# Expectations and Credit Slumps*

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**Abstract**

Bank expectations are an important explanation for the slow recovery of U.S. lending after the 2008-09 financial crisis. Using new micro data, we document two facts about bank expectations: banks extrapolate from past events and bank pessimism after the crisis was a drag on lending as well as several financial and real outcomes of borrowers during the recovery. In a dynamic model, a realistic degree of bank extrapolation estimated from the data generates the pace of aggregate credit recovery after the crisis. Relative to a rational expectations benchmark, distorted bank beliefs induce sizable aggregate credit losses of 1.5%.

**JEL codes**: E7, G01, G21

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# 1 Introduction

The Great Recession associated with the 2008-09 financial crisis was one of the worst economic downturns in U.S. history. Bank lending declined significantly and the Federal Reserve responded quickly by cutting interest rates and aggressively expanding the monetary base. Nonetheless, one puzzling aspect of the recovery is why bank lending failed to recover, even after most measures of economic activity improved (Figures 1 and A.1).[1] The sluggish recovery in bank credit has attracted attention from academics and policy makers. For example, Bernanke (2023) noted in his Nobel Prize lecture: "Even though financial institutions were strengthened by government capital injections and private capital raises, lenders remained exceptionally cautious for some years."[2]

In this paper, we propose an explanation for the puzzle based on bank pessimism. Specifically, using newly-available micro data on bank expectations from the Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS), we document two new facts: 1) banks over-react to past events and were pessimistic about the future long after the crisis, and 2) pessimistic banks are more likely to cut future lending, which in turn hinders future growth of their borrowers. We use an otherwise standard dynamic model where banks extrapolate from past realizations to quantify the aggregate implications. A realistic degree of extrapolation estimated from the data generates the pace of aggregate credit recovery observed after the crisis. Relative to a rational expectations benchmark, distorted bank beliefs hamper the effectiveness of stimulus and induce sizable aggregate credit losses of 1.5%.

Our study contributes to the post-crisis debate regarding the role of banks in the financial and business cycle. The large disruption in credit in the global financial crisis and the slow recovery afterwards highlight the importance to better understand the sources and consequences of bank reluctance to lend after a crisis. While the policy de-

[1] Figure 1 shows the total loans in the U.S. banking system from 2000 to 2020. Intermediated credit grows steadily through the early 2000s, peaks in mid-2008 and declines through 2009. Growth resumes around 2012 but at a slower pace than in the early 2000s. The dotted line shows the trend from 2000 to 2008 projected out through the rest of the period. Figure A.1 provides further supporting evidence using a longer sample, and scaling total loans by U.S. GDP. Notably, loan growth has been slow to recover even relative to the growth in GDP post-2008.

[2] Other instances include a speech by McAndrews (2015) at the New York Fed: "Based on data from the Financial Accounts of the United States, real credit to both corporations and households in prior recoveries generally started to grow fairly quickly after the end of the recession. By contrast, in the most recent recovery the real credit outstanding of businesses (corporations and non-corporations) declined for about two years after the end of the recession. And only recently – more than five years after the end of the recession – has it attained pre-recession levels. More dramatically, real credit to households continued to decline for about four years and, while it has finally begun to expand, is still well below its pre-recession levels."

bate and academic literature had considered other factors, such as capital and liquidity regulation, the role of bank beliefs has surprisingly received limited consideration.

The key measurement hurdle is to identify banks who are overly optimistic or pessimistic. To that end, we use a newly available module of the Federal Reserve's Senior Loan Officer Opinion Survey of Bank Lending Practices (SLOOS).[3] The module includes a list of special questions that inquire about banks' expectations of future loan performance. In our baseline analysis, we use the bank responses to construct a *bank-level* measure of expectations of future loan performance between 2005 and 2020. Using actual loan performance for each bank measured as the reported charge-off and delinquency rates from the Call Reports, we operationalize our main measure of bank over-optimism or pessimism as the one-year ahead forecast error for each bank, which is constructed as the difference between the actual and expected change in bank loan performance.

Our measure of individual bank beliefs allows us to study their belief formation as well as the link between bank beliefs and their future lending decisions. First, we document a new fact about banks' expectation formation: they extrapolate from loan performance with a delay. They under-react to recent changes in loan performance and over-react to past changes. They were over-optimistic at the beginning of the crisis and over-pessimistic during the recovery. This bank-level evidence, which is robust to a battery of sensitivity checks, constitutes a rejection of the rational component of the full-information rational expectations (FIRE) hypothesis (Bordalo, Gennaioli, Ma, and Shleifer, 2020), under the reasonable assumption that loan performance is within banks' information sets. In addition, the evidence is stronger for a sub-sample of banks whose CEOs are young and inexperienced, which is consistent with earlier findings in the literature on expectation formation (see, for example, Haruvy, Lahav, and Noussair, 2007; Greenwood and Nagel, 2009) and corroborates the interpretation that the estimates stem from psychological biases.

