign restriction identification more broadly. The impact on sentiment indicators is left ambiguous.

Data. The macroeconomic time series used in the parsimonious BVAR follow Gertler & Karadi 2015. Activity is represented by the real GDP annualized quarterly growth rate and prices by core PCE inflation. Monetary policy is proxied by the one year Treasury rate. Credit conditions are proxied by the Gilchrist & Zakrajšek 2012 excess bond premium (EBP), which is interpreted as an indicator of the capacity of intermediaries to extend loans or more generally the overall credit supply conditions in the economy. Household sentiment is represented by the University of Michigan Survey of Consumers' index of consumer sentiment. Bank sentiment is represented by the bank loan rate premium (the loan-weighted average bank loan rate minus the policy rate).[25] Data are

[25] Using the loan rate premium as an indicator for bank sentiment follows from both the theoretical framework presented in Section 2.1 —which indicates that bank sentiments will affect loan rates after accounting for capital borrowing costs— and the literature on financial market sentiment. For example, López-Salido *et al.* 2017 use the EBP as an indicator for corporate bond market sentiment.

Figure 6: Variance decomposition of policy, activity, prices, and credit conditions



Notes: This plot presents the variance decomposition of business cycle fluctuations into contributions by structural shocks. The contribution of structural shocks account for 100 percent of the horizon-variable innovation. GDP growth is the annualized real quarterly growth rate, inflation is core PCE inflation, financial conditions are proxied by the Gilchrist & Zakrajšek 2012 EBP, and the policy rate is proxied by the one year Treasury rate.

quarterly from 1985 through 2023 and are further detailed in Appendix A.2.

Estimation. Model parameters are estimated with standard Minnesota priors via a Gibbs sampler with 150 thousand draws and a 50 thousand burn-in. Draws are thinned so that every fifth draw is accepted to reduce autocorrelation in the resulting posterior chain. A structural impact matrix is constructed for each draw following the Cesa-Bianchi & Sokol 2022 procedure for combining IV and sign restriction identifications.

4.2 The role of sentiment over the business cycle

I will first describe the importance of bank sentiment shocks over the business cycle, then turn to describing their role in specific historical episodes and economic recoveries.

Credit conditions and policy. Bank sentiment shocks are an important determinant of credit conditions. Figure 6 shows the variance decomposition of activity, prices, policy, and credit conditions into contributions from the six identified structural shocks. More specifically, Figure 6 shows that bank sentiment shocks are the dominant source of fluctuations in credit conditions over the short and medium term. Panel (D) shows that bank sentiment shocks account for 39 percent of fluctuations in credit conditions for three years after impact. In comparison, aggregate demand and supply shocks account for between 31 and 21 percent of credit condition fluctuations, while financial risk shocks only account for 16 percent and monetary policy shocks for 13 percent on average. Lastly, household sentiment shocks contribute the least to fluctuations in credit conditions on impact — only 0.9 percent— and then grow to account for about 10 percent, which is approximately equal to the contribution of either aggregate supply or monetary policy shocks. Lagerborg *et al.* 2023 similarly find a relatively small role for household sentiments in determining credit conditions.

Bank sentiment is a similarly important driver of monetary policy fluctuations. Panel (C) shows that bank sentiment is the single most important determinant of the policy rate on impact, accounting for approximately 26 percent of policy rate fluctuations on average over the business cycle. Meanwhile, household sentiments grow in influence from accounting for less than one percent of policy rate fluctuations on impact to 14 percent, approximately as much as monetary policy shocks themselves, by three years after impact.

Activity and prices. In comparison, bank sentiment is an important, but not a dominant, source of fluctuations in prices and is starkly less important in driving fluctuations in activity. Starting with inflation, bank sentiment is initially more important than household sentiment, explaining 14 versus 1 percent of fluctuations in prices, but is less influential than monetary policy, aggregate demand, supply, or financial risk shocks. However, the importance of bank sentiment shocks grows monotonically over time. Three years after impact, bank sentiment shocks account for the plurality of price fluctuations, 26 percent, which is greater than both aggregate demand and supply shocks combined. Similarly, the influence of household sentiment grows over time, but accounts for 13.5 percent of fluctuations in prices at its peak influence three years after impact.

Lastly, bank sentiment accounts for approximately 10 percent of fluctuations in GDP growth over the business cycle, the least of any structural shock. In contrast, household sentiment is the most

Table 6: Long run variance decomposition of policy, activity, prices, and credit conditions

Endog. Variable	Horizon (quarters)	Percent of innovation explained by: Bank Sentiment	Household Sentiment	Aggregate Demand	Aggregate Supply	Monetary Policy	Financial Risk
Credit conditions	0	38.83	0.94	19.08	12.54	15.26	13.36
	4	41.06	9.15	11.29	8.71	14.17	15.62
	8	38.15	10.68	13.30	9.44	12.35	16.08
	12	38.36	10.78	13.68	9.63	11.43	16.12
	16	38.99	10.63	13.52	9.78	10.82	16.25
	20	39.37	10.50	13.55	9.78	10.39	16.41
	100	41.23	10.23	12.78	9.41	9.45	16.90
GDP growth	0	8.39	31.95	14.62	16.09	14.78	14.17
	4	9.93	19.28	19.20	18.28	15.82	17.49
	8	11.09	17.69	18.89	18.24	16.34	17.76
	12	11.33	17.35	18.70	18.03	16.87	17.71
	16	11.26	17.38	18.69	17.85	17.31	17.50
	20	11.22	17.44	18.63	17.80	17.60	17.31
	100	11.05	17.57	18.51	17.96	18.23	16.68
Inflation	0	14.11	1.66	21.47	21.75	21.83	19.18
	4	23.88	13.01	12.70	7.29	21.47	21.65
	8	25.17	13.69	15.12	7.74	16.61	21.68
	12	26.38	13.46	15.35	8.08	14.77	21.96
	16	27.31	13.30	15.22	8.14	13.91	22.13
	20	27.98	12.88	15.42	8.27	13.08	22.36
	100	30.06	12.02	14.91	8.62	11.34	23.07
Policy rate	0	26.43	0.83	18.77	16.97	16.93	20.08
	4	30.59	10.08	11.96	17.33	14.33	15.71
	8	26.70	14.01	12.49	16.36	14.95	15.50
	12	26.69	14.41	12.83	16.19	14.15	15.73
	16	27.19	14.24	12.80	16.18	13.41	16.19
	20	27.43	14.19	12.83	16.03	13.02	16.50
	100	30.04	13.68	12.37	14.52	11.47	17.92

Notes: This table shows the variance decomposition of credit condition, policy, activity, and price fluctuations into contributions by structural shocks. The contribution of structural shocks account for 100 percent of the horizon-variable innovation. GDP growth is the annualized real quarterly growth rate, inflation is core PCE inflation, Financial conditions are proxied by the Gilchrist & Zakrajšek 2012 EBP, and the policy rate is proxied by the one year Treasury rate.

influential of any shock on impact, accounting for 32 percent of fluctuations in GDP growth. Although the impact of household sentiment then falls over time and is approximately equal in influence to the real and policy shocks by three years after impact.

The importance of bank sentiments is consistent across short, medium, and long run horizons. Table 6 shows that bank sentiments' role in determining policy, credit conditions, activity, and prices, appears to stabilize by three years after impact, while the general patterns described so far hold in the medium term (two to five years after impact) and in the long run steady state (proxied by 100 quarters after impact).

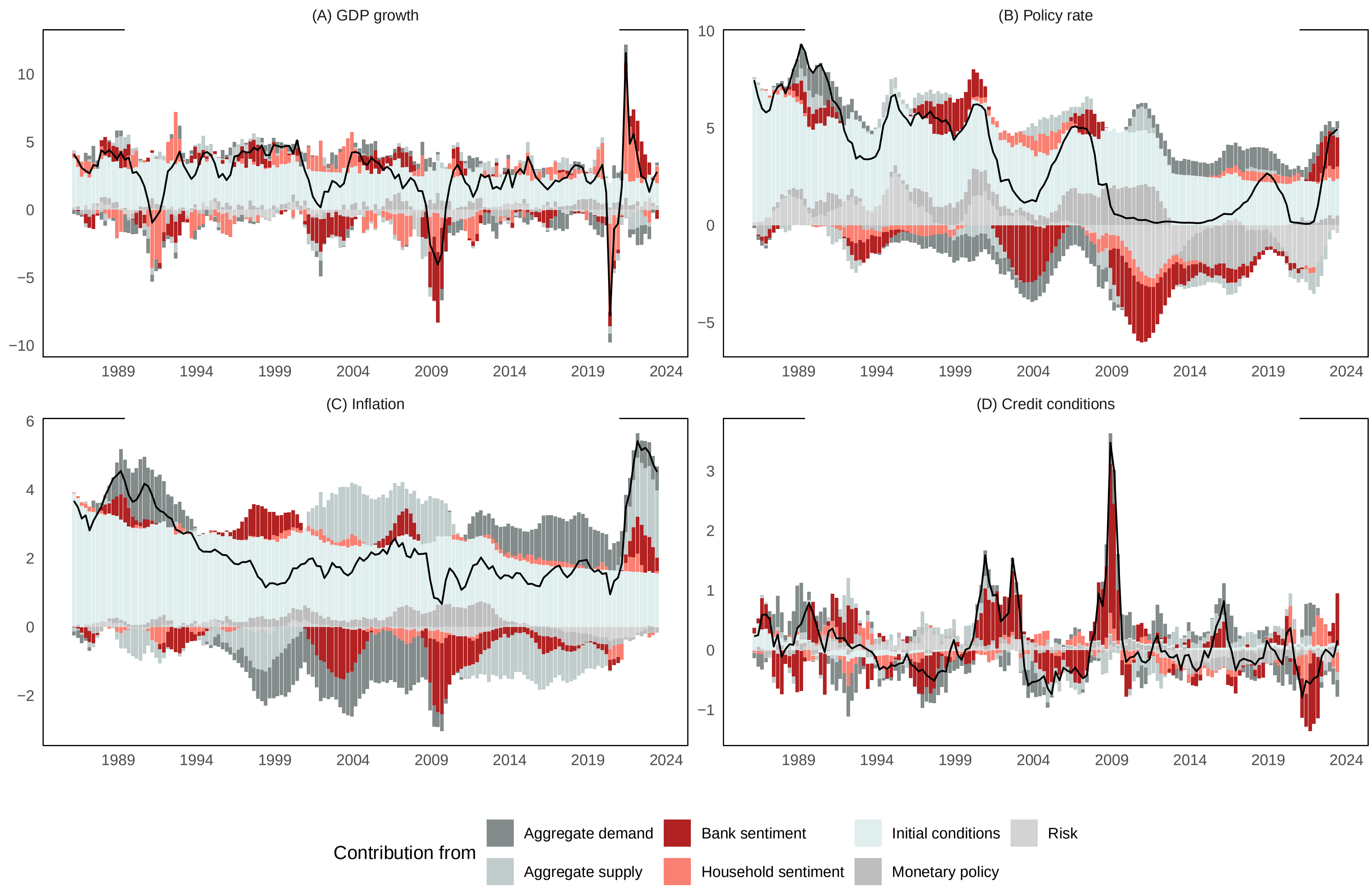
4.3 The role of sentiment during historical episodes

Bank sentiment is an important source of credit conditions and business cycle fluctuations on average, although its actual contribution to the economy varies over time. Figure 7 shows the historical decomposition of GDP growth, inflation, policy rate, and financial conditions, into the cumulative contributions of the six identified structural shocks over time. For example, in the late 1980s, bank sentiment was boosting GDP growth and inflation, while easing financial conditions (making credit easier to obtain) and inducing tighter monetary policy to lean against the booming economy. Conversely, in the wake of the 1991 recession, bank sentiment was generally working against the economy by tightening financial conditions while slowing GDP growth and inflation.

Most notably, bank sentiment appears to have helped set the stage for, amplified, and then slowed the recovery from the GFC. First, optimistic bank sentiment was the primary force creating easy credit conditions during the mid-2000s, which is when the U.S. mortgage crisis was created by extending too much credit to risky borrowers. Bank sentiment then quickly turned pessimistic once the recession began in 2007, and turned into the primary force (along with deteriorating aggregate demand) tightening credit conditions during the crisis. However, while bank sentiment appears to have made credit conditions easier (perhaps too easy) during the mid-2000s, there was only a modest increase in GDP growth as a result. This later gave way to bank sentiment being the primary drag on GDP growth during the GFC, and a subsequent headwind to recovery after the crisis.

While examining the role of bank sentiment during and after the GFC in isolation is informative about one crisis, a clear pattern emerges by examining the full historical decomposition. Bank

Figure 7: Historical decomposition of policy, activity, prices, and credit conditions



Notes: This plot presents the historical decomposition of business cycles and credit conditions into contributions by structural shocks. GDP growth is the annualized real quarterly growth rate, inflation is core PCE inflation, credit conditions are proxied by the Gilchrist & Zakrajšek 2012 EBP, and the policy rate is proxied by the one year Treasury rate. GDP growth, policy rate, and inflation data are in percent, and financial conditions are percentage points. Data are quarterly from 1986:Q1 through 2023:Q3.

sentiment generally slows down economic recovery after recessions. For example, bank sentiment appears to slow GDP growth and inflation, while continuing to tighten financial conditions, in the wake of the 1991, 2001, and 2008 recessions (although one might argue that bank sentiment quickly recovered from the GFC but then deteriorated again alongside the European "double-dip" recession in 2011-2012). The exception is the COVID-19 recovery, in which bank sentiment boosted the economy, before being neutralized by the pessimistic move in sentiment coinciding with the Silicon Valley Bank collapse.

5 Transmission of sentiment shocks

Having found bank sentiments to be an important determinant of credit conditions and source of business cycle fluctuations, I lastly turn to understanding the transmission of sentiment shocks from bank lending to the broader economy.

5.1 Expanded econometric framework

I will continue to use the a BVAR framework to estimate the effects of bank sentiments. However, as I now turn to focusing on the transmission and impacts of bank sentiment shocks, I will adopt a more comprehensive representation of the economy. To do so, I will make three changes to the previous model. First, I will replace the six variable representation of the economy with a more nuanced 26 variable model of the economy, which includes a set of financial variables summarizing the bank lending market, corporate bond market, stock market, and Treasury yield curve, as well as an expanded set of real variables that give a more detailed view of production, labor market, consumption, and trade. The full set of endogenous variables is presented in Appendix A.2. Second, since the focus of this exercise is to evaluate the impact of bank sentiment shocks, I do not need to meaningfully name the real shocks driving the economy, thus leave the statistical identification of non-bank sentiment shocks to a standard Cholesky decomposition of the BVAR's reduced-form error variance–covariance matrix. Third, I reduce the lag structure to a parsimonious AR(1) process, following the Akaike and Bayesian Information Criteria.

5.2 Impact on bank lending and other financial asset markets

I first study the impact of bank sentiment on nine variables that together holistically characterize the U.S. lending market: the loan rate premium, total lending growth, banking sector net worth growth, the percent of banks increasing costs for a line of credit for medium and large firms (or small firms), the percent of banks tightening lending covenants for medium and large firms (or small firms), and the percent of banks tightening lending standards for medium and large firms (or small firms).[26] The first five measures describe the price and quantity of bank loans as well as the general health and lending capacity of the banking sector, and require little explanation. The latter four measures are less frequently discussed so I will define them here. From Broadbent *et al.* 2024: *lending standards* are the processes that banks follow for approving or denying loan applications, and tightening (easing) lending standards indicate an increase (decrease) in the financial health requirements faced by borrowers seeking new loans. Conversely, *loan covenants* are the specific conditions included in loan contracts, such as collateral requirements and credit limits, and tightening (easing) loan covenants indicate, among other things, more (less) restrictive borrowing constraints faced by borrowers. Therefore, lending standards tend to capture variations in the extensive margin of lending, while terms are more closely related to the intensive margin.

A one standard deviation increase in bank risk sentiment —a pessimistic shock— leads to a broad deterioration in bank lending, which spills into other financial markets.