Our second fact is about the link between bank expectations and future loan growth. Namely, individual banks' forecast errors have significant predictive power for their future loan growth up to three years ahead. Our estimates imply that more pessimistic banks will cut back on their future lending. An important concern with interpreting the correlation between forecast errors and future lending is that it may spuriously reflect other factors, such as past loan performance, that may be also independently correlated with future loan growth. To rule out such spurious correlation, we show that the link

[3]For a complete description of the SLOOS panel selection criteria, wording of individual questions, and methods used to conduct the survey, we refer to the public release of the Federal Reserve, available at www.federalreserve.gov/data/sloos.htm.

between bank forecast errors and future loan growth continues to hold in a shift-share design. This design instruments for the potentially endogenous forecast errors with a Bartik instrument, which is defined as the product of a shift variable, equal to the "consensus" forecast error for other banks, times a share variable, equal to the lagged ratio of total loans to total assets. The intuition behind this approach is that there are "news shocks" to the supply or quality of information about loan performance that are common across banks but play out differently across banks. For example, the releases of news about future firm performance, either in the quarterly earnings conference calls or in the releases of new analyst estimates, provide information about the quality of bank C&I loans. These news shocks are common across banks and, as such, are captured by the shift. However, banks that rely more on lending prior to the shocks are more impacted, which is captured by the share. As detailed in Borusyak, Hull, and Jaravel (2022), this design is valid under the identifying assumption that the news shocks that drive our shift variable are plausibly exogenous to each bank. That said, identification also requires that other aggregate variables that may be correlated with the shifter impact banks with high vs. low loan shares uniformly, which we address in robustness analysis.[4]

We also documented two subsidiary facts. With the exception of consumer loans, lending is sensitive to bank beliefs for all loan types, with commercial and industrial (C&I) and residential real estate loans being the most sensitive.[5] In addition, we link borrowers to their lenders using the Shared National Credit Program (SNC), which is a confidential supervisory data set jointly administered by the Federal Reserve, FDIC, and OCC (see Chodorow-Reich and Falato, 2022 for details). Banks' forecast errors have significant predictive power for a variety of their borrowers' future financial and real outcomes up to three years ahead, including borrower total debt, investment both in tangible and intangible assets, employment, sales and profits growth. This evidence indicates that bank pessimism over the recovery transmitted to their borrowers and hampered their ability to grow after the crisis.

In the second part of the paper, we use a dynamic model to assess the aggregate implications of bank expectations for the slow recovery of lending after the crisis. The model adds distorted bank expectations to an otherwise standard setup where a bank is defined as a company that finances risky loan portfolios by equity and deposits and

[4]We also show that the estimates are robust to adding controls for alternative hypotheses for the slow recovery, including weak loan demand (as measured by the SLOOS response on loan demand), bank securitization (as measured by securitization income to net interest income ratio) and tightened bank capital and liquidity regulations (as measured by tier 1 capital and cash ratios, respectively).

[5]This result is consistent with the conventional wisdom that "residential mortgage lending has been particularly sluggish" (Bernanke, 2012).

is susceptible to a large financial crisis ("disaster") with a small but time-varying probability (Gourio, 2012, 2013). As it is also standard, banks face a balance sheet constraint and external financing is costly. As a result, the speed of lending recovery depends on how quickly banks can rebuild their capital.[6] The key innovation is that banks systematically deviate from perfect rationality and form forecasts that overstate the importance of past shocks. We show that by extrapolating from the recent trend, banks are over-optimistic at the beginning of a crisis, and over-pessimistic during the recovery, as in the data.[7] This environment is well suited to our purpose because it provides a reasonably simple and quantitatively plausible link from bank belief distortions to aggregate outcomes.

For a realistic parameterization that is calibrated to match bank leverage, profit-to-equity, bank default rate and the dynamics of bank forecast errors, the model implies that, relative to a rational expectations benchmark, distorted bank beliefs induce sizable aggregate credit losses of 1.5%. The model also outperforms the rational expectations benchmark in matching the slow recovery of aggregate credit as well as other key aggregate business cycle statistics in the data. Loan growth exhibits a hump-shaped recovery path in the data, and only returns to the pre-crisis level after seven years. This feature is only present in the delayed extrapolation model due to two channels. The first one is the expectation channel: banks' lending policy is not only a function of the current state of the economy, but also the past state, so their lending decisions respond to economic recovery with a lag. The second channel is an interaction of expectations with bank balance sheets, as bank net worth recovers more slowly in the delayed extrapolation model, and this exacerbates the slow recovery in bank equity values (Sarin and Summers, 2016) and lending. Finally, stimulative policies, such as quantitative easing, have positive effects on lending and bank value, but are significantly hampered by bank extrapolation bias.[8] [9]

**Related Literature** Our paper makes two main contributions. First, we contribute to the literature on expectations formation, which so far has examined the expectations of professional forecasters, firms, households, and financial market investors (see, for

[6]This feature speaks to a well-established literature that emphasizes how the depletion of bank capital in an economic downturn hinders a bank's ability to intermediate funds (see, among others, Gertler and Kiyotaki, 2011, 2015).

[7]As in Barberis, Greenwood, Jin, and Shleifer (2015), we do not take a stand on the source of banks' extrapolative expectations (see Section 3.3 for a further discussion).

[8]The model also produces a larger increase in risk premia relative to the rational benchmark, in line with the evidence that risk premia increase substantially in financial crises (Muir, 2017).

[9]We show that it is challenging to match the slow recovery of bank credit after the crisis with alternative models of rational as well as biased bank expectations.

example, Greenwood and Shleifer, 2014; Coibion and Gorodnichenko, 2015; Bordalo, Gennaioli, and Shleifer, 2017; Bouchaud, Krueger, Landier, and Thesmar, 2019; Bordalo, Gennaioli, Ma, and Shleifer, 2020; Angeletos, Huo, and Sastry, 2020; Rozsypal and Schlafmann, 2020; Kohlhas and Walther, 2021; Giglio, Maggiori, Stroebel, and Utkus, 2021; Angeletos and Lian, 2022; Meeuwis, Parker, Schoar, and Simester, 2022; Farmer, Nakamura, and Steinsson, 2023). Our contribution is to provide, to the best of our knowledge, the first evidence that banks expectations are extrapolative. Our evidence is complementary to recent work by Ma, Paligorova, and Peydró (2022), who use data on banks' economic projections about metropolitan statistical areas in the U.S. to study the impact of lenders' expectations. We offer a complementary angle by using the SLOOS responses, which cover the crisis period and post-crisis recovery and allow us to focus on the credit slump after the crisis. We contribute to the literature by showing that bank expectations shape their lending long after a crisis, suggesting that the role of expectations is more pervasive than it had been previously recognized. Understanding bank expectations during financial disruptions is important in light of the existing evidence that disruptions in banking are central to financial crises and specifically to the global financial crisis (see, for example, Bernanke, 2018; Gertler and Gilchrist, 2018).

Second, we contribute to the literate on the aggregate implications of behavioral bias for boom-bust cycles. For example, Bordalo, Gennaioli, Shleifer, and Terry (2021) and Bianchi, Ilut, and Saijo (2023) quantify the aggregate implications of diagnostic expectations in a Real Business Cycle model and a New Keynesian model, respectively; Krishnamurthy and Li (2020) and Maxted (2023) consider the impact of belief distortions in models with financial intermediation. Our contribution here is that we focus on banks and provide a new explanation for the slow recovery after crises based on imperfect bank expectations. Existing studies have focused on the amplification role of expectations – i.e., on explaining the frothy pre-crisis behavior and sudden reversals in crisis times. Our new insight is that delayed extrapolation is a propagation mechanism of shocks to fundamentals in that it can account for the slow recovery of lending long after the initial shock in 2008.[10] Our results provide to the best of our knowledge the first quantification of the aggregate credit losses from bank bias. In addition, the results indicate that deviations from rationality can help to make progress on understanding the serially correlated and persistent response of credit to shocks that characterizes the recovery phase of credit cycles, which is well known to be challenging for standard

[10]Our paper shares the broad focus on the slow recovery as Kozlowski, Veldkamp, and Venkateswaran (2020), who provide a learning explanation to the persistent changes in beliefs and GDP growth. While both models deviate from FIRE, the key friction in theirs is imperfect information, while in ours it is behavioral bias. Our modeling choice is informed by the evidence on bank expectations: their forecast errors are predictable from current and past loan performance, which are observed by banks.

frameworks based on rational expectations (see, for example, Kiyotaki, 2011).[11]

The rest of the paper is organized as follows. In Section 2, we present new facts on bank expectations. In Section 3, we build a dynamic model with extrapolative banks. In Section 4, we first discuss the calibration, and then perform our main exercise, that is, we analyze the aggregate implications and study the effectiveness of policies. In Section 5, we present model extensions and discuss the implications of other types of behavioral bias. Section 6 concludes.

# 2 Empirical Evidence

## 2.1 Data Sources

**Bank Expectations** To measure bank expectations, we use a newly available module of the Federal Reserve's Senior Loan Officer Opinion Survey of Bank Lending Practices (SLOOS).[12] Since the early 1990s, the SLOOS queries banks about changes in their lending standards for the major categories of loans to households and businesses and about changes in demand for most of those types of loans. The survey is usually conducted four times per year by the Federal Reserve Board, and the current reporting panel consists of up to 80 large domestically chartered commercial banks and up to 24 large U.S. branches and agencies of foreign banks.[13] While the list of actual respondents is confidential, the survey panel contains domestic banks headquartered in all 12 Federal Reserve Districts, and the current minimum asset size for panel institutions is $2 billion in consolidated assets, which ensures that not just the largest banks but also a fair number of large and medium-size regional banks are included.

In 2004, the survey began to include a list of special questions that inquire about

[11]Finally, our paper is also related to recent theories of banking, in particular those which are quantitative in nature (see, for example, Egan, Hortaçsu, and Matvos, 2017; Gourio, Kashyap, and Sim, 2018; Corbae and D'Erasmo, 2021; Elenev, Landvoigt, and Van Nieuwerburgh, 2021; Begenau and Landvoigt, 2022; Gomes, Grotteria, and Wachter, 2023; Jermann and Xiang, 2023). Among these, our modeling choice of the financial crisis as a rare disaster with time-varying probability follows Gourio, Kashyap, and Sim (2018), and Gomes, Grotteria, and Wachter (2023). The key difference in our paper is that we introduce belief distortions, and we characterize the post-crisis dynamics generated by the interaction of behavioral and financial frictions. To the best of our knowledge, our paper is the first to apply banking theory to the slow recovery in intermediated credit.

[12]For a complete description of the SLOOS panel selection criteria, wording of individual questions, and methods used to conduct the survey, we refer to the public release of the Federal Reserve, available at www.federalreserve.gov/data/sloos.htm.