Loan rates increase and total lending decreases. Figure 8 panel (A) shows that a one standard deviation pessimistic bank sentiment shock immediately increases loan rates by 8.5 basis points.[27] The loan rate then continues to increase through one year after impact, elevating rates by approximately 19 basis points before beginning to slowly recover. Loan rates remain elevated by more than 10 basis points three years after impact, although no longer at a statistically significant level. Conversely, panel (B) shows a delayed but economically significant decline in bank lending growth. Bank lending slows by more than half a percent (approximately 0.6 percentage points) by one year after impact. Lending, similar to loan rates, then does not fully recover before three years after the sentiment shock. Relatedly, panels (F) and (I) show that the number of banks increasing the indirect costs of borrowing, namely the cost of maintaining credit lines (the option for firms to borrow from the bank on demand) increases as well.

Loan covenants tighten for both large and small firms. Figure 8 panels (E) and (H) 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

[26] The first three variables are constructed using bank-level data from U.S. Call Reports, while the latter six are from the Federal Reserve Board's Senior Loan Officer Opinion Survey (SLOOS). The SLOOS is a quarterly survey of a representative panel of U.S. banks that asks loan officers about their outlook on loan demand, as well as their terms and standards for extending loans.

[27] In comparison, Aruoba & Drechsel 2024 estimate a one standard deviation monetary policy shock to increase the one year Treasury rate by approximately the same amount. Because the two shocks increase interest rates by similar amounts, the macroeconomic response to a monetary policy shock serves as a good benchmark for comparing the macroeconomic responses to a pessimistic bank sentiment shock.

wave of tightening does not stop after the shock, rather it builds and the number of banks tightening covenants increases 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 borrowing constraints, within two years after the pessimistic shock passes.

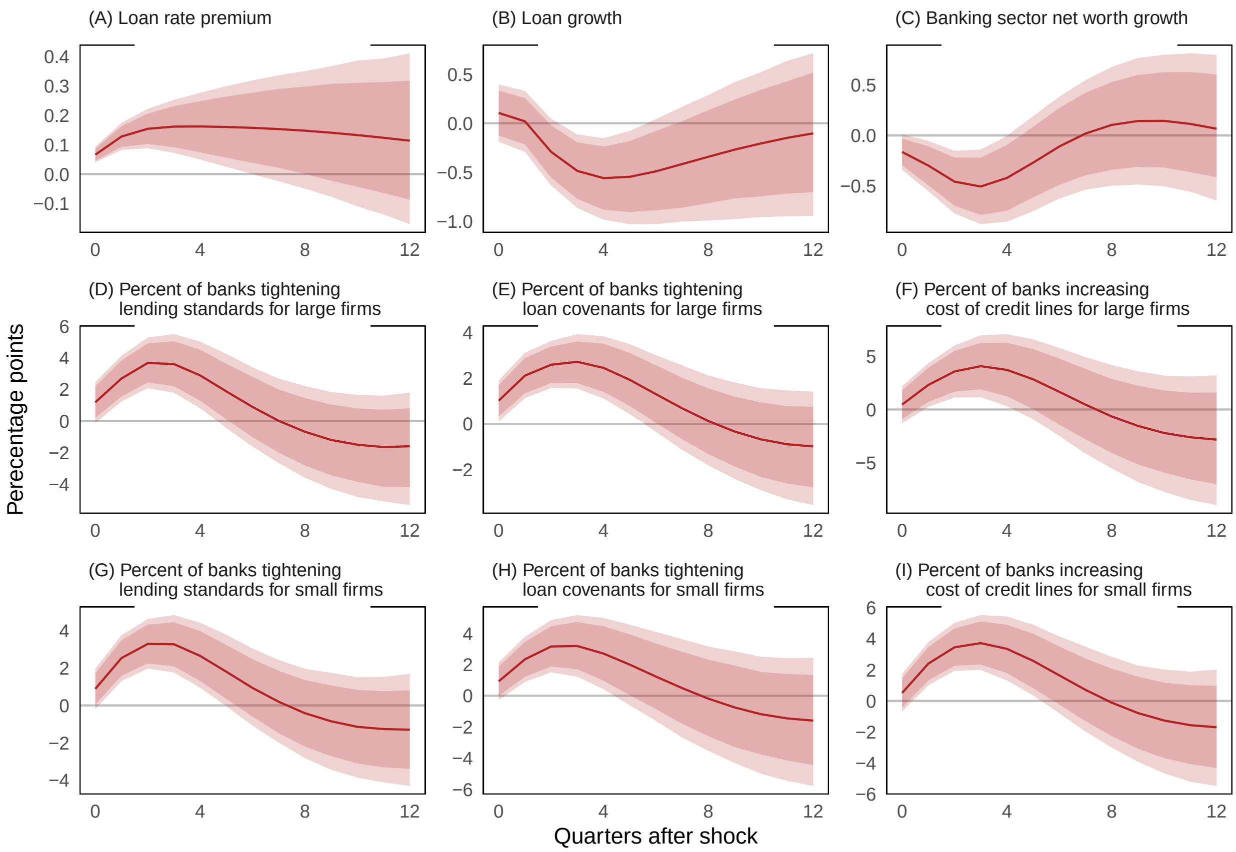
Banks tighten lending standards. Figure 8 panel (D) and (G) show that the number of banks reporting that they tightened lending standards to small and large firms, respectively, increases on impact. That is, banks become more pessimistic and then increase the financial health required of borrowers to 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, making it more difficult for new and existing borrowers alike to obtain loans for at least two years after the pessimistic shock.

Banking sector net worth growth declines. Figure 8 panel (C) lastly shows that the net worth of the banking sector grows more slowly, if not becoming negative. Banking sector net worth is a typical measure of both banking sector health and financial stability, as bank lending has been shown to be constrained by a bank's net worth (see for example Buchak *et al.* 2024 for an industrial organization perspective or Gertler & Kiyotaki 2010 for a macroeconomic model with financial intermediary lending net worth constraints). Moreover, Ottonello & Song 2022 shows that a granular surprise decline in a bank's net worth can lead to a contraction in macroeconomic activity. Therefore, sentiment shocks have both a direct effect by increasing the borrowing cost in the economy, and an indirect effect by decreasing net worth growth and counterfactually making bank balance sheets more constrained than they would have been absent the sentiment shock.

A pessimistic bank sentiment shock further leads to a broad based deterioration across financial markets. First, there is a decline in Treasury yields, indicating investors are bidding up bond prices in a flight to safety, suggesting a loss of confidence in the real economy. Second, the corporate bond spread —an indicator of risk premia in the economy— increases, making it more expensive for corporations to borrow via the bond market, in addition to the increase in loan rates directly precipitated by the bank sentiment shock. Third, stock prices decline, further evincing a decrease in investor confidence in the economy's current and future ability to generate dividends.

Loan-level impacts. I also analyze the loan-level impacts of bank sentiment shocks, using syndicated loan data and a multi-borrower multi-lender identification strategy à la Khwaja & Mian 2008. An increase in a bank's risk sentiment causes a 0.47 percentage point increase in loan rates

Figure 8: Bank lending market response to a pessimistic bank sentiment shock



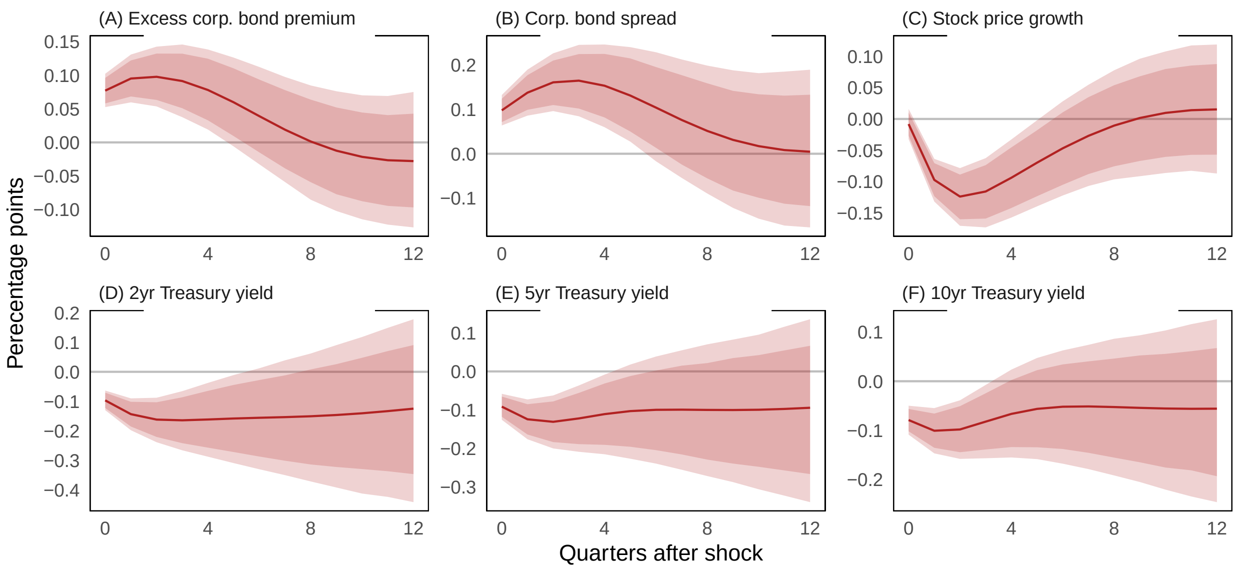
Notes: This plot presents the response of bank loan market conditions to a one standard deviation, pessimistic, bank sentiment shock. The red line marks the mean response. Shaded bands mark the 68 and 90 percent credible sets. All responses are in percentage points.

for the syndicated loans the bank leads. The full exercise is presented and discussed in Appendix D.

The transmission channels of bank sentiment shocks. The bank lending and financial market impacts of bank sentiment shocks highlight three potential transmission channels through which sentiment shocks may impact the real economy.

First, the increase in loan rates (prices) and slowdown in lending (quantities) follows the patterns of a standard negative supply shock. Thus, bank sentiment shocks may be characterized as credit supply shocks, and in turn inherit the effects of such shocks enumerated in a long history of both theoretical (e.g. Jermann & Quadrini 2012, Gertler & Kiyotaki 2010, Christiano *et al.* 2014) and empirical study (e.g. Bernanke *et al.* 1996, Amiti & Weinstein 2018, Greenstone *et al.* 2020).

Figure 9: Financial market response to a pessimistic bank sentiment shock



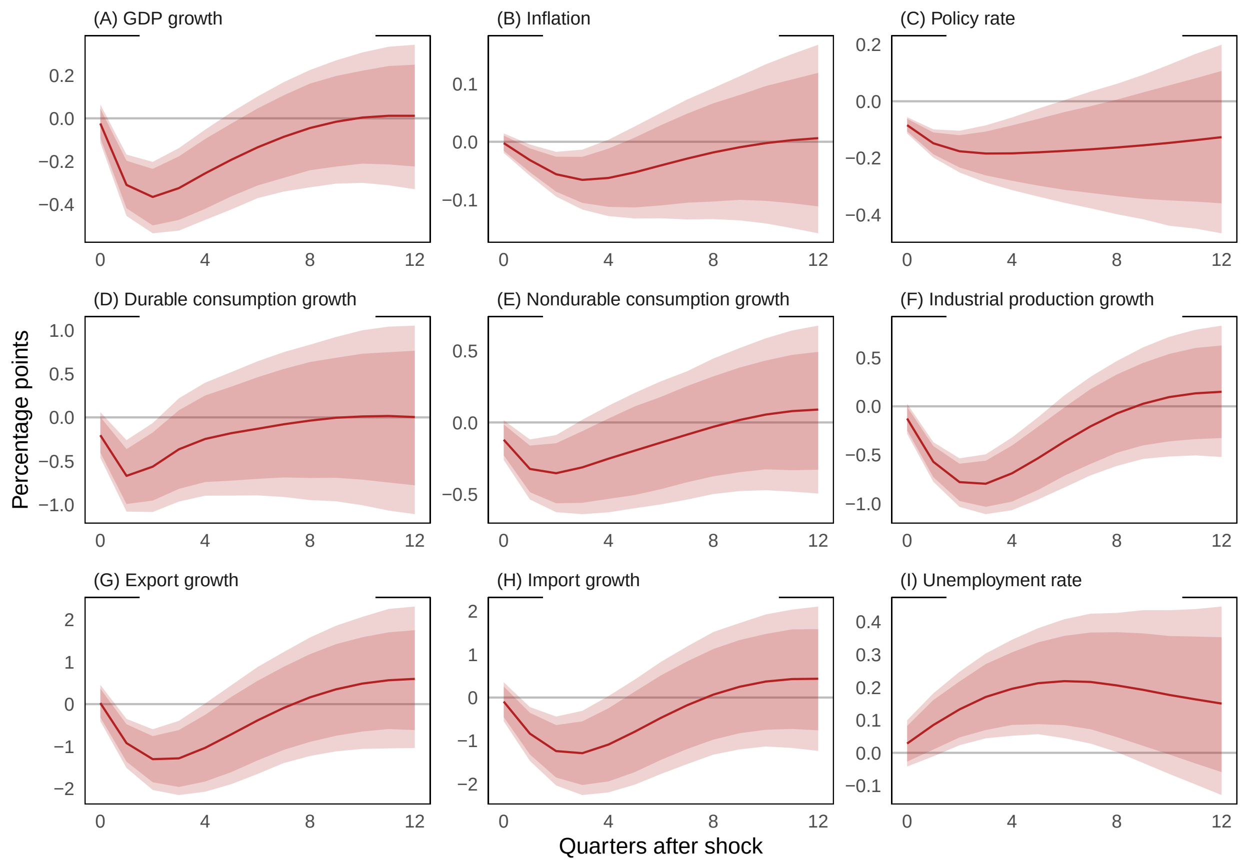
Notes: This plot presents the response of financial markets to a one standard deviation, pessimistic, bank sentiment shock. The red line marks the mean response. Shaded bands mark the 68 and 90 percent credible sets. All responses are in percentage points.

Second, there is additionally a long literature examining how fluctuations in lending standard shocks impact the real economy, similar to more generic credit supply shocks, by specifically impacting the extensive margin of lending activity (see for example Lown & Morgan 2006, Bassett *et al.* 2014, and Broadbent *et al.* 2024). However, there is less written on what drives changes in standards. Figure 9 shows that bank sentiment shocks may be one such driver of lending standards, and by extension, real activity and prices.

Third, as 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 & 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 sentiment shocks affect loan covenants, they in turn impact earnings-based borrowing constraints and effectively tighten or ease borrowing limits in the economy.[28] At the macro-level, shocks directly impacting financial constraint parameters follow in the tradition of works like Jermann & Quadrini 2012, which links this type of credit supply tightening with severe economic downturns.

[28]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 & Moore 1997.

Figure 10: Macroeconomic response to a pessimistic bank sentiment shock



Notes: This plot presents the response of real activity, policy rate, and prices to a one standard deviation, pessimistic, bank sentiment shock. The red line marks the mean response. Shaded bands mark the 68 and 90 percent credible sets. All responses are in percentage points.

5.3 Impact on macroeconomic activity and prices

Pessimistic bank sentiment shocks act like negative demand shocks. Figure 10 shows that activity (i.e. real GDP growth) declines by 37 basis points while prices (i.e. inflation) decreases by approximately 7 basis points. The simultaneous decline in activity and prices induce a 20 basis point monetary policy rate easing, falling in line with the predictions of any standard Taylor rule. Moreover, domestic production growth slows, declining by as much as 75 basis points within a year after impact, reflecting the increased costs of capital inputs and working capital. Meanwhile the labor market slackens and the unemployment rate rises by 20 basis points.

However, the transmission of the shock to the broader economy is asymmetric. For example, Panel (D) and (E) show that both durable and nondurable consumption decline in response to the pessimistic sentiment shocks, although durable consumption falls by more than twice as much as nondurable consumption. The asymmetric response most likely reflects the shock's origin in credit markets. Durable consumption goods are often purchased with credit (e.g. cars and large appliances), thus are directly impacted by the increase in loan rates. In comparison, nondurable consumption (e.g. groceries) is not as reliant on financing as durable consumption, thus only indirectly impacted by the sentiment shock. The asymmetric impact across consumption suggests that while the broad economy negatively responds to the increase in loan rates, it is production and consumption most reliant on credit that first declines and then slows the economy more broadly (following the same logic behind the aggregate demand externalities that amplify the impact of monetary policy shocks in standard New Keynesian DSGE models).