[13]The respondents account for a substantial fraction of the total loans held by the banking system and of each of tnhe main loan categories covered by the survey. As of March 31, 2017, the assets of the panel banks totaled $11.8 trillion and accounted for about 69 percent of the $17.0 trillion in total assets of all domestically chartered institutions.

banks' expectations of future loan performance as measured by delinquencies and charge-offs. Specifically, these annual special questions ask about banks' expectations for loan delinquencies and charge-offs on selected categories of commercial and industrial, commercial real estate, residential real estate, and consumer loans in the coming year. These questions follow the general pattern of

> *Assuming that economic activity progresses in line with consensus forecasts, what is your outlook for delinquencies and charge-offs on your bank's type X loans in the following categories in the coming year?*[14]

Banks answer each question using a qualitative scale ranging from 1 to 5. The possible answers are: 1 =improve substantially; 2 =improve somewhat; 3 =remain around current levels; 4 =deteriorate somewhat; 5 =deteriorate substantially. In other words, the survey inquires bank responses on the expected change in the loan default rate. Let $I^k_{i,t+1}$ denote the performance of type-$k$ loan in year $t+1$. We summarize these responses into a one-year ahead bank-level forecast for each type $k$-loan given year $t$ information, $E_{it}[I^k_{i,t+1}] =$

$$\begin{cases} 1 & \text{if bank } i \text{ in year } t \text{ expects an improvement in type-}k \text{ loan performance in } t+1 \\ 0 & \text{if bank } i \text{ in year } t \text{ expects no change in type-}k \text{ loan performance in } t+1 \\ -1 & \text{if bank } i \text{ in year } t \text{ expects a worsening in type-}k \text{ loan performance in } t+1 \end{cases}$$

where an "improvement" ("worsening") indicates that the bank expects a lower (higher) loan default rate next year compared to the current year. While the questions on lending standards have been used in the prior literature (Bassett et al., 2014; Cavallo et al., 2024), to the best of our knowledge we are the first to use the module on bank expectations.

In our baseline analysis, we construct a bank-level index of expectations of future loan performance, aggregated across loan types, between 2005 and 2020.[15] To this end, we use data from the Reports of Condition and Income (Call Reports) about the amount of outstanding loans each respondent bank has in each loan category, and compute the following weighted average for each bank:

$$E_{it}[I_{i,t+1}] = \sum_k \omega^k_{it} \times E_{it}[I^k_{i,t+1}],$$

[14]The survey questions do not allow us to identify the source of bias – in other words, whether banks are biased (or have limited information) about the consensus forecasts of future macroeconomic conditions or about the performance of their own loan portfolios. However, this does not matter for our purpose, which is to test whether banks expectations are rational and how they affect their lending decisions.

[15]We also analyze bank expectations of each type of loans separately, as shown in Section 2.5.

where $\omega_{it}^k$ is the fraction of bank $i$'s core loan portfolio that is accounted for by loans in category $k$, as reported on bank $i$'s Call Report at the end of year $t$. The higher the index, the more optimistic a bank is about the performance of its loan portfolio in the following year.

One might be concerned that commercial banks have strategic reasons for answering the survey, such as to reassure regulators on their stringent standards. However, there is little evidence for bias in their responses (Bassett et al., 2014). Moreover, in order to ensure that respondents are as comfortable as possible in providing accurate information about their credit policies, the individual bank responses are confidential and are not shared with the Federal Reserve System staff acting in a supervisory or regulatory capacity.

**Loan Performance and Forecast Errors** To maintain comparability with the measure of expectations, we measure the actual loan performance for each bank using the reported charge-off and delinquency rates from the Call Reports for our sample period. We compute, for each bank, the annual change in loan performance on a particular type of loans, and define $I_{it}^k =$

$$\begin{cases} 1 & \text{if bank } i \text{ experiences an improvement in type-}k \text{ loan performance in year } t \\ 0 & \text{if bank } i \text{ experiences no change in type-}k \text{ loan performance in year } t \\ -1 & \text{if bank } i \text{ experiences a worsening in type-}k \text{ loan performance in year } t \end{cases}$$

where an "improvement" ("worsening") is defined as a decline (increase) in the sum of charge-offs and delinquency rates compared to the previous year. Then we compute the weighted average across loan types:

$$I_{it} = \sum_k \omega_{i,t-1}^k \times I_{it}^k,$$

where $\omega_{i,t-1}^k$ is the same weight that is used to construct the expectation measure $E_{i,t-1}[I_{it}]$. Finally, we define the one-year ahead forecast error of bank $i$ at year $t$ as the difference between the actual and expected change in loan performance:

$$FE_{i,t+1|t} = I_{i,t+1} - E_{it}[I_{i,t+1}],$$

where a positive (negative) $FE_{i,t+1|t}$ indicates that bank $i$ has been too pessimistic (optimistic) in year $t$ about the performance of its loan portfolio in the coming year.

**Bank Lending and Other Bank-Specific Information** We use bank-level data on outstanding loan balances from the Call Reports to construct one of the dependent variables – the logarithm change of total bank loans relative to the pre-crisis level.[16] In addition, we also obtain standard bank balance sheet data from the Call Reports, including bank size (the logarithm of total assets), capital (the ratio of common equity Tier 1 (CET1) capital to risk-weighted assets), and liquidity (the cash ratio). For the analysis of borrower outcomes, we complement these data with information on borrower-lender links from the Shared National Credit Program (SNC), which is a confidential supervisory data set jointly administered by the Federal Reserve, FDIC, and OCC. SNC collects information on all loans of at least $20 million shared by three or more unaffiliated financial institutions under the regulatory purview of one of the SNC administrators (see Chodorow-Reich and Falato, 2022 for details).[17] Borrowers' balance sheet information is from Compustat.