Meanwhile, trade slows and the sentiment shock is transmitted globally. Export and import growth falls by approximately 1.6 and 1.35 percentage points, respectively. This may indicate both a shrinking domestic economy —which is evident in Figure 10— along with a potential coinciding decline in foreign economies as well. Many international banks rely on dollar funding, so as U.S. banks decrease lending, the negative credit supply shock is effectively transmitted as a negative liquidity shock to foreign financial sectors. Akinci *et al.* 2022, for example, trace a similar foreign transmission of U.S. productivity uncertainty shocks.

Robustness. The response of macroeconomic conditions to bank sentiment shocks is robust to being estimated with the parsimonious model, local projections, and with or without the COVID-19 pandemic. Each robustness exercise is outlined in greater detail in Appendix F.

Comparing the macroeconomic impacts of different sentiment shocks. The estimated impact of sentiment shocks on the macroeconomy creates an important complementarily between this work and the literature estimating the macroeconomic effects of corporate bond market sentiment and household sentiment shocks. First, both López-Salido *et al.* 2017 and Boeck & Zörner 2023 find that a pessimistic increase in corporate bond market sentiment leads to greater capital costs and in turn decreases macroeconomic activity. I similarly find that an increase in bank sentiment leads to a deterioration in activity, suggesting that pessimism in either credit market is detrimental to the broader economy.

Second, Lagerborg *et al.* 2023 find household sentiment shocks account for a substantial amount of fluctuations in industrial production, but do not meaningfully impact credit conditions. In comparison, I estimate that bank sentiment shocks are a primary driver of fluctuations in credit conditions but are less impactful for activity. These two papers together show that a decline in sentiments — originating in either financial markets or households— leads to a deterioration in broader economic outcomes, but with the former primarily accounting for variation in financial markets and the latter primarily accounting for variation in real activity. Alternatively put, pessimistic sentiment shocks are bad for economic outcomes, but the source of the sentiments matters. This hints at potentially different optimal responses by policymakers to sentiment shocks depending on whom the shock hits, but I leave this to future research.

6 Conclusion

This paper measures animal spirits in the U.S. banking sector and asks whether they are an important determinant of credit conditions and source of business cycle fluctuations. I find that bank sentiments are characterized by sharp increases in pessimism during periods of uncertainty and crisis, although with substantial heterogeneity at the bank level. Fluctuations in aggregate bank sentiment in turn drive fluctuations in credit conditions, activity, prices, and the monetary policy rate. Bank sentiments precipitate this business cycle variation by directly impacting loan rates and by adjusting lending standards and covenants before spilling over to other financial markets. The tightening financial conditions then lead to a deterioration in real activity and prices, similar to an aggregate demand shock.

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Online Appendix

Table of Contents

A Data

A.1 Bank data

Bank-level data are from the Consolidated Report of Condition and Income, also known as Call Reports. A form of Call Report data was first collected in 1933 by the Federal Deposit Insurance Corporation (FDIC) as a part of the regulatory reform responding to the Great Depression. However, there was a substantial update to the required reporting frequency, the number of variables collected, and variable definitions in 1984, resulting in a bifurcation between the pre- and post-1984 Call Report sample history. Because of the incongruity between variable definitions across the two sample periods modern Call Report data effectively begins in 1984.

The bank-level sample is representative of the U.S. banking sector. Figure 13 shows that the sum of deposits and loans reported in the micro-data (approximately) match the level of deposits and loans reported by the Federal Reserve Board at the national-level. Figure 13 likewise shows that the loan-weighted charge-offs ratio reported in the micro-data matches the national charge-off ratio reported by the Federal Reserve. The sample extends from 1984 through 2023, and includes over 18 thousand unique banks, although banks enter and exit the sample due to failures, mergers, and acquisitions, so that maximum number of banks any given period is no more than 13 thousand (see Figure 14 for further description of the number and entry/exit of banks).

Call Reports do not have information on offered loan rates, so they must be inferred from the realized loan returns. Note that given $R^* = (1-\lambda)R + \lambda \cdot 0$, then, $R = \frac{R^*}{1-\lambda}$.[29] Therefore, with R^* and λ, two observable bank-level characteristics, one can infer the bank-level portfolio average R. Figure 11 shows the industry-wide (loan-weighted) average loan rate, and compares it to the risk-free rate proxied by three month Treasury Bill yield, and the Federal Reserve reported two year personal loan rate. Loan rates follow a similar pattern as the realized loan and default rates —falling since the 1980s, while increasing during recessions.

Lastly, Figure 12 shows the quarterly median interest income and costs. The difference between these two loan characteristics is the observable net interest margin, which is used for estimating the regulatory costs and markups described in Section 2.3. Note that similar to the inferred loan rates, both interest income and costs have been in secular decline since the 1980s, but unlike loan rates, have a pro-cyclical component increasing before recessions.

[29] Recall that λ is the portfolio average loan-level haircut, net recoveries, and so incorporates the average level of recoverable collateral. This implies that in an empirical setting one can assume a loan yields $R = 0$ if $\lambda = 1$, because the actual collateral recovery rate is incorporated into the average non-default yield via λ.

Table 7: Bank-level variable details

Variable	Formula	Call Report variables
Loan rates	loan interest income / total loans	RIAD4010, RCON2122
Log inverse net worth	log(1/N)	RCON3210
Loan share	$L_{i,t}/(\sum_{j\in\mathscr{B}_t} L_{j,t})$	RCON2122
Capital funding costs	total interest expense / total loans	RIAD4073, RCON2122
Charge-off ratio	charge offs / total loans	RIAD4635, RCON2122

A.1.1 Estimating banks' regulatory costs and markups

First, the regulatory cost function can be consistently estimated from the net realized loan return. To see this, I write the log-linearized realized return equation as follows:

$$r^*_{i,t} = \log\left(\frac{1}{\beta_i}\right) + \log\left(\frac{\theta_t}{\theta_t - 1}\right) + s_{i,t} + c_{i,t} + \Gamma'(L_{i,t}/N_{i,t}) - (\lambda_{i,t} - \mathbb{E}\lambda_{i,t}) \implies$$

$$\underbrace{r^*_{i,t} - s_{i,t} - c_{i,t} - (\lambda_{i,t} - \mathbb{E}\lambda_{i,t})}_{\equiv \chi_{i,t}} = \underbrace{\Gamma'(L_{i,t}/N_{i,t})}_{\equiv\, \zeta_t \cdot N^{-1}_{i,t}} + \underbrace{\log\left(\frac{1}{\beta_i}\right) + \log\left(\frac{\theta_t}{\theta_t - 1}\right)}_{\equiv\, \upsilon_{i,t}}$$

where $\chi_{i,t}$ is observable, $\upsilon_{i,t}$ are the unobservable pricing factors, ζ_t is the time-varying regulatory cost coefficient from assuming a linear functional form for $\Gamma(L_{i,t}/N_{i,t})$. The regulatory cost coefficient ζ_t can thus be estimated, quarter-by-quarter, by projecting observable $\chi_{i,t}$ onto the bank's inverse log net worth, maintaining the identifying assumption that the bank-specific discount factor and industry-wide elasticity of substitution are not correlated with the firms time t net worth.

Second, I then turn to estimating bank-specific markups. For the markups I require a measure of a bank's loan market share —which is easily constructed from Call Report balance sheets— and the elasticity of substitution θ_t. Following the "demand function approach" widely employed by the industrial organization literature, I estimate θ_t by matching the first moment of the observed realized return distribution with the return equation implied by the banks' FOC conditions.[30] The

[30] See De Loecker *et al.* 2020 for a practical overview of the three primary strategies for estimating markups. I take the "demand function approach" in contrast to Corbae & D'Erasmo 2021 or Jamilov & Monacelli 2025 who use the "production function approach" because the former subsumes all unexplained variation in loan rates, over and above the marginal cost, and defines it as a bank's markup, leaving no room for sentiments to play a role.

strategy is to first rewrite the loan pricing equation:

$$\underbrace{r^*_{i,t} - s_{i,t} - c_{i,t} - (\lambda_{i,t} - \mathbb{E}\lambda_{i,t}) - (\zeta_t)N^{-1}_{i,t-1}}_{\equiv \hat{\chi}_{i,t}} = \log\left(\frac{\theta_t}{\theta_t - 1}\right) + \log\left(\frac{1}{\beta_i}\right)$$

and as β_i converges to 1, $\hat{\chi}_{i,t}$ converges to $\log \frac{\theta_t}{(\theta_t - 1)}$. Therefore, the ratio $\log \frac{\theta_t}{(\theta_t - 1)}$ can be consistently estimated as either the mean of the $\hat{\chi}$ assuming a small enough $|1 - \beta_i|$. In the other case, if $\log(\beta_i^{-1})$ is non-zero and confounds the estimated markup, the estimation will be biased by $\mathbb{E}\log(\beta_i^{-1})$. However, this is not a concern for my estimation of sentiments because the bank fixed effect in the loan rate schedule, Equation 8, will subsume the bias.

A.1.2 Estimating bank-specific appeal

I use bank-specific appeal as a proxy for aggregate and bank-level demand shocks when testing the forecastability of bank-level risk sentiments. To estimate these measures I go back to the CES preferences of the representative borrower, which yields the aggregate composite loan:

$$L_t = \left(\prod_{i \in \mathscr{B}} \psi_{i,t} L_{i,t}^{\frac{\theta_t - 1}{\theta_t}} d_i\right)^{\frac{\theta_t}{\theta_t - 1}}$$

where $\psi_{i,t}$ is bank i appeal in time t. Taking the log of the composite loan yields:

$$\left(\frac{\theta_t - 1}{\theta_t}\right) l_t = \sum_{i \in \mathscr{B}} \log \psi_{i,t} + \left(\frac{\theta_t - 1}{\theta_t}\right) l_{i,t}$$

where $l_{i,t} = \log L_{i,t}$ and $l_t = \log L_t$. I then recast the problem in vector form:

$$l_t = \left(\frac{\theta_t}{\theta_t - 1}\right) \overline{\log \psi_t} \cdot \bar{l}_t$$

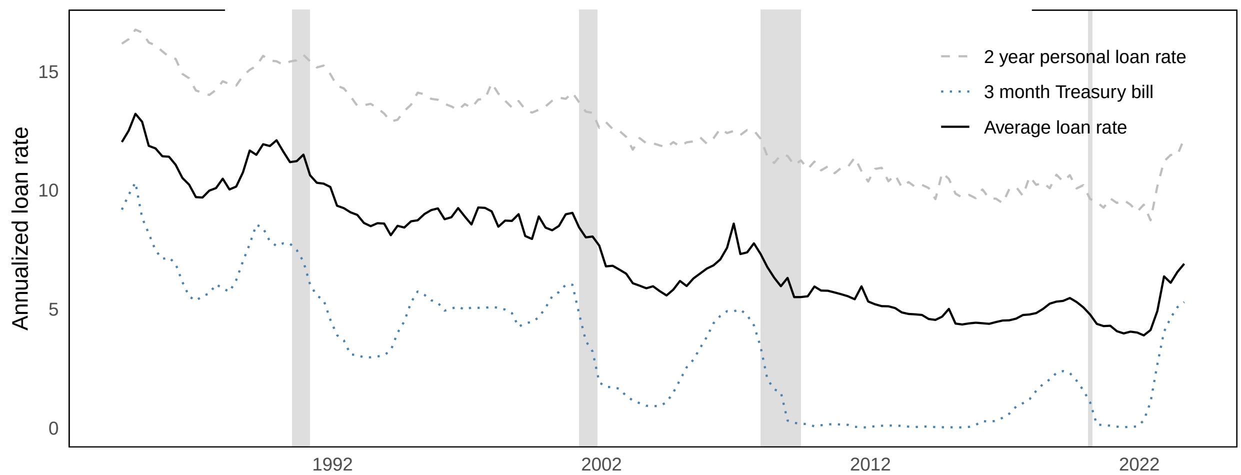
where the overline now marks the vector of bank-level log loans or appeal. Define the vector $\bar{l}_t^{-1} = [l_{1,t}^{-1}\ l_{2,t}^{-1}\ ...l_{n,t}^{-1}]'$ and post-multiple both sides by $\bar{l}_t^{-1}$ so that:

$$l_t \cdot l_t^{-1} = \left(\frac{\theta_t}{\theta_t - 1}\right) \overline{\log \psi_t} \cdot \bar{l}_t \cdot \bar{l}_t^{-1}$$

$$l_t \cdot \bar{l}_t^{-1} = \left(\frac{\theta_t}{\theta_t - 1}\right) \overline{\log \psi_t} \implies \Big[\log \psi_{1,t}\ \log \psi_{2,t}\ ...\ \log \psi_{n,t}\Big]' = \left(\frac{\theta_t - 1}{\theta_t}\right) \left[\frac{l_t}{l_{1,t}}\ \frac{l_t}{l_{2,t}}\ ...\ \frac{l_t}{l_{n,t}}\right]'$$

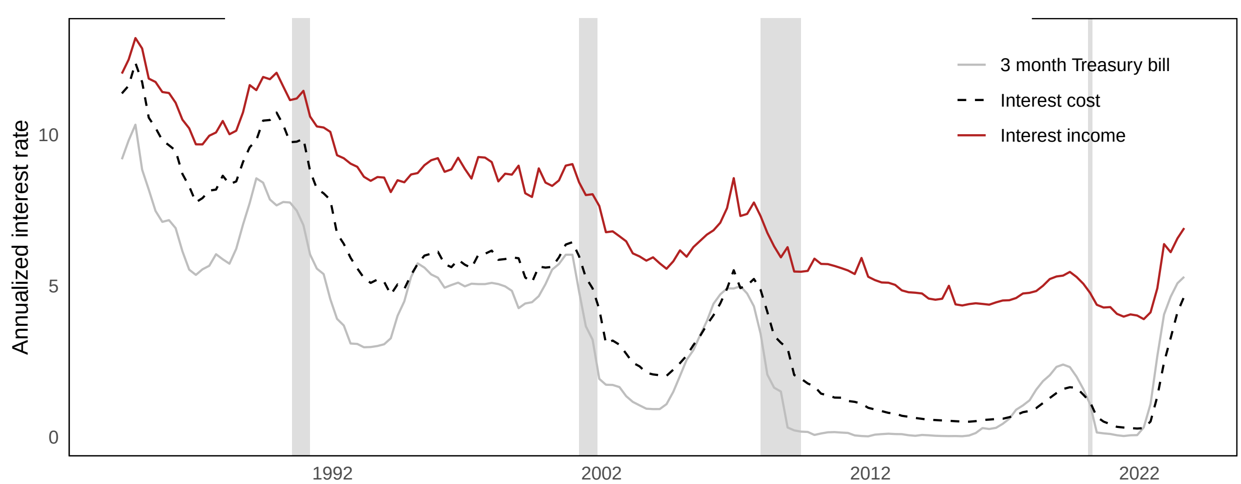
and the elasticity of substitution adjusted ratio of log lending reflects the bank-level preference weight and appeal. Note that with θ_t estimated separately following Section 2.3, calculating log appeal is a simple accounting exercise using observable loans quantities from the U.S. Call Reports.

Figure 11: Commercial bank loan rates



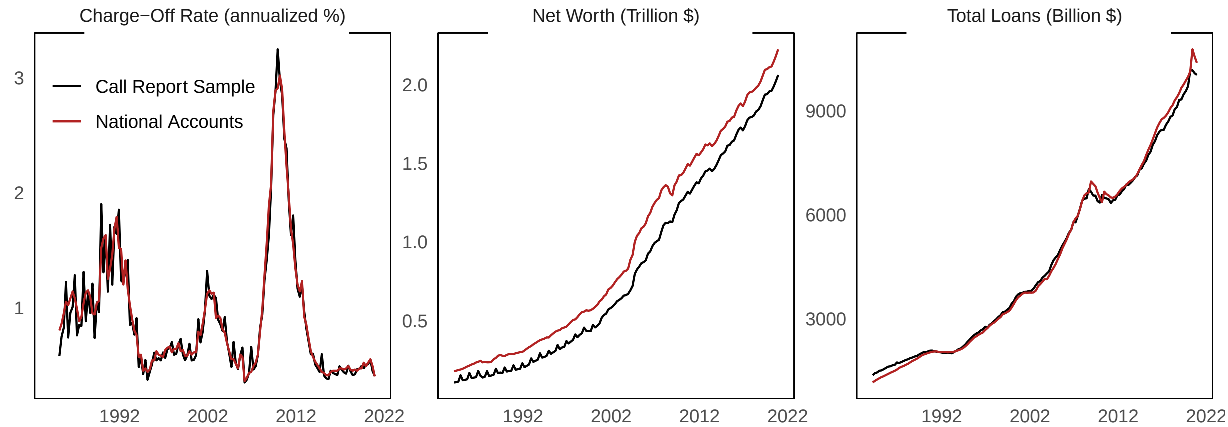
Notes: This plot compares the sample implied loan-weighted loan rate to published risk free and consumer loan rates. The bank-level sample loan rate is calculated as the reported quarterly loan income divided by total loans, scaled by the inverse one minus net charge-off ratio. The average loan rate is then the loan-weighted average of bank-level loan rates over the cross-section of banks in the given quarter. The risk-free rate is proxied by the US 3-month T-bill. The consumer loan rate is the Finance Rate on Personal Loans at Commercial Banks, 24 Month Loan, reported by the Federal Reserve Board's G.19 Consumer Credit. Gray shaded regions mark NBER dated recessions. Data are quarterly from 1984:Q1 through 2023:Q3.

Figure 12: Loan income and costs



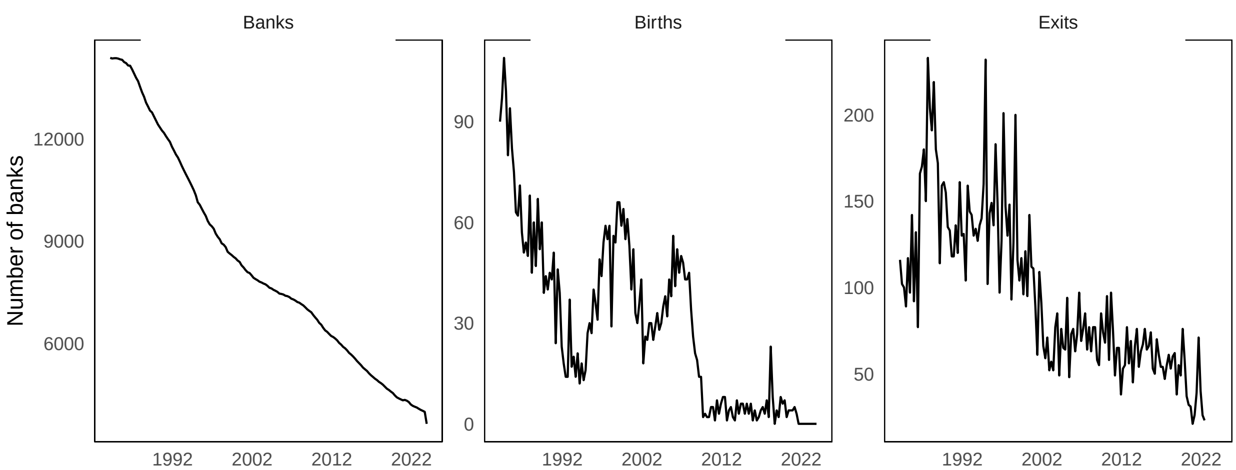
Notes: This plot presents loan interest income, costs, and the 3-month Treasury rate for comparison. Bank loan interest income and costs are loan-weighted. Gray shaded regions mark NBER dated recessions. Data are quarterly from 1984:Q1 through 2023:Q3.

Figure 13: Banking industry size and loan performance



Notes: These plots compare the charge-off ratio, total loans, and banking sector net worth in the sample to those reported by National Accounts. The sample covers the set of U.S. commercial banks that report FFIEC Call Reports. The National Account values are from the H.8 Assets and Liabilities of Commercial Banks in the United States, reported by the Federal Reserve Board. Charge-offs are net of recoveries. Data are quarterly from 1984:Q1 through 2020:Q3.

Figure 14: Banks, entry, and exit

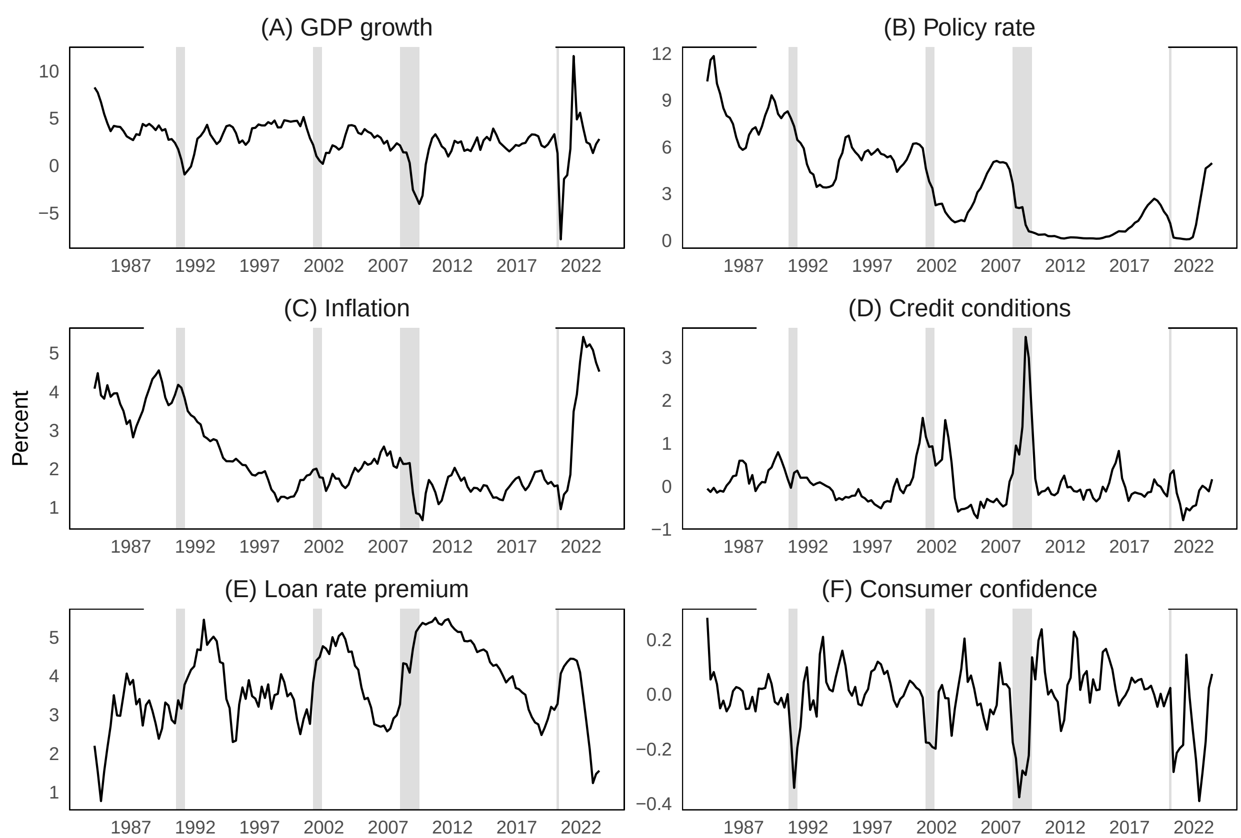


Notes: These plots present the number, entry, and exits of banks from the FFIEC Call Reports. A bank is borne when its unique RSSD ID is observed for the first time in the sample, while a bank is considered to have exited when its RSSD ID has been observed for the last time. Bank exits are not necessarily failures, but can also represent acquisitions and mergers. Data are quarterly from 1984:Q1 through 2023:Q3.

A.2 Macroeconomic data

The endogenous variables used to represent the economy in the parsimonious BVAR used in Section 4 and the medium-size BVAR used in Section 5 are standard. The endogenous variables used in the parsimonious BVAR are presented in Figure 15. The endogenous variables used in the medium-size BVAR are listed in Table 8, as well as their data sources and stationary transformations. Note that the variables used in the parsimonious BVAR are additionally used in the medium-size BVAR, thus are listed in Table 8.

Figure 15: Parsimonious BVAR endogenous variables



Notes: This plot presents the endogenous variables that define the parsimonious BVAR used in Section 4. Gray shaded regions mark NBER dated recessions. Data are from 1985:Q1 through 2023:Q3.

Table 8: Medium-size BVAR endogenous variables

Variable	Source	Transformation
Banking sector		
Loan rate	Call Reports	None
Total loans	Call Reports	%YoY growth
Total net worth	Call Reports	%YoY growth
Percent of banks tightening lending standards for large and medium size firms	FRED, *DRTSCILM*	None
Percent of banks tightening lending standards for small firms	FRED, *DRTSCIS*	None
Percent of banks tightening loan covenants for large and medium size firms	FRED, *SUBLPDCISTLNQ*	None
Percent of banks tightening loan covenants for small firms	FRED, *SUBLPDCILTLNQ*	None
Percent of banks increasing cost of credit lines for large and medium size firms	FRED, *SUBLPDCILTCNQ*	None
Percent of banks increasing cost of credit lines for small firms	FRED, *SUBLPDCISTCNQ*	None
Activity, prices, and policy		
GDP	FRED, *GDPC1*	%YoY growth
Inflation (Core PCE)	FRED, *PCEPILFE*	%YoY growth
Policy rate	FRED, *DGS1*	None
Consumer sentiment	FRED, *UMCSENT*	None
Durable consumption	FRED, *PCEDG*	%YoY growth
Nondurable consumption	FRED, *PCEND*	%YoY growth
Industrial production	FRED, *INDPRO*	%YoY growth
Exports	FRED, *EXPGS*	%YoY growth
Imports	FRED, *IMPGS*	%YoY growth
Unemployment rate	FRED, *UNRATE*	None
Financial markets		
Excess bond premium	Gilchrist & Zakrajšek 2012	None
GZ spread	Gilchrist & Zakrajšek 2012	None
Stock prices	Robert Shiller's website	None
2-year Treasury rate	FRED, *DGS2*	None
5-year Treasury rate	FRED, *DGS5*	None
10-year Treasury rate	FRED, *DGS10*	None
30-year Treasury rate	FRED, *DGS30*	None

Notes: This table lists the endogenous variables that define the medium-size BVAR used in Section 5. Data sourced from FRED lists the mnemonics in italics. Loan rates are the loan-weighted average rates, while total loans and net worth are the simple sum of either object per period. The %YoY growth is calculated as $100 \cdot log(X_t/X_{t-4})$. Data are quarterly from 1985:Q1 through 2023:Q3.

B Theoretical framework

B.1 Competitive Equilibrium

The loan market competitive equilibrium is characterized by the set of prices $\{R_{i,t}, C_{i,t}\}_{i \in \mathscr{B}}$, exogenous shocks and preferences $\{\psi_{i,t}, \varepsilon_{i,t}\}_{i \in \mathscr{B}}$, and stationary loan supply function such that:

- Borrowers demand loans $\{L_{i,t}\}_{i \in \mathscr{B}}$ according to Equation (1)
- Each Bank i supplies $L_{i,t}$, given $N_{i,t}$, $C_{i,t}$, $\varepsilon_{i,t}$, and $\psi_{i,t}$, that satisfies its dynamic programming problem, Equation (2)
- Each bank-specific loan market, $i \in \mathscr{B}$, clears.

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

B.2 Bank sentiment shocks and aggregate outcomes

Bank-level sentiment shocks will increase aggregate loan rates. This conclusion follows simply from the CES preferences of the representative borrower implied effective loan rate:

$$R_t = \left(\int_{i \in \mathscr{B}} \psi_{i,t}^{\theta} R_{i,t}^{1-\theta} d_i \right)^{\frac{1}{1-\theta}}$$

which can be log-linearized to:

$$(1-\theta_t) r_t = \sum_{i \in \mathscr{B}} \theta_t \log \psi_{i,t} + (1-\theta_t) r_{i,t}$$

and substituting in the log-linearized loan rate, Equation 7 yields:

$$r_t = \sum_{i \in \mathscr{B}} \frac{\theta_t}{\theta_t - 1} \log \psi_{i,t} + \gamma_i + \rho_1 \lambda_{i,t-1} + \rho_2 \lambda_{t-1} + \varepsilon_{i,t} + \log\left(\frac{1}{\beta}\right) + \log\left(\frac{\theta_t}{\theta_t - 1}\right) + s_{i,t} + c_{i,t} + \Gamma'(L_{i,t}/N_{i,t})$$

The derivative of aggregate log loan rates with respect to a sentiment shock is positive.

Result 1 (Bank risk sentiment and the aggregate loan rate)
The aggregate loan rate is a weighted average of the Specialists' loan rates. Thus, a granular increase in a single bank's risk sentiments will increase the aggregate loan rate of the economy.

Bank-level sentiment shocks will decrease aggregate lending. The CES preferences of the representative borrower, yield the aggregate composite loan:

$$L_t = \left(\int_{i \in \mathscr{B}} \psi_{i,t} L_{i,t}^{\frac{\theta_t - 1}{\theta_t}} d_i \right)^{\frac{\theta_t}{\theta_t - 1}}$$

where $\psi_{i,t}$ is bank i appeal in time t. Thus, aggregate lending is a strictly increasing function of bank-specific lending. Simultaneously, bank-specific loan demand is:

$$L_{i,t} = \psi_{i,t} \left(\frac{R_t}{R_{i,t}} \right)^{\theta_t} L_t$$

which is a strictly decreasing function in aggregate loan rates. Therefore, by Result 1, a pessimistic bank-level sentiment shock will decrease bank-specific and aggregate lending.

Result 2. (Bank risk sentiment and the aggregate loan supply)
An increase in bank-level sentiments will decrease the aggregate supply of loans in the economy.

B.3 Loan rate proof

Theorem 1 *A bank charges the loan portfolio average interest rate:*

$$R_{i,t} = \frac{1}{\beta_i} \frac{\theta_t}{\theta_t - 1} \frac{C_{i,t} + \Gamma'(L_{i,t}/N_{i,t})}{(1 - \lambda_{i,t})} \frac{1}{1 - s_{i,t}}$$

Proof. The bank's problem in series form follows:

$$\max_{\{R_{i,t}\}_{t=0}^{\infty}} \quad \sum_{t=0}^{\infty} \beta_i^t \Pi_{i,t} \quad \text{s.t.}$$

$$\Pi_{i,t} = R_{i,t}^* L_{i,t} - (L_{i,t} - N_{i,t}) C_{i,t} - \Gamma(L_{i,t}/N_{i,t}) \qquad \text{(Profit function)}$$

$$R_{i,t}^* = (1 - \lambda_{i,t}) R_{i,t} \qquad \text{(Realized gross return)}$$

$$N_{i,t} = N_{i,t-1} + \Pi_{i,t-1} \qquad \text{(Net worth LoM)}$$

After using the bank-specific demand curve $L_{i,t} = \psi_{i,t} \left(\frac{R_{i,t}}{R_t} \right)^{\theta_t} L_t$ to replace the loan rate $R_{i,t}$, the

Lagrangian is:

$$\mathscr{L} = \sum_{t=0}^{\infty} \beta^t \left[(1-\lambda_{i,t+1}) R_{i,t} L_{i,t} - (L_{i,t} - N_{i,t}) C_{i,t} - \Gamma\left(L_{i,t}/N_{i,t} \right) \right] \quad \text{s.t.}$$

$$N_{i,t} = N_{i,t-1} + \Pi_{i,t-1} \quad \text{with } N_{i,0} \text{ given}$$

Then, assuming the regulatory cost term takes a linear functional form: $\Gamma(L_{i,t}/N_{i,t}) = \zeta_t(L_{i,t}/N_{i,t})$ where $\zeta_t > 0$, the first order condition (FOC) is

$$\frac{\partial \mathscr{L}}{\partial L_{i,t}} = \beta_i L_i^{1/\theta_t} (1-\lambda_i) \psi_i R^{1-1/\theta_t} L_i^{-1/\theta_t} \left(\frac{\theta_t - 1}{\theta_t} \right) - C_{i,t} - \zeta_i/N_i + \ldots$$
$$\ldots + \beta_i \left(\frac{L_t}{R_t} \right)^{1/\theta_t} \frac{\partial R}{\partial L_i} R_t^{1-1/\theta_t} \psi_i (1-\lambda_i) \left(\frac{\theta_t - 1}{\theta_t} \right) - \left[\sum_{j=1}^{\infty} \beta^j \eta_{i,j} \right] - \left[\sum_{j=1}^{\infty} \beta^j \zeta_{i,j} \right] = 0$$

where $\eta_{i,j}$ is the marginal increase in net worth due to relaxing regulatory costs in period j from the marginal increase in retained earnings in period t, and $\zeta_{i,j}$ is the marginal increase in net worth due to decreasing capital funding costs in period j from the marginal increase in retained earnings in period t. Note that the condition

$$[\sum_{j=1}^{\infty} \beta^j \eta_{i,j}] = [\sum_{j=1}^{\infty} \beta^j \zeta_{i,j}] = 0$$

must be true in the absence additional constraints (assuming a non-zero term implies a profit improving, thus net worth increasing, loan rate exists; formalizing a proof by contradiction using this logic is straightforward). Thus the FOC becomes a static equation:

$$\frac{\partial \mathscr{L}}{\partial L_i} = \beta_i L_i^{1/\theta} (1-\lambda_i) \psi_i R^{1-1/\theta} L_i^{-1/\theta} \left(\frac{\theta - 1}{\theta} \right) - C_i - \zeta_i/N_i + \beta_i \left(\frac{L}{R} \right)^{1/\theta} \frac{\partial R}{\partial L_i} R^{1-1/\theta} \psi_i (1-\lambda_i) \left(\frac{\theta - 1}{\theta} \right) = 0$$

where I have dropped the t subscripts.