## 2.2 Motivating Evidence

Descriptive evidence from bank-level data highlights the disconnect between actual loan performance and expected loan performance in our full sample (Figure 2). Specifically, we compare, for each year since 2005, the net fraction of banks that actually experienced a worsening of loan performance with the net fraction of banks that expected a worsening of loan performance in that year. The "net fraction" is defined as the number of banks that experienced (or expected) a worsening of loan performance minus the number of banks that experienced (or expected) an improvement, divided by the total number of banks.

The main takeaway from Figure 2 is that the actual loan performance and banks' expected loan performance diverged significantly during and after the 2007-09 financial crisis. At the height of the crisis (2008-09), loan performance worsened substantially in the U.S., with notably more banks experiencing higher loan defaults on their balance sheets. Nonetheless, U.S. banks were on average over-optimistic during these years, as the net fraction of banks that expected worsening lagged behind the net fraction that experienced worsening.

[16]This variable includes all loans on banks' balance sheets; in other words, the change reflects both new loans and drawdowns from existing credit lines. Drawdowns from credit lines spiked in the crisis but were a lesser factor in the post-crisis recovery (Ivashina and Scharfstein, 2010). Even then, we have confirmed that the results on lending in Table 3 are robust to using an alternative measure of lending that is defined as the sum of total loans and unused loan commitments, which does not include drawdowns. For multi-bank holding companies, outstanding loans across all banks within the same holding company are summed. In the SLOOS data, there is one respondent per bank.

[17]In 2018, the minimum commitment size was raised to USD 100 million.

We see the opposite pattern during the recovery period. Notably, the divergence between bank expectations and actual loan performance has been persistent. Since 2010, actual loan performance had started to improve, with proportionally more banks experiencing lower loan defaults by 2011. However, most U.S. banks remained over-pessimistic about their loan portfolios well beyond 2010. For instance, about 8 out of 10 banks on net expected further worsening of their loan performance in 2011, and even later on, in 2013 about 6 out of 10 banks still expected further worsening. By contrast, the net fraction of banks that experienced an actual worsening of their loan performance was negative in these years, at about -40 percent in 2011 and -20 percent in 2013. Only by 2015 bank expectations became more aligned with actual performance, on average.

Furthermore, we provide corroborating evidence on bank forecast errors in Figure A.2. In 2007-08, the median forecast errors across banks were negative, but since 2009, forecast errors had been persistently positive, indicating that the median bank was over-optimistic before 2009 and over-pessimistic thereafter. In all, together with Figures 1 and A.3, the descriptive evidence here suggests that there is a connection between the speed of recovery in bank lending and the speed of recovery in bank expectations.[18] Next we turn to panel evidence to further buttress this connection. We document two new stylized facts. First, banks underreact to recent realizations but overreact to past realizations; in other words, they extrapolate with a delay. Second, their lending decisions are sensitive to beliefs, so delayed over-pessimism was a drag on lending growth during the recovery.

## 2.3 Delayed Extrapolation

Our first fact is about bank expectation formation. Under full information rational expectations (FIRE), banks' forecast errors should not be predictable using variables in their information set of the banks, which includes past loan performance. We examine whether banks' forecast errors are instead predictable by lagged loan performance, which would constitute a violation of FIRE. To that end, we regress banks' forecast errors on current ($I_{it}$) and lagged ($I_{i,t-1}$) change in loan performance:

$$FE_{i,t+1|t} = \alpha_i + \beta_1 I_{it} + \beta_2 I_{i,t-1} + \gamma Z_{it} + \tau_t + u_{it} \tag{1}$$

[18] Figure A.3 in the appendix provides further corroborating evidence from the Call Reports for the slow recovery in lending, focusing on the same sample of banks as in Figure 2, thus allowing a more direct comparison between bank expectations, actual loan performance, and lending activities.

for our full sample (2005-2020). In our baseline specification, we include bank and year fixed effects, denoted by $\alpha_i$ and $\tau_t$, respectively, as well as bank size (the logarithmic of total assets) as a control, $Z_{it}$. We assess robustness of the estimates with several sensitivity checks on the baseline specification. Standard errors are clustered at the bank level. This specification follows the test of extrapolation in the literature (for example, Kohlhas and Walther, 2021; Bordalo et al., 2021; Barrero, 2022), with the innovation that we allow for richer dynamics by including both current and lagged fundamentals.[19]

Panel A of Table 1 reports the baseline estimates of coefficients $\beta_1$ and $\beta_2$. First, both estimates are strongly statistically significant, $\beta_1 \neq 0$ and $\beta_2 \neq 0$, which constitutes a clear rejection of FIRE.[20] Second, the estimate on current loan performance, $\beta_1$, is positive while the estimate on lagged loan performance, $\beta_2$, is negative. These estimates imply that banks under-react to recent realizations of loan performance and over-react to past realizations. Intuitively, a negative realization of past loan performance will make banks overly pessimistic today about their loan performance outlook.