Solving the FOC for $R_{i,t}$ is then a simple matter of algebra:

$$\frac{\partial \mathscr{L}}{\partial L_i} = 0 \implies \frac{1}{\beta_i} \frac{\theta}{\theta - 1} \frac{C_i + \zeta_i/N_i}{\psi_i(1-\lambda_i)} = \frac{L_t}{L_{i,t}}^{1/\theta} R^{1-1/\theta} + L^{1/\theta} R^{-1/\theta} \frac{\partial R}{\partial L_i} L_i^{1-1/\theta}$$

define $\chi_i = \frac{1}{\beta_i}\frac{\theta}{\theta-1}\frac{C_i+\zeta_i/N_i}{\psi_i(1-\lambda_i)}$ for convenience, then

$$\begin{aligned}\chi_i R^{1/\theta} &= L^{1/\theta} L_i^{-1/\theta} R_t + L_t^{1/\theta}\frac{\partial R}{\partial L_i} L_i L_i^{-1/\theta} \\ &= s_i^{-1/\theta} + s_i^{-1/\theta}\frac{L_i}{R}\frac{\partial R}{\partial L_i}\end{aligned}$$

where $s_i = L_i/L$ is the bank's loan market share, and using Shepard's Lemma, $-\frac{\partial R}{\partial L_i} = s_i$ we have:

$$\chi_i R^{-1/\theta} = s_i^{-1/\theta} - s_i s_i^{-1/\theta} = s_i^{-1/\theta}(1-s_i)$$

$$\Longrightarrow \frac{1}{\beta_i}\frac{\theta}{\theta-1}\frac{C_i+\zeta_i/N_i}{\psi_i(1-\lambda_i)}\frac{1}{1-s_i} = \left(\frac{L}{L_t}\right)^{1/\theta} R^{1/\theta-1}$$

$$\Longrightarrow \frac{1}{\beta_i}\frac{\theta}{\theta-1}\frac{C_i+-\zeta_i/N_i}{(1-\lambda_i)}\frac{1}{1-s_i} = \psi_i L^{1/\theta} L_i^{-1/\theta} R^{1/\theta-1} = L_i R_i$$

so the loan rate for a one unit loan is:

$$\frac{1}{\beta_i}\frac{\theta}{\theta-1}\frac{C_i+\Gamma'(\frac{L_i}{N_i})}{(1-\lambda_i)}\frac{1}{1-s_i} = R_i$$

where $\Gamma'(\frac{L_i}{N_i})$ is the marginal regulatory cost with respect to bank lending $L_{i,t}$. ■

C Measurement

C.1 Macro-approach and portfolio composition robustness

I will complement my baseline estimation of bank risk sentiment with an additional measurement strategy, a "macro-approach" that requires no additional assumptions beyond the theoretical model already introduced, but is restricted to only identifying sector-wide sentiments. The macro-approach will then be used to test the robustness of the bank sentiment measure against different postulated laws of motion for loan losses, as well as the effects of loan portfolio composition effects, namely loan maturity and borrower quality.

C.1.1 Macro-approach measurement strategy

A bank's risk sentiment is the bank's deviation from its rational expectations forecast of loan defaults. That is, taking $E_{RE}(\lambda_{i,t})$ as the rational expectations forecasting function of loan losses, sentiments can then be expressed as a wedge $\varepsilon_{i,t}$ between the bank's actual forecast of the default rate and the rational expectations forecast of the default rate:

$$\mathbb{E}\lambda_{i,t} = E_{RE}(\lambda_{i,t}) + \varepsilon_{i,t}$$

It then follows that sentiments directly impact loan rates through the forecasted losses, thus demanded compensation for risk:

$$R_{i,t} = \frac{1}{\beta_i} \cdot \frac{\theta_t}{\theta_t - 1} \frac{1}{1 - s_{i,t}} \cdot \frac{1}{1 - f(I_{i,t}) - \varepsilon_{i,t}} \cdot (C_{i,t} + \Gamma'(L_{i,t}/N_{i,t})) \tag{14}$$

so that positive sentiments (a belief that defaults will be higher than the rational expectations forecast would suggest) increase loan rates and decrease loan issuance.

While an agent's rational expectations forecast is unobservable, sentiments may be directly inferred from the bank's interest income. Given the structure of the loan market and resulting loan rates, the log realized return is

$$
\begin{aligned}
R^*_{i,t} &= \frac{1-\lambda_{i,t}}{1-\mathbb{E}\lambda_{i,t}} \cdot \frac{1}{\beta_i} \cdot \frac{\theta_t}{\theta_t - 1} \frac{1}{1-s_{i,t}} \cdot (C_{i,t} + \Gamma'(L_{i,t}/N_{i,t})) \\
&= \frac{1-f(I_{i,t})-\nu_{i,t}}{1-f(I_{i,t})-\varepsilon_{i,t}} \cdot \frac{1}{\beta_i} \cdot \frac{\theta_t}{\theta_t - 1} \frac{1}{1-s_{i,t}} \cdot (C_{i,t} + \Gamma'(L_{i,t}/N_{i,t})) \implies \\
r^*_{i,t} &= \varepsilon_{i,t} - \nu_{i,t} + \log\left(\frac{1}{\beta_i}\right) + \log\left(\frac{\theta_t}{\theta_t - 1}\right) + s_{i,t} + c_{i,t} + \Gamma'(L_{i,t}/N_{i,t})
\end{aligned}
$$

for small enough default rates, marginal capital costs, and market shares. Note that the realized default rate $\lambda_{i,t}$ is rewritten as the rational expectations forecast and forecast error $\nu_{i,t}$. The rational expectations forecast ultimately falls out of the net return equation because the bank is compensated for the predictable risk, but bank's sentiment and forecast error remain.

By the properties of rational expectations with full information, we have that

$$
\lambda_{i,t} = f(I_{i,t}) + \nu_{i,t}, \qquad \nu \sim \mathcal{N}(0, \Sigma)
$$

for all banks, where $\nu_{i,t}$ is the bank-specific forecast error. Thus, the cross-sectional average forecast error is zero, and the sector-wide average realized return is:

$$
\mathbb{E}r^*_{i,t} = \mathbb{E}\left[\varepsilon_{i,t} + \log\left(\frac{1}{\beta}\right) + \log\left(\frac{\theta_t}{\theta_t - 1}\right) + s_{i,t} + c_{i,t} + \Gamma'(L_{i,t}/N_{i,t})\right] \tag{15}
$$

where $\mathbb{E}\nu_{i,t} = 0$ and consequentially falls out of the equation. Therefore, with observable proxies for the bank's markups, market share, marginal capital cost, and marginal regulatory costs, the log-linearized realized return equation can be estimated with standard econometric techniques, and the banking sector average sentiment may in turn be inferred from the cross-sectional average residual realized return.

C.1.2 Postulated law of motion for loan losses robustness test

The strength of the "macro-approach" is that it does not require an assumed law of motion for bank-level loan losses. In fact, the approach does not require any information on banks' rational expectations forecast of losses, which is advantageous given the unobservable nature of these forecasts. Since one is not required to postulate a law of motion for bank-level loan losses, the macro-approach is a useful robustness check on potential bias in the aggregate sentiment series introduced by a possibly misspecified law of motion.

However, there are two key limitations to the macro-approach. First, the implicit assumption that there is no aggregate risk. If this identifying assumption is violated, then the cross-sectional average $v_{i,t}$ is not necessarily zero, and one cannot separate BRS from aggregate shocks increasing default rates among borrowers. Second, the macro-approach does not allow for identifying bank-level sentiments.

C.1.3 Portfolio composition robustness tests

I will further use the macro approach to test the robustness of the aggregate bank risk sentiment to two portfolio composition considerations.

First, I will use the macro-approach to additionally test whether the composition of the loan portfolio influences the measure of aggregate bank risk sentiments. If it does, then the empirical measure does not successfully isolate animal spirit shocks. I first test whether bank risk sentiment may be capturing underlying features of the loan portfolio composition by loan type, for example, changes in the effective portfolio term premia. To do so, I include measures for the relative loan share of commercial, consumer, and real estate loans in the estimated log loan return equation that identifies bank sentiment in the macro-approach. These three types of loans vary in their average maturity, with real estate loans having the longest maturity on average. Thus, if BRS is capturing changes in term premia, then one would expect that an increase in the real estate share of the loan portfolio would be positively correlated with bank sentiment.

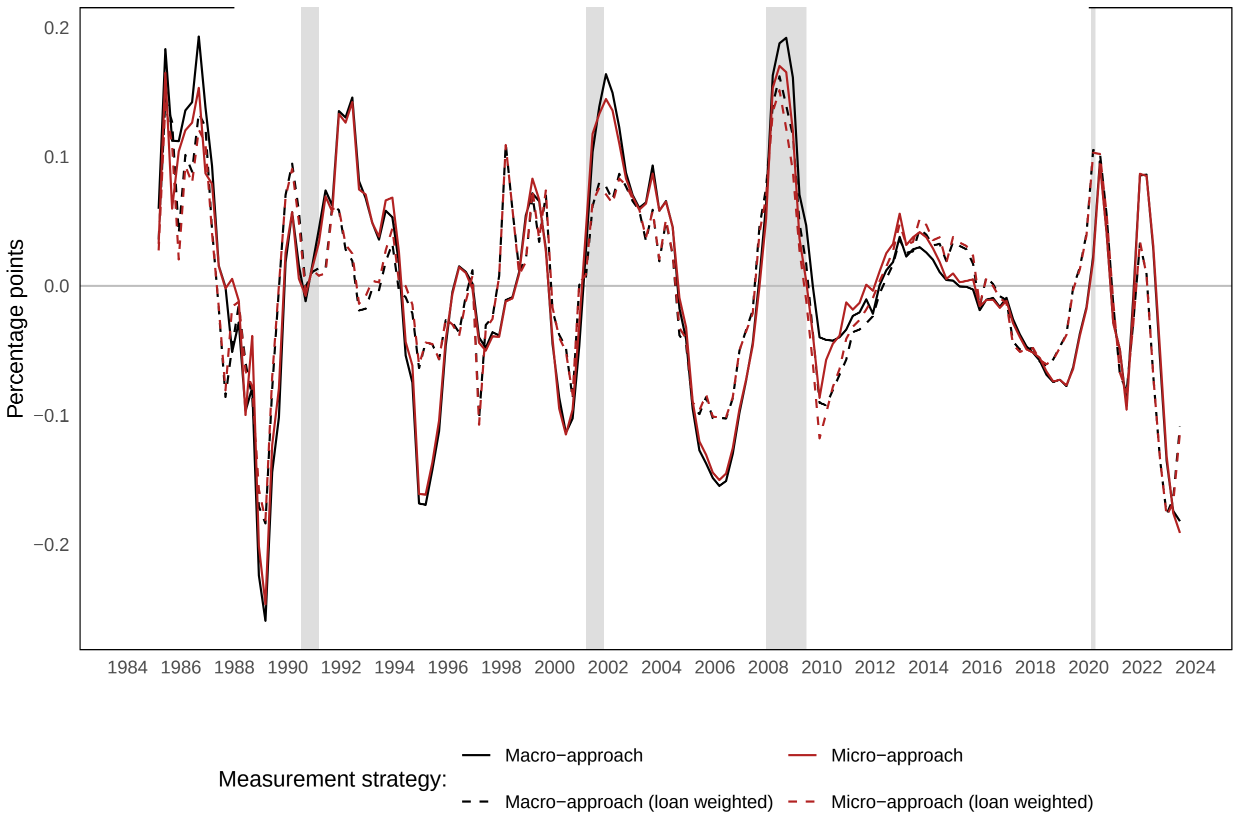
Second, I additionally test whether underlying portfolio borrower risk is influencing the bank risk sentiment. If so, then the BRS contains information about the riskiness of the portfolio, thus should be included in the rational expectations forecast of risk and cannot be reasonably described as noisy animal spirits. To do so, I include a measure of changes in the relative riskiness of borrowers in banks' loan portfolios. The relative risk proxy is the difference in the percent of banks responding to the Fed's Senior Loan Officer Opinion Survey (SLOOS) that they have observed an increase in demand for loans from small and medium size businesses and the percent of banks responding to the same survey that they have observed an increase in demand for loans from large businesses. This measure is meant to capture the changing allocation in the loan portfolio from safer large businesses to riskier small and medium-size businesses.

Table 9: Bank risk sentiment measurement equations

	Micro-approach (estimating $r_{i,t}$)		Macro-approach (estimating $r^*_{i,t}$)			
	(1)	(2)	(3)	(4)	(5)	(6)
capital cost: $c_{i,t}$	0.250***	0.487***	0.243***	0.489***	0.537***	0.460***
	(0.021)	(0.024)	(0.021)	(0.023)	(0.031)	(0.022)
regulatory cost: $\Gamma'_{i,t}$	−0.023	0.049*	−0.004	0.060**	0.101***	0.037
	(0.014)	(0.029)	(0.015)	(0.028)	(0.031)	(0.024)
markups: $\log(\frac{\sigma_t}{\sigma_t - 1}\frac{1}{1-s_{i,t}})$	−0.007	0.001	−0.004	0.001	0.002	0.005
	(0.010)	(0.010)	(0.010)	(0.010)	(0.016)	(0.011)
idio. defaults: $\lambda_{i,t-1}$	−0.007**	−0.008				
	(0.003)	(0.011)				
agg. defaults: λ_{t-1}	−0.233***	−0.141*				
	(0.043)	(0.078)				
Portfolio risk					−0.000	
					(0.000)	
Consumer loan share						0.012
						(0.012)
Real estate loan share						−0.001
						(0.008)
Commercial loan share						0.013
						(0.011)
Loan share weighted		✓		✓	✓	✓
Time trend	✓	✓	✓	✓	✓	✓
Bank FE	✓	✓	✓	✓	✓	✓
Observations	690,084	690,084	690,084	690,084	559,076	688,689
Total R^2	0.879	0.901	0.876	0.901	0.863	0.904
Within R^2	0.781	0.800	0.776	0.797	0.722	0.804

Notes: This table presents the sentiment measurement equations. Columns (1) and (3) are the unweighted; Columns (2), (4), (5) and (6) are quarter-loan-share weighted. All models include a linear time trend and bank fixed effects. All models are estimated as within-group fixed effect linear panel models. The quarterly, unbalanced, panel includes 19.5 thousand banks from 1984:Q1 through 2023:Q3. Parentheses wrap the robust standard errors, which are clustered at the bank level, and * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

Figure 16: Bank risk sentiment measured by micro-approaches and macro-approaches



Notes: This plot shows the quarterly aggregate bank risk sentiment of U.S. commercial banks. The black lines present bank sentiment measured by the macro-approach. The red lines present bank sentiment measured by the micro-approach. Solid lines present the unweighted version of either measure, while the dashed lines present the loan-weighted version of either measure. Gray shaded regions mark NBER dated recessions. Data is from 1985:Q1 through 2023:Q3.

C.1.4 Measurement equations and robustness results

Following the measurement strategies laid out above, I estimate aggregate bank risk sentiments with the macro-approach. Table 9, columns (3) and (4), report the estimated loan pricing equations, estimated with and without loan-weighted observations. The macro-approach estimation accounts for a large percentage of bank-level realized income variation, which is quantitatively similar to the micro-approach (reproduced in Table 9 columns (1) and (2) for comparison). This is perhaps a reflection of the similarities in estimated pricing factor loadings across the two measurement equations. For example, the capital costs coefficients are almost identical, and the regulatory costs are only separated by approximately one basis point.

Postulated law of motion for losses. I also calculate aggregate bank risk sentiment —the quarter-by-quarter cross-sectional average residual realized income, which following Equation 15 is identifiable as the aggregate bank risk sentiment. Figure 16 shows a high degree of similarity between the aggregate bank risk sentiment estimated by micro- or macro-approach, whether weighted or unweighted by bank loans. The similarity across the two approaches is affirmative evidence that the postulated law of motion used in the micro-approach does not alter the measure of aggregate sentiments, thus does not pose a risk to the estimation of the macroeconomic importance and impacts of aggregate bank sentiment shocks.

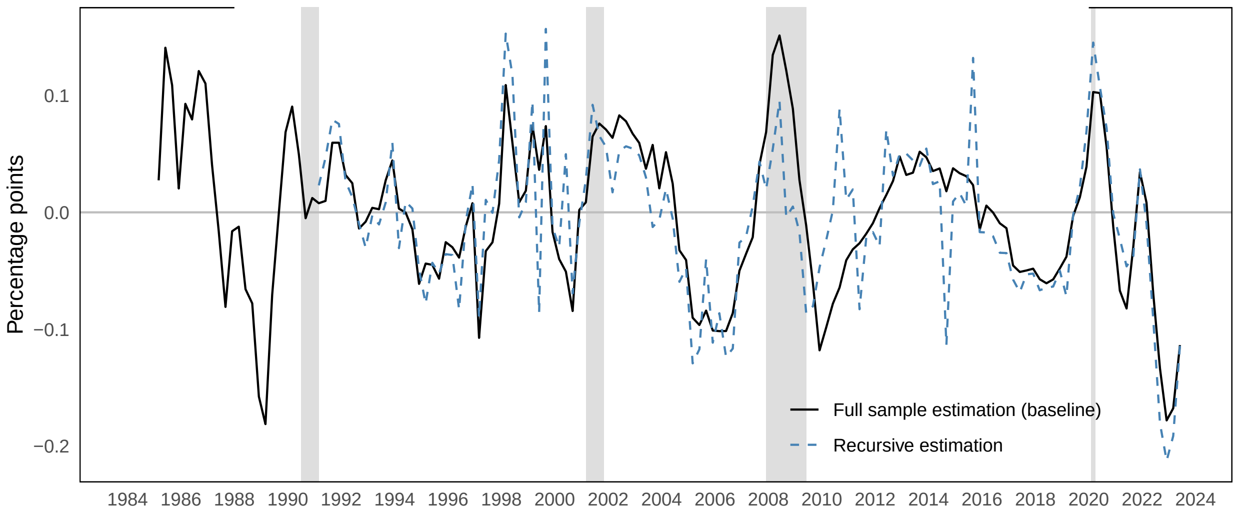
Portfolio composition tests. First, bank sentiment is not correlated with underlying portfolio risk. Table 9 column (5) shows that I cannot distinguish the impact of relative risk on the measurement equation (thus bank sentiments) from zero at any standard statistically significant level. Second, bank sentiment is not correlated with term premia. Table 9 column (6) shows that the log loan return is not conditionally correlated with changes in maturity structure of the banking sector loan portfolio (proxied by the loan share of commercial or real estate loans), at least not at any standard statistically significant level. As a result, I may conclude that the empirical measure of aggregate bank risk sentiment does not contain rationally useful information about the underlying riskiness or maturity composition of the banking sector's loan portfolio.

C.2 Recursive information set and historical robustness

Lastly, and related to the previous robustness check regarding the postulation law of motion for loan losses, I test how sensitive bank sentiments are to being estimated with the full sample. In particular, 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. To test this concern, 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 there is a high degree of similarity in aggregate BRS between using the full sample to estimate all bank-level risk sentiments with one estimated loan rate equation versus estimating bank-level sentiments one quarter at a time with an expanding window information set. Figure 17 shows similar qualitative dynamics between aggregate BRS estimated with the full sample compared to aggregate BRS estimated one quarter at a time. Additionally, the correlation coefficient between the two series is high, 0.799, and both series have a historical mean near zero.

Figure 17: Recursive estimation of aggregate bank risk sentiment



Notes: This plot shows the quarterly aggregate bank risk sentiment of U.S. commercial banks, estimated with the full sample or with an expanding window starting in 1990:Q1. The solid black line presents the loan-weighted sentiment index and the dashed blue line presents aggregate sentiments estimated identically but with an expanding window information set starting in 1990:Q1. Gray shaded regions mark NBER dated recessions. Data is from 1985:Q1 through 2023:Q3.

This exercise additionally shows that estimated bank-level sentiment is qualitatively robust to removing influential periods, such as the GFC and COVID-19 pandemic.

D Loan-level analysis

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

$$y_{l,f,i,t} = \gamma_{f,t} + \gamma_{f,i} + \delta \chi_{i,t} \varepsilon_{i,t} + \beta \Theta_t + \eta_{l,f,i,t} \tag{16}$$

where $y_{l,f,i,t}$ is the loan rate for loan l, firm f (i.e. borrower), bank i, and date t; $\gamma_{f,t}$ denotes a firm-quarter fixed effect, and $\gamma_{f,i}$ a borrower-lender fixed effect; $\varepsilon_{i,t}$ is the bank risk sentiment of bank i at date t; $\chi_{i,t}$ is the indicator function equal to one when bank i is the lead arranger of the syndicated loan (following Chodorow-Reich 2014); Θ_t collects the vector of loan and firm characteristics. My coefficient of interest when evaluating Equation 16 is δ, the response of loan outcome $y_{l,f,i,t}$ to a one percentage point change in a bank's risk sentiment.

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.[31] 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

[31] 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.

Table 10: Summary statistics of matched bank-loan data

	Mean	SD	p(5)	p(25)	p(50)	p(75)	p(95)
Loan characteristics							
Loan amount	1832.9	2776.5	150.0	451.3	1018.0	2100.0	5854.6
Loan rate	252.9	134.2	75.0	175.0	225.0	325.0	475.0
Covenants present	64.0%						
Secured by collateral	80.5%						
Bank characteristics							
BRS	0.049	0.174	-0.208	-0.054	0.050	0.146	0.348
Bank net worth	1.581	2.924	0.001	0.039	0.672	1.808	5.472

Notes: This table reports the summary statistics for data used in estimating the loan-level impact of a change in BRS. The loan amount is reported in millions USD, and bank net worth in billions USD. The Loan rate is the margin over reference (e.g. LIBOR), quoted in basis points. Covenant present and Secured by collateral are binary indicators. Loan characteristics are from DealScan. Bank characteristics are from U.S. Call Reports and author calculations. Dates range from 1992:Q3 through 2023:Q3.

syndicated loans from the LPC DealScan database.[32] The data 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.[33] 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 create my measure of bank-level BRS.[34] The matched bank-loan data set ultimately includes 180.5 thousand facility observations, ranging from 1992:Q2 through 2023:Q3, representing 250 unique lenders (banks) and 1752 borrowers (firms). However, my estimation sample will be a subsample of this matched-data set, with observations only being included if all model variables being present and the multi-lender multi-borrower requirements are met.

The DealScan data contains two types of observations, loan originations and loan refinancing agreements. I will focus on borrowers renegotiating the terms of a loan held on a bank's bal-

[32]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.

[33]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.

[34]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 11: Loan-level rate spread response to a bank sentiment shock

	(1)	(2)	(3)	(4)
bank sentiment × lead: $\varepsilon_{i,t} \cdot \chi_{i,t}$		0.643^{***}	0.646^{***}	0.646^{***}
		(0.137)	(0.137)	(0.137)
Bank sentiment: $\varepsilon_{i,t}$	-0.035	-0.041	-0.040	-0.037
	(0.047)	(0.048)	(0.047)	(0.047)
Lead: $\chi_{i,t}$		-0.128^{***}	-0.128^{***}	-0.128^{***}
		(0.028)	(0.028)	(0.028)
Borrower-Quarter FE	✓	✓	✓	✓
Lender-Borrower FE	✓	✓	✓	✓
Loan characteristics			✓	✓
Bank characteristics				✓
Observations	9,833	9,833	9,833	9,833
R^2	0.887	0.887	0.887	0.887

Notes: This table reports a (within) fixed effects regression of loan outcomes onto the issuing bank's risk sentiment. Columns 1-4 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. The loan rate has been winsorized at the 1st and 99th percentiles. Loan characteristics are included in specifications (3) and (4), and include an indicator if the loan is secured by collateral and an indicator for the presence of covenant terms. A measure of the lender's net worth is also included as a bank characteristic in specification (4). 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 date levels, and * indicates significance at the 10% level, ** at the 5% level, and *** at the 1% level.

ance sheet to ensure that the loan is actually held by the bank. A majority of DealScan loans are originated by commercial banks, but in turn sold to non-bank lenders. Therefore, studying how changes in BRS impacts all syndicated loans would include studying how a bank's sentiment impacts loans that it will almost immediately sell off of its balance sheet. In the context of the analytical model used to identify BRS, there should be no relationship between a bank's risk sentiment and loans not held on its balance sheet, even if it is the entity that originates the loan. For a discussion of who participates in the syndicated loan market and the origination to distribution pipeline, see Fleckenstein *et al.* 2020, Buchak *et al.* 2024a, or Buchak *et al.* 2024b.

The sample covers a large range of loan, borrower, and lender sizes. Table 10 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 1.8 billion dollars, but the majority are for less than one billion dollars, with the median facility being for 1.018 billion dollars and the 5th percentile worth only 150 million dollars. Banks and borrowers that participate in the syndicated loan market are likewise varied. The interquartile range of participating banks' net worth (i.e. equity) is approximately 334 million dollars, while the difference between the 95th and 5th percentiles is more than 1.7 billion dollars.

Results. A bank-level sentiment shock increases loan rates. Table 11 shows that when the lead bank of a lending syndicate is hit with a one percentage point increase in risk sentiment (a pessimistic shock) then the loan rate margin increases by approximately 47 basis points. The increase in the loan rate is robust to including loan characteristics, namely the presence of collateral and covenant terms (column 3), as well as including the bank's net worth as a proxy for lender balance sheet pressures (column 4).

E BRS as a valid instrument for sentiment shocks

For bank risk sentiment to be a valid instrument for bank sentiment shocks, then it must satisfy the standard relevance condition and exclusion restrictions. Put more formally, let ε_t^b be the structural bank sentiment shock and Z_t^b be the proposed instrumental variable. To be a valid instrument for the sentiment shock, Z_t^b must satisfy the conditions:

$$E[Z_t^b \varepsilon_t^{b'}] \neq 0$$

$$E[Z_t^b \varepsilon_t^{-b'}] = \mathbf{0}$$

or in words, Z_t^b must be correlated with ε_t^b but orthogonal to ε_t^{-b}, the vector of all other structural shocks. While BRS satisfies both theoretically given the structural model presented in Section 2.1, I will also show both conditions are satisfied empirically as well.

E.1 Relevance condition

The relevance condition is easily shown to be satisfied. I will test this through the lens of an IV-local projection, as in Stock & Watson 2018. The econometric model is formally written as:

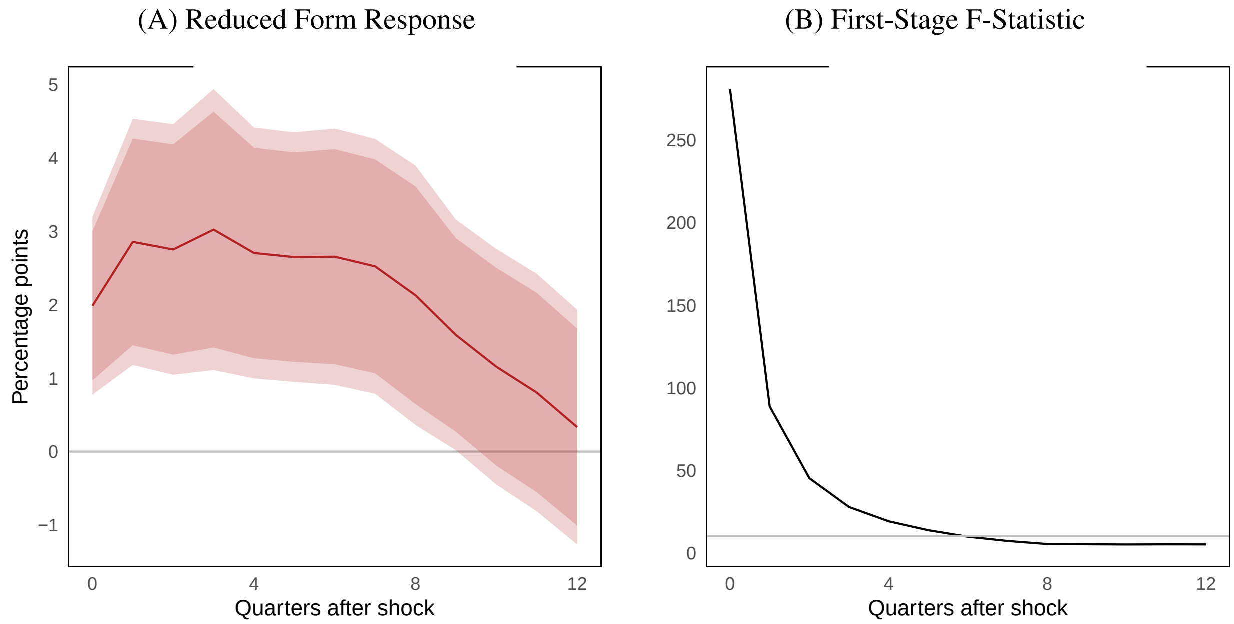
$$Y_{t+h} - Y_{t-1} = \alpha^h + \theta^h \hat{R}_t + \beta^h X_{t-1} + \varepsilon_{t+h} \tag{17}$$

$$R_t = \chi + \omega BRS_t + \zeta X_{t-1} + \eta_t, \quad \eta_t \perp \varepsilon_{t+h} \ \forall h \tag{18}$$

where Y_t is the economic outcome of interest in period t, α^h is the constant, $\hat{R}_t$ is the predicted aggregate loan rate, and X_{t-1} is the vector of four auto-regressive lags of real GDP growth, core PCE inflation, policy rate (proxied by the one year Treasury rate), excess bond premium, loan rate premium, and consumer sentiment, while the remaining unobserved determinants of Y_t are left to the residual ε_t. Note that in the local projection framework, the second stage, Equation 19, is estimated forecast horizon-by-horizon, thus coefficients depend on the horizon h. The first stage, Equation 20, in contrast is estimated once, projecting loan rate premium R_t onto bank risk sentiment, BRS_t, as a proxy for bank sentiment shocks at time t, while controlling for second stage regressors X_t and constant χ. Note that this local projection is the theoretically agnostic analog to the BVAR studied in Section 4.

First, Figure 18 shows that the reduced form response of the loan rate premium is positive and statistically significant at the 95 percent confidence level. Following Angrist & Kolesár 2024, since bank sentiment shocks are just identified with one instrument, then given the first stage impact is positive as expected, the t-score of the second stage can be used for valid statistical inference.

Figure 18: Relevance of BRS as an instrument for bank sentiment shocks



Notes: This plot shows relevant instrument diagnostics for bank risk sentiment in an IV-LP model of the macroeconomy. Panel (A) shows the reduced from response of loan rate premiums to a one standard deviation bank sentiment shock, instrumented by fluctuations in bank risk sentiment. Panel (B) shows the first-stage F-statistics from the same model. The red band mark the Newey-West adjusted 95- and 90-percent confidence interval.