In Panel B of Table 1 we show that the estimates are stable across a variety of sensitivity checks that address potential concerns with our baseline specification. An important such concern is that the negative estimate on lagged performance may be spurious and simply due to the fact that both forecast errors and changes in loan performance are persistent variables. To mitigate this concern, we show that both coefficient estimates and specifically the estimate on lagged loan performance, $\beta_2$, remain strongly significant and are relatively stable when we drop either the control for bank size (Row A) or the time and bank fixed effects (Rows B-D). To the extent that bank fixed effects control for some of the persistence in forecast errors, the fact that their inclusion does not materially change the estimates should help to mitigate the concern about serial correlation. A related concern is that multi-collinearity may be driving the estimates if current and lagged loan performance are highly correlated, which we address by showing that the estimates are also stable and remain significant when we use them individually instead of together in separate regressions (Rows E-F). A related concern is that the estimates may be sensitive to outliers because forecast errors are constructed using loan performance, which thus appears on both sides of the regression (as dis-

[19] Another class of tests of over- and under-reaction in the literature examines the predictability of forecast errors from forecast revisions (Coibion and Gorodnichenko, 2015; Bordalo et al., 2020). We cannot perform this revision-based analysis since the SLOOS data only reports forecasts for the one-year ahead horizon.

[20] In the appendix, we show that the predictability of forecast errors is not due to the categorical nature of the survey data (Table A.3). We run a placebo test by generating pseudo bank beliefs that are generated randomly for each bank to mimic the rational expectations benchmark, and discretize them using the same approach as in our baseline analysis. We show that both the random beliefs and discretized random beliefs generate unpredictable forecast errors.

cussed in Kohlhas and Walther, 2021 and Bordalo et al., 2020). The influence of outliers is mitigated in our setting by the categorical nature of the bank expectations and corresponding measure of changes in loan performance. Even then, the estimates do not appear to be sensitive to the extreme tails of the forecast errors, which correspond to survey responses equal to 1 and 5 (Row G). And they remain stable and significant even if instead of forecast errors we use bank forecasts as dependent variable (Row H). As a final set of sensitivity checks, we show that the estimate on lagged performance is not sensitive to adding one more lag (Row I) and it is not just driven by the smallest banks (bottom quartile of bank size) in the sample (Table A.1).

Next, we more fully leverage the cross-section of banks in our data and use heterogeneity analysis by bank CEO characteristics to further corroborate our interpretation that the estimates reflect bank expectation biases. We retrieve information on CEO characteristics from ExecuComp, which is available for most of our banks. If the estimates indeed reflect psychological bias, then they should be systematically related in the cross-section to characteristics of bank CEOs that lead to greater psychological bias. Banks' extrapolative expectations could be driven by representativeness heuristic (Barberis et al., 1998; Rabin, 2002) or experience effects (Malmendier and Nagel, 2011). A common finding in the literature on expectation formation is that young and inexperienced individuals tend to extrapolate more. For example, Haruvy et al. (2007) find that inexperienced subjects extrapolate recent price movements. Greenwood and Nagel (2009) show that young equity fund managers bought more tech stocks during the late 1990s tech stock boom, presumably because they were more optimistic. And Malmendier and Nagel (2011) show that households who have experienced poor stock market returns in their lifetimes take less financial risk.

In line with this reasoning, Table 2 shows that the estimate on lagged performance is larger for banks whose CEOs are younger (Row A) and more inexperienced (as measured by shorter tenure, Row B). Interestingly, the estimate is also larger for banks whose CEOs were younger in the crisis (Row C), which all indicate higher extrapolation by younger and more inexperienced CEOs. Consistent with extrapolation being associated with excessive pessimism, the bias is mitigated for over-confident CEOs based on the measure of Malmendier and Tate (2005). Finally, the bias is also mitigated for CEOs with a golden parachute, for whom bad performance is presumably less salient because they are shielded from the cost of performance-related firings.

Overall, the evidence on bank expectation formation supports delayed extrapolation, indicating that, after bad loan performance materialized in the crisis, banks became over-pessimistic during the recovery.

## 2.4 Expectations and Lending Dynamics

Our second fact is about the link between bank expectations and the slow recovery in lending after the crisis. We regress the logarithmic change of total loans in year $t+k$ relative to the pre-crisis (2005-2007) average, $\Delta Loans_{i,t+k}$, where $k$ is the predictive horizon of 1-, 2-, 3-, or 4-years ahead, on current forecast errors:[21]

$$\Delta Loans_{i,t+k} = \alpha_i + \delta_k FE_{i,t+1|t} + \gamma Z_{it} + \tau_t + u_{i,t+k}. \tag{2}$$

Time $\tau_t$ and bank $\alpha_i$ fixed effects are included in all specification. We do not include additional controls in the baseline but consider more saturated specifications with additional controls in robustness analysis. We report estimates for up to four years ahead and for both the full sample (2005-2020) and the sub-sample that isolates the recovery period after the great recession (2010-2020).