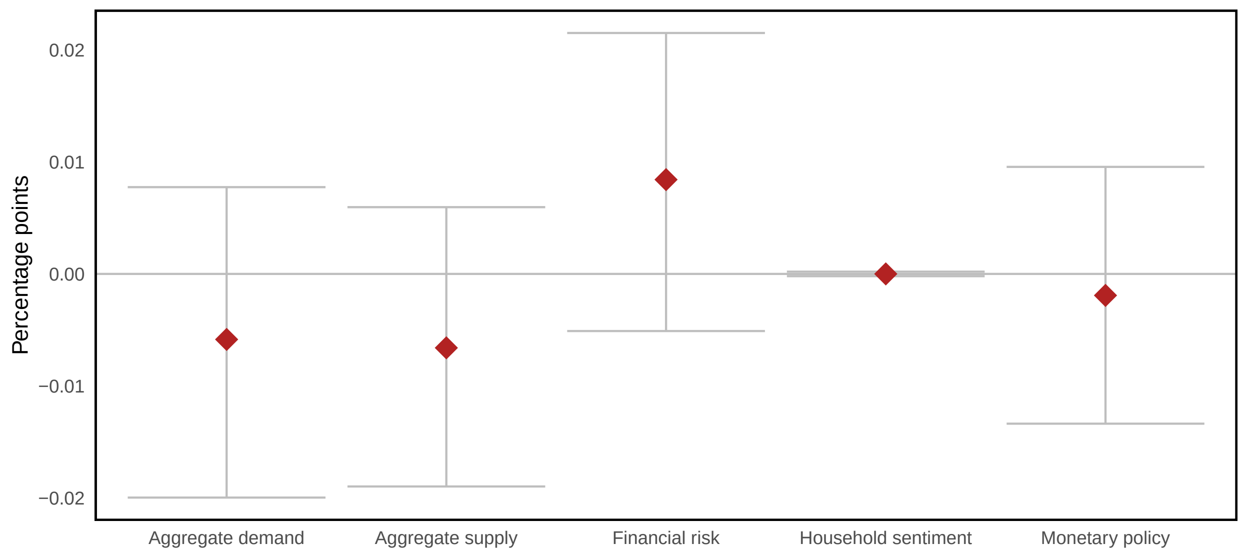
Moreover, the statistically significant impact of bank risk sentiment on the loan rate premium can be taken to indicate it is a relevant instrument.

Second, Figure 18 shows that the first-stage F-statistics is above 200 on impact, indicating a very strong instrument. Moreover, the F-statistic stays above the heuristic relevant cutoff value of 10 through 7 quarters after impact. This indicates that BRS is a relevant instrument for studying fluctuations in loan rate premiums both on impact, through almost two years after impact.

E.2 Exclusion restriction

I will use bank risk sentiment as an instrument for bank sentiment shocks in a parsimonious BVAR. Therefore, the bank risk sentiment must be statistically independent of the structural shocks in the VAR to satisfy the standard exclusion restriction. I will verify this to be the case by estimating an alternative specification of the BVAR studied in Section 4. The BVAR will be the same as specified in Section 4, but including BRS as an observable endogenous variable and excluding bank sentiment shocks. As a result, the remaining five estimated structural shocks of interest (aggregate

Figure 19: Response of bank risk sentiment to aggregate structural shocks



Notes: This plot shows the response of bank risk sentiment to five aggregate shocks identified via IV and sign restrictions in a Bayesian VAR. Red diamonds mark the mean response in the BVAR posterior, while the gray bars mark the 68 percent credible set. The change in bank risk sentiment is measured in percentage points.

demand, supply, monetary policy, financial risk, and household sentiment) will not be orthogonalized to to bank risk sentiment by construction. I can then inspect the response of bank risk sentiment to these structural shocks, and if it does not respond, then it can be interpreted as statistically independent of the other structural shocks.

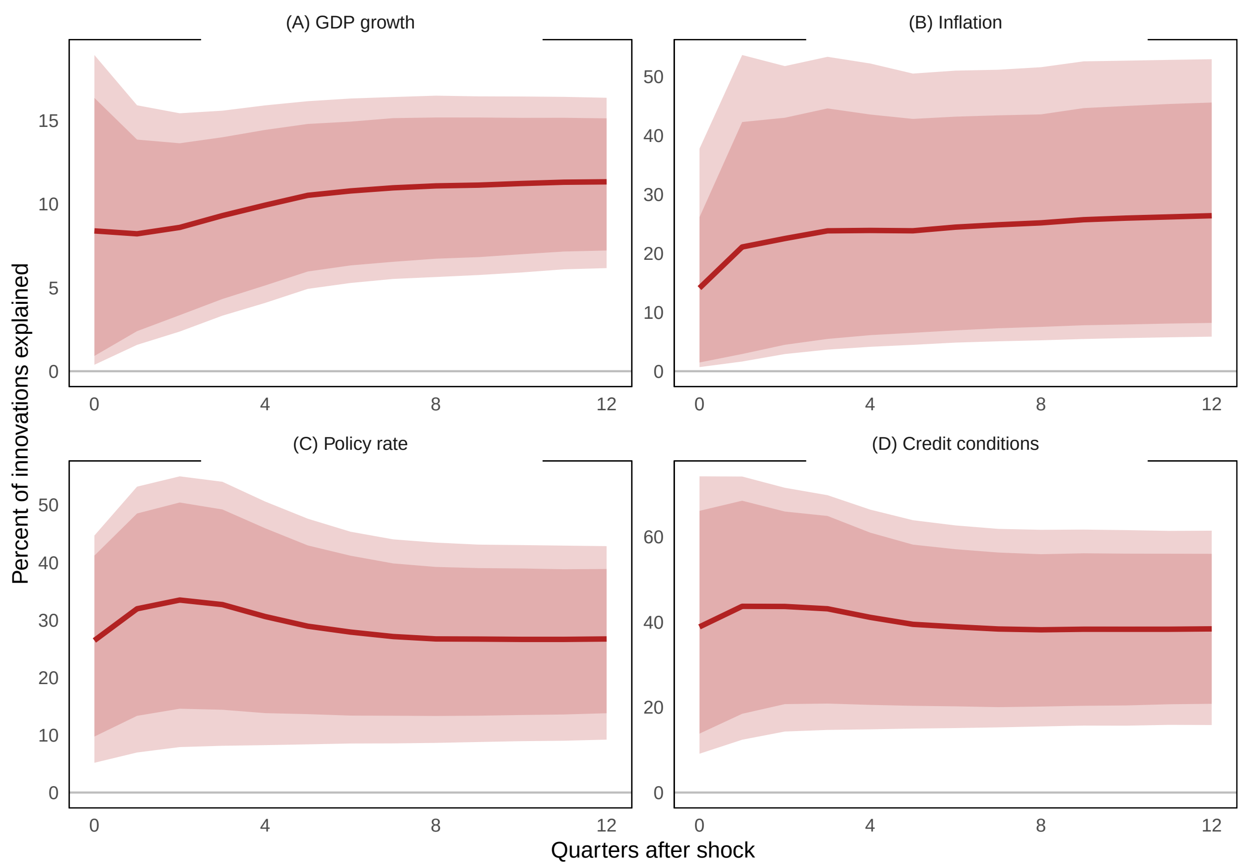
Bank risk sentiment satisfies the exclusion restriction. Figure 19 shows the response of bank risk sentiment to aggregate structural shocks on impact. BRS does not respond to any shock at any standard statistically significant level —Figure 19 in fact shows very conservative 68 percent credible sets around the impacts. As a result, BRS may be interpreted as being statistically independent of the other structural shocks in the BVAR of interest, thus is a valid instrument for bank sentiment shocks in the macroeconometric model.

F Macroeconomic analysis

F.1 FEVD confidence intervals

The parsimonious BVAR presented in Section 4 produces both point estimates for the variance decomposition of endogenous variables in the system, as well as the credible set around such estimates. Figure 20 shows the credible sets around the forecast error variance decomposition of the contribution of bank sentiment shocks.

Figure 20: Contribution of bank sentiment shocks to policy, activity, prices, and credit conditions

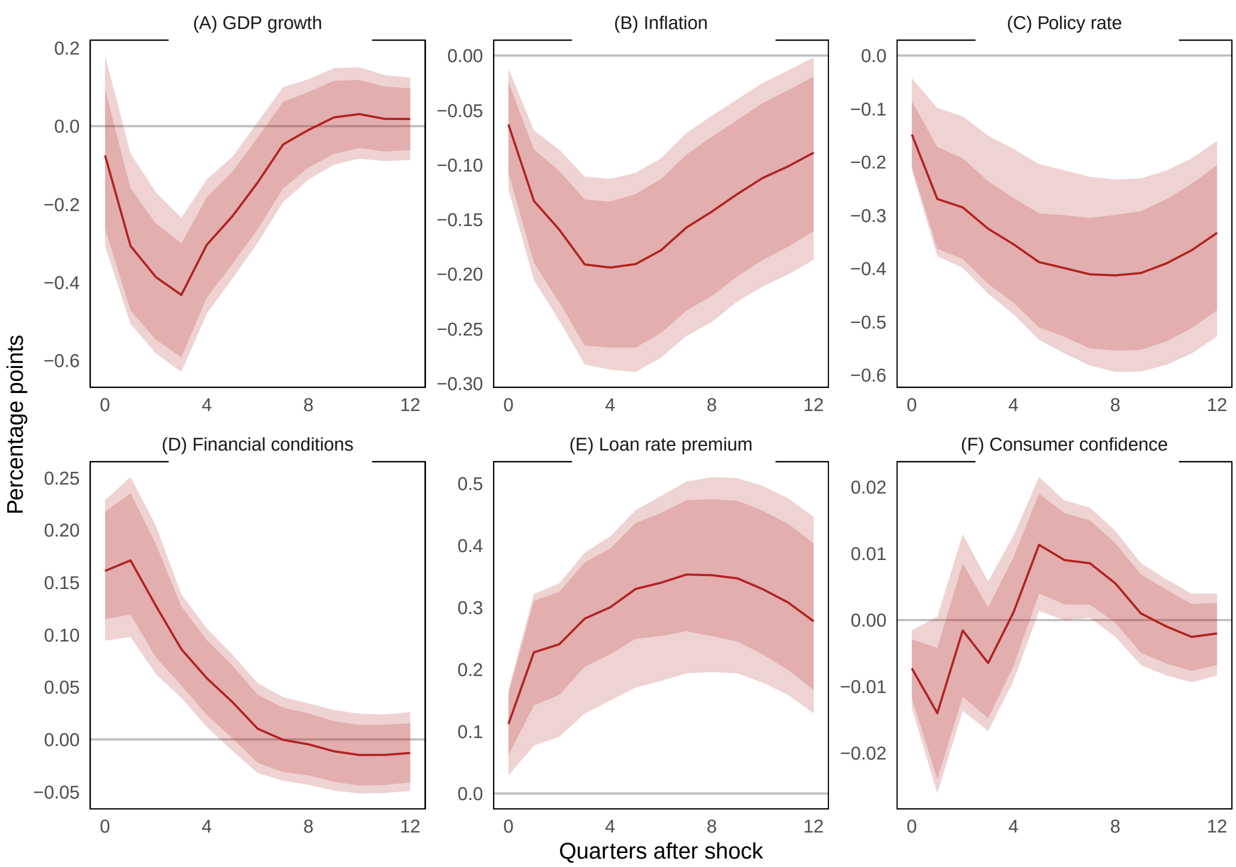


Notes: This plot presents the contribution to business cycle fluctuations in activity, prices, and credit conditions by bank sentiment shocks. Shaded bands mark the 68 and 90 percent credible sets. The solid red line marks the mean contribution to the variance decomposition.

F.2 Impulse response functions

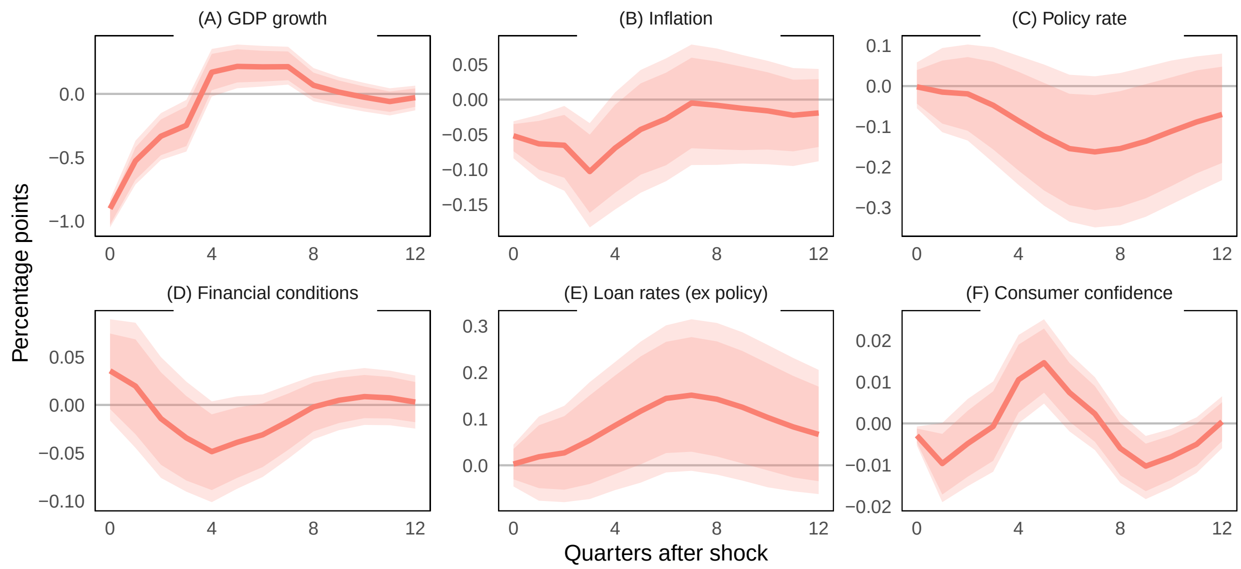
The parsimonious BVAR presented in Section 4 can also be used to estimate Impulse Response Functions (IRFs) to study the effect that one time, unanticipated, structural shocks have on the endogenous variables that make up the economy. This appendix presents the IRFs for pessimistic bank sentiment shocks, Figure 21, pessimistic household sentiment shocks, Figure 22, and all other structural shocks, Figure 23.

Figure 21: Response of activity, prices, and credit conditions to a pessimistic bank sentiment shock



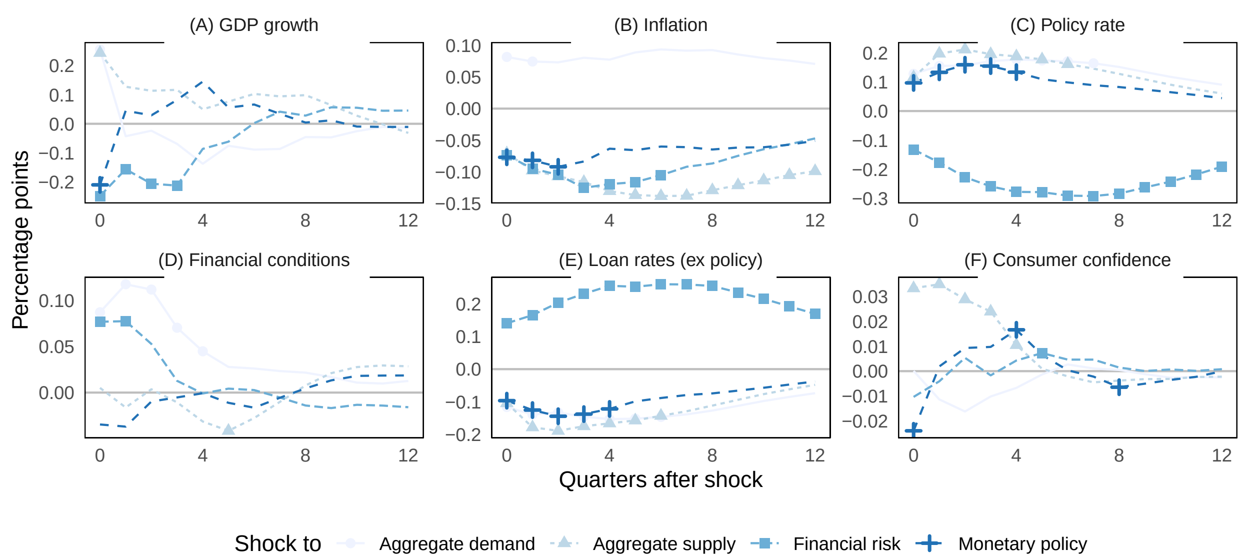
Notes: This plot presents the impulse response function of business cycle variables and credit conditions to a one standard deviation, pessimistic, bank sentiment shock. The loan rate premium is the loan-weighted average loan rate less the policy rate, proxied by the one year Treasury yield. Bank sentiment shocks are instrumented by changes in BRS that act through the loan rate premium. Shaded bands mark the 68 and 90 percent credible sets.

Figure 22: Response of activity, prices, and credit conditions to a pessimistic household sentiment shock



Notes: This plot presents the impulse response function of business cycle variables and credit conditions to a one standard deviation, pessimistic, bank sentiment shock. Shaded bands mark the 68 and 90 percent credible sets.

Figure 23: Response of activity, prices, and credit conditions to a pessimistic other shocks



Notes: This plot presents the impulse response function of business cycle variables and credit conditions to a one standard deviation, pessimistic, bank sentiment shock. Markers indicate responses with 68 percent credible sets do not include zero.

F.3 Local projection robustness

I additionally estimate a theoretically agnostic empirical macroeconomic model, taking the form of an IV-local projection. The local projection, using a vector of lagged controls mirroring the endogenous variables in the BVAR presented in Section 4, asymptotically reproduces the same IRFs as the analogous VAR (Plagborg-Møller & Wolf 2021). However, in this small sample setting, such as the one presented here, Li *et al.* 2024 point out that the local projection framework is more robust to misspecification than a VAR, while Olea *et al.* 2024 prove that local projections is as accurate in its confidence intervals as a locally miss-specified VAR.

The econometric model is formally written as:

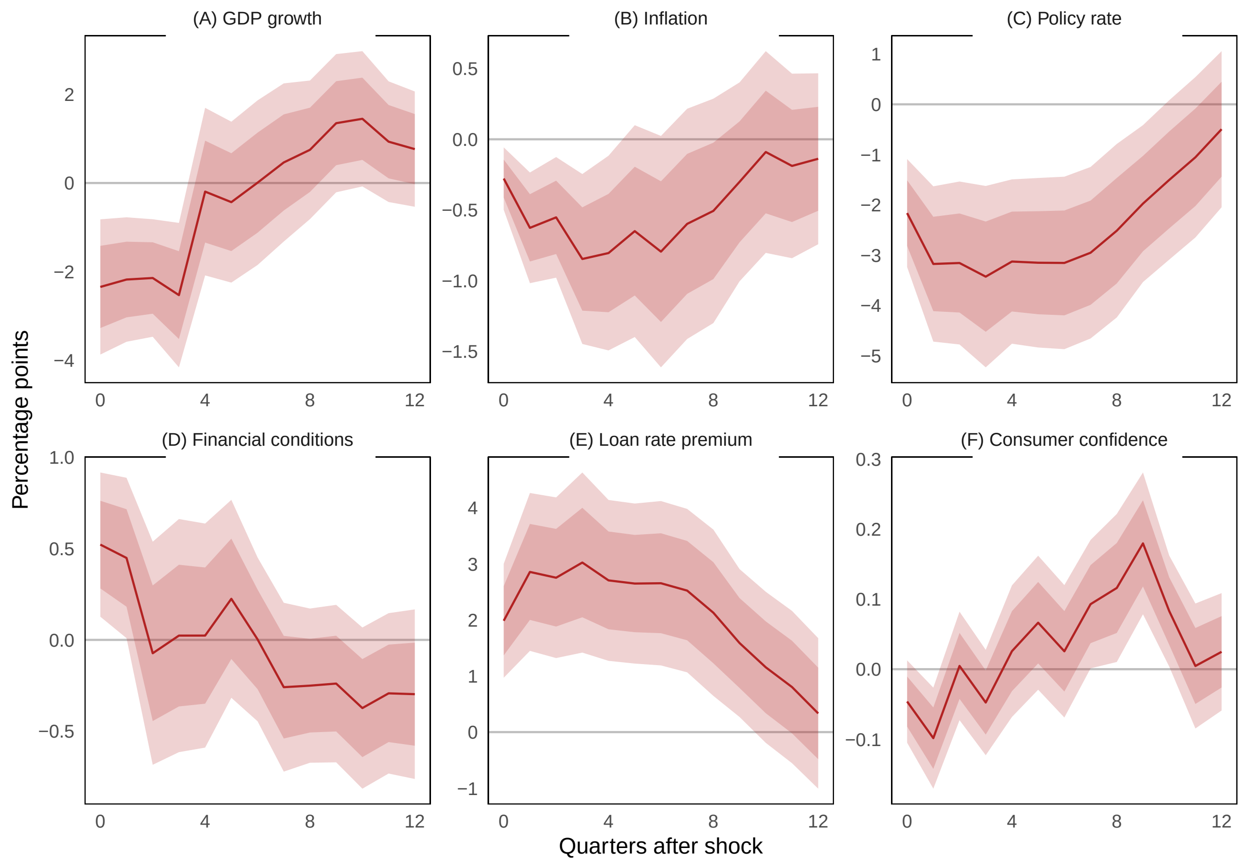
$$Y_{t+h} - Y_{t-1} = \alpha^h + \theta^h \hat{R}_t + \beta^h X_{t-1} + \varepsilon_{t+h} \tag{19}$$

$$R_t = \chi + \omega BRS_t + \zeta X_{t-1} + \eta_t, \quad \eta_t \perp \varepsilon_{t+h} \ \forall h \tag{20}$$

where Y_t is the economic outcome of interest in period t, α^h is the constant, $\hat{R}_t$ is the predicted aggregate loan rate, and X_{t-1} is the vector of four auto-regressive lags of real GDP growth, core PCE inflation, policy rate (proxied by the one year Treasury rate), excess bond premium, loan rate premium, and consumer sentiment, while the remaining unobserved determinants of Y_t are left to the residual ε_t. Note that in the local projection framework, the second stage, Equation 19, is estimated forecast horizon-by-horizon, thus coefficients depend on the horizon h. The first stage, Equation 20, in contrast is estimated once, projecting loan rate premium R_t onto bank risk sentiment, BRS_t, as a proxy for bank sentiment shocks at time t, while controlling for second stage regressors X_t and constant χ.

The dynamics characterized by the impulse response functions estimated via BVAR are robust to estimation via IV-LP. Figure 24 shows the response of activity, prices, policy, and credit conditions to a one standard deviation pessimistic bank sentiment shock, proxied by fluctuations in bank risk sentiment impacting the loan rate premium. While the sign of the impact of pessimistic sentiment shocks on different aspects of the macroeconomy is the same across LP and BVAR estimations, the magnitude of the impact is stronger in the local projection.

Figure 24: Macroeconomic response to a pessimistic bank sentiment shock, estimated via LP



Notes: This plot presents the impulse response function of business cycle variables and credit conditions to a one standard deviation, pessimistic, bank sentiment shock. The loan rate premium is the loan-weighted average loan rate less the policy rate, proxied by the one year Treasury yield. Bank sentiment shocks are instrumented by changes in BRS that act through the loan rate premium. Shaded bands mark the 68 and 90 percent Newey-West adjusted confidence intervals.

F.4 COVID-19 robustness

Lastly, I test the robustness of the macroeconomic analysis to estimation with and without the COVID-19 pandemic. To do so, I will test the influence of the COVID-19 shock by re-estimating the parsimonious VAR with data ending in 2019:Q4 and comparing the results with the baseline model estimated on the full sample presented in the body of the paper, following the guidance of Lenza & Primiceri 2022.

Figure 25 compares the response of macroeconomic outcomes to a one standard deviation pessimistic bank sentiment shock, where the solid red line is the response from the full sample model and the dashed black line is the mean response from the short sample model. The responses in financial conditions, loan rate premium, consumer confidence, and the policy rate are all quantitatively similar across the two models. In fact, the two sets of responses cannot be statistically distinguished from one another at the five percent confidence level. In comparison, the response of GDP growth and inflation are both muted when excluding the COVID-19 shock from the sample. However, the qualitative responses are still the same, with GDP growth falling by more than 20 basis points within a year after impact and inflation falling by approximately eight basis points.

Table 12 shows the forecast error variance decomposition estimated by the short sample model. Bank sentiment becomes even more important for explaining long run fluctuations in the policy rate, while its influence is attenuated across GDP growth, inflation, and credit conditions more broadly. More specifically:

- Credit conditions: Bank sentiment goes from explaining 38 to 22 percent of credit condition variation on impact and from 41 percent to 15 percent in the long run. The decline in importance is largely explained by an increase in the importance of aggregate demand and supply shocks. That is, bank sentiment is an important source of credit condition fluctuations in the short run (on impact) before credit conditions are disciplined by non-financial economic fundamentals in the medium and long run.

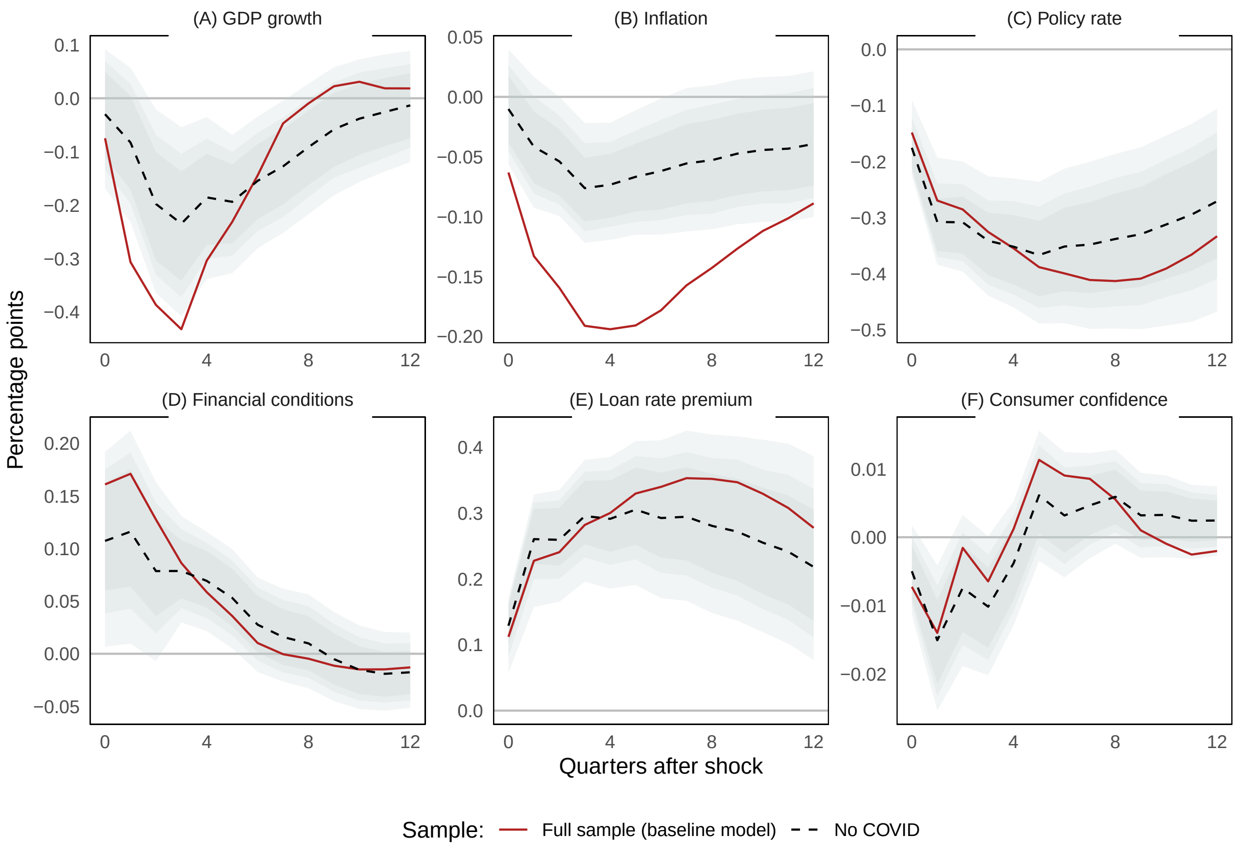
- GDP: Bank sentiment goes from explaining 10 to 6 percent of the variation in activity. Household sentiment goes from 32 to 56 percent and aggregate supply increases from 16 to 20, while the importance of the remaining shocks decline.

- Inflation: Bank sentiment goes from explaining 14 percent of the variation in inflation to 4 percent on impact, and 30 percent in the long run to 12 percent in the long run. TThe declining importance of bank sentiment is compensated by increasing importance of aggregate supply shocks. This is perhaps not surprising, since the bank sentiment spiked during COVID and the majority of inflation variation in the sample is the post-COVID inflationary period.

- Policy rate: the importance of bank sentiment in explaining the policy rate increases from 30 percent in the long run to 42 percent.

In summary, bank sentiment is an important source of business cycle fluctuations whether estimated with or without the COVID-19 pandemic period. However, the pandemic volatility is largely described by fluctuations in sentiment (see Figure 7), so excluding the pandemic diminishes the relative role of sentiments in driving the real economy.

Figure 25: Response of activity, prices, and credit conditions to a pessimistic bank sentiment shock, estimated with sample ending in 2019



Notes: This plot presents the impulse response function of business cycle variables and credit conditions to a one standard deviation, pessimistic, bank sentiment shock. The loan rate premium is the loan-weighted average loan rate less the policy rate, proxied by the one year Treasury yield. Bank sentiment shocks are instrumented by changes in BRS that act through the loan rate premium. Shaded bands mark the 68, 90, and 95 percent credible sets.

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Table 12: Long run variance decomposition of policy, business cycles, and credit conditions, estimated with sample ending in 2019

Endog. Variable	Horizon (quarters)	Percent of innovation explained by: Bank Sentiment	Household Sentiment	Aggregate Demand	Aggregate Supply	Monetary Policy	Financial Risk
Credit conditions	0	21.60	7.85	19.20	19.30	28.50	3.59
	4	14.90	10.20	22.40	15.60	20.30	16.50
	8	14.60	10.50	22.30	16.10	19.10	17.40
	12	15.40	10.30	22.10	16.30	18.30	17.60
	16	15.30	10.40	22.40	16.70	17.70	17.50
	20	15.40	10.40	22.70	17.00	17.10	17.40
	100	14.90	11.30	24.70	18.00	14.90	16.20
GDP growth	0	4.63	55.8	6.50	20.4	6.72	5.96
	4	6.32	21.3	18.0	19.9	17.2	17.2
	8	6.96	18.5	19.2	21.4	16.8	17.1
	12	6.98	17.9	19.4	21.7	17.3	16.7
	16	6.87	17.6	19.6	22.0	17.8	16.2
	20	6.74	17.6	19.6	22.0	18.2	15.8
	100	6.27	18.2	19.6	21.9	19.5	14.4
Inflation	0	3.49	0.96	18.1	38.0	21.2	18.3
	4	7.39	7.74	19.8	35.9	10.2	18.9
	8	8.41	9.68	17.2	35.8	10.5	18.4
	12	8.92	11.2	15.5	34.1	11.3	18.9
	16	9.26	12.2	15.2	32.3	11.7	19.3
	20	9.55	13.0	15.0	30.6	12.0	19.9
	100	12.5	14.7	14.3	21.7	12.3	24.6
Policy rate	0	33.4	0.61	21.5	12.6	11.1	20.8
	4	37.0	9.45	14.5	11.7	10.7	16.7
	8	34.8	11.4	13.8	10.8	11.5	17.6
	12	35.0	11.4	13.8	10.7	10.9	18.2
	16	35.7	11.4	13.6	10.1	10.5	18.7
	20	36.5	11.2	13.4	9.78	10.1	19.1
	100	41.6	9.94	11.6	7.56	8.23	21.1

Notes: This table shows the variance decomposition of credit condition, policy, activity, and price fluctuations into contributions by structural shocks. The contribution of structural shocks accounts for 100 percent of the horizon-variable innovation. GDP growth is the annualized real quarterly growth rate, inflation is core PCE inflation, Financial conditions are proxied by the Gilchrist & Zakrajšek 2012 EBP, and the policy rate is proxied by the one year Treasury rate.

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