We recognize that the interpretation of ordinary-least-squares (OLS) estimates is complicated by identification issues as our first fact shows that forecast errors are correlated with other factors, such as past loan performance, that may be also independently correlated with future loan growth, and thus may lead to spurious correlation between forecast errors and future loan growth. To rule out spurious correlation, we use a shift-share or Bartik design.[22] The design either replaces or instruments for the potentially endogenous forecast errors with with a Bartik instrument, $S_{it-1}\overline{FE}_{it+1|t}$, which is defined as the product of a shift variable, $\overline{FE}_{it+1|t}$, equal to the "consensus" forecast error for other banks measured as the mean of their forecast error $\overline{FE}_{it+1|t} = \sum_{j \neq i} \frac{FE_{jt+1|t}}{n-1}$, times a share variable, $S_{it-1}$, equal to the lagged ratio of total loans to total assets. The intuition behind this approach is that there are "news shocks" to the supply or quality of information about loan performance that are common across banks but play out differently across banks. For example, the releases of news about future firm performance, either in the quarterly earnings conference calls or in the releases of new analyst estimates, provide information about the quality of bank C&I loans. These news shocks are common across banks and, as such, are captured by the shift. However, banks that rely more on lending prior to the shocks are more impacted, which is captured by the share. As detailed in Borusyak et al. (2022), this design is valid under the identifying assumption that the news shocks that drive the shift variable are plausibly exogenous to each bank (exogeneity also of the share is not required for identification). Analo-

[21] We consider alternative pre-crisis benchmark in the robustness exercise in Table A.2 (Panel B).

[22] See Chodorow-Reich, Nenov, and Simsek (2021) for an example of recent applications and Goldsmith-Pinkham, Sorkin, and Swift (2020) and Borusyak, Hull, and Jaravel (2022) for details on the econometrics of shit-share designs.

gously to previous Bartik designs as well as applied work (see, for example, Bertrand, 2004) that have used market prices or exchange rates, we use an equilibrium object as shifter. That said, identification also requires that other aggregate variables that may be correlated with the shifter (and not controlled for in $\gamma Z_{it}$) impact banks with high vs. low loan shares uniformly. We address this requirement in robustness analysis.

Table 3 reports the OLS and instrumental-variables (2SLS-IV) estimates. Panel A shows that forecast errors are significantly and negatively correlated with future loan growth up to four years ahead with statistical significance weakening at longer horizons. Intuitively, the estimates imply that if banks were pessimistic today ($FE_{it|t-1} > 0$), that would predict lower future lending relative to its pre-crisis level. Panel B shows that the results continues to hold when we replace the potentially endogenous forecast errors with the shift-share instrument, which predicts future loan growth up to three years ahead. The result also holds when we use the shift-share variable as an instrument for forecast errors in a 2SLS-IV specification (Panel C). The first-stage F-statistics are well over 16, suggesting that the shift-share instrument is not weak (see Panel A of Table A.2 for the first-stage estimates). For this specification in the full sample, one standard deviation increase in bank pessimism leads to about half a standard deviation decrease in loan growth up to three year ahead (Columns 1-4), which is economically significant magnitude.

As discussed, a potential threat to identification is that other aggregate variables that may be correlated with the consensus forecast (and not controlled for in $\gamma Z_{it}$) may have a differential impact on banks with high vs. low loan shares. To address this concern, we take two approaches. First, we saturate the 2SLS-IV specification with several additional controls for the interaction of the share variable with other shocks that includes GDP growth, the change in the Federal Funds Rate and the VIX, as well as average changes in other bank characteristics (profitability as measured by the ratio of total income to assets, loan performance, bank capital and liquidity as measured by tier 1 capital and cash ratios, respectively). The estimates for this more saturated specification, which are reported in Panel D of Table 3, remain strongly statistically and economically significant. In additional robustness (Panel C of Table A.2), we also show that the estimates are robust to adding controls for alternative hypotheses for the slow recovery, including weak loan demand (as measured by the SLOOS response on loan demand),[23] bank securitization (as measured by securitization income to net interest income ratio) and tightened bank capital and liquidity regulations (as measured by tier

[23] In our main data source (SLOOS), banks report changes in demand for the major categories of loans four times a year since October 1991. We use this information to control for loan demand, as in Bassett et al. (2014).

1 capital and cash ratios, respectively).

Second, we recognize that adding controls mitigates but does not resolve the issue because there may be other aggregate variables that are omitted from our more saturated specification that may be correlated with the consensus forecast and have a differential impact on banks with high vs. low loan shares. Our second approach tackles the issue more directly by using bank-specific or idiosyncratic forecast errors that are purged of potential aggregate confounds to construct the shift variable. Specifically, similar to Leary and Roberts (2014) (see equation (7); see also Dessaint, Foucault, Frésard, and Matray, 2019) we construct idiosyncratic forecast errors as the estimated residuals from a regression of forecast errors for each type of loan (C&I, CRE, RRE, and Consumer) on the consensus forecast error. To construct the shift variable, we then use for each bank the idiosyncratic forecast error in the primary loan type, which is assigned based on the largest share of loan type (C&I, CRE, RRE, and Consumer) relative to total assets. The share variable is constructed as the lagged ratio of the primary loan type to total assets. Intuitively, this version of the shift variable captures bank-specific optimism or pessimism of other banks over and above what is predicted by aggregate shocks that may affect the consensus forecast. For example, it captures times when other banks that are primarily active in C&I loans have excess pessimism over C&I loan performance. And the share gives more weight to these realizations of the shift for banks that are primarily active in C&I. Thus, this version of the shift-share instrument captures shifts in other banks' expectations that are by construction orthogonal to aggregate shocks to the consensus forecast. The results reported in Panel E of Table 3 show that the estimates remain strongly statistically and economically significant and are quite stable relative to those in Panel C, which should help to further mitigate concerns about aggregate confounds.

Another potential threat to identification is if any particular individual bank influences the forecast of all other banks, which we address by repeating the analysis for a sub-sample that excludes the largest banks (top quartile of size) who may be presumably more likely to exert such an influence. Reassuringly the estimates for this sub-sample of banks are little changed (Panel D of Table A.2).[24]

## 2.5 Heterogeneity by Loan Type and Real Effects on Borrowers

Next, we further solidify our second fact on the link between bank expectations and the slow recovery in lending by examining different loan types and a variety of bor-

[24]In Panels E-F of Table A.2 we also address potential serial correlation in the shift-share by showing that the estimates are robust to including the first lag (Panel E) as well as the first and second lags (Panel F) of the shift-share variable as instruments

rower real and financial outcomes. First, we repeat the OLS estimation of equation (2) separately for each of the four categories of core loans reported in SLOOS: commercial and industrial (C&I) loans, residential real estate (RRE) loans, commercial real estate (CRE) loans, and consumer loans. The estimates reported in Table 4 show that future bank lending in all but consumer loans is negatively related to forecast errors on that particular type of loans, with C&I loans and residential loans (RRE) being the most sensitive to forecast errors.

Second, we examine the link between bank expectations and a wide range of financial and real outcomes of their borrowers. If a contraction in lending limits the availability of bank credit for borrowers, then bank pessimism over the recovery should transmit to their borrowers and hamper their ability to growth after the crisis. To examine this possibility, we link borrowers to their lenders using the Shared National Credit Program (SNC), which is a confidential supervisory data set jointly administered by the Federal Reserve, FDIC, and OCC (see Chodorow-Reich and Falato, 2022 for details). For each borrower-year, we assign as lender the lead lender on their syndicated loans, which is the bank that manages the servicing of the loan and typically provides the largest share of the funds (see, for example, Chodorow-Reich, 2014). There are 19 unique lenders in our sample, which is comparable to previous papers in the literature. Borrowers' balance sheet information is from Compustat.

Table 5 reports the results for repeating the 2SLS-IV analysis for borrower financial and real outcomes. The estimates indicate that there is a strong negative and statistically significant relation between lender instrumented C&I forecast errors and the future real and financial outcomes of their borrowers. For example, Panel A shows a significant relation with borrower total debt growth up to two years ahead (Columns 1-4), consistent with the contraction in credit from lender pessimism hampering the ability of firms to access debt financing. Panel A (Columns 5-8) and Panel B show a negative and significant relation again up to two years ahead with borrower investment both in tangible and intangible assets as well as borrower employment, consistent with limited debt financing from bank pessimism having real effects for their borrowers. Further corroborating this point, Panels C and D show a significant relation with growth measured based on total sales, assets, and profitability. And finally, Columns 5-8 of Panel D show a positive relation with the probability of firm exit.[25]

[25]Appendix Table A.5 show that there is a significant relation also with an additional measure of growth based on property, plant, and equipment (PPE) but not with borrower total payouts, which are well-know to be sticky.

## 2.6 Taking Stock of the Evidence

In this section, we document two new set of facts about bank expectations and lending dynamics in the U.S.:

1. Banks extrapolate with a delay, a finding that is robust to several sensitivity checks; they under-react to recent changes in loan performance and over-react to past changes. They were over-optimistic at the beginning of the crisis and over-pessimistic during the recovery.

2. Bank forecast errors have significant predictive power for future loan growth, a finding that continues to hold after instrumenting for potentially endogenous forecast errors with a shift-share instrument and other robustness checks. This suggests that bank expectations are linked to the slow recovery in lending post-crisis: as banks were persistently over-pessimistic, intermediated credit stayed below the pre-crisis level long after the recovery of actual loan performance.

We also documented two subsidiary facts:

3. Other than consumer loans, bank lending in all loan types are sensitive to fluctuations in bank beliefs, with C&I and residential real estate loans being the most sensitive.

4. Bank forecast errors have significant predictive power for a variety of their borrowers' future financial and real outcomes.

Our next goal is to quantify the aggregate implications for credit from banks' deviation from FIRE.

**Implications of the Evidence for Modeling Expectation Formation** Assume that change in loan performance ($I_{it}$) follows an AR(1) process:

$$I_{i,t+1} = \rho_1 I_{it} + u_{i,t+1}, \tag{3}$$

while bank expectation are influenced by the current outcome and the recent trend:

$$\begin{aligned} \mathbb{E}^{\mathcal{P}}_{it}[I_{i,t+1}] &= \phi_1 I_{it} + \phi_2 (I_{it} - I_{i,t-1}) \\ &= (\phi_1 + \phi_2) I_{it} - \phi_2 I_{i,t-1} \end{aligned}$$

where $\mathcal{P}$ denotes the subjective belief. Let $\hat{\rho}_1 \equiv \phi_1 + \phi_2$ and $\hat{\rho}_2 \equiv -\phi_2$. Then bank forecast errors are given by:

$$FE_{i,t+1|t} = I_{i,t+1} - \mathbb{E}^{\mathcal{P}}_{it}[I_{i,t+1}] = \underbrace{(\rho_1 - \hat{\rho}_1)}_{\substack{>0 \\ \text{underreaction}}} I_{it} \underbrace{- \hat{\rho}_2}_{\substack{<0 \\ \text{overreaction}}} I_{i,t-1} + u_{i,t+1}. \tag{4}$$

The signs of estimates for $\hat{\beta}_1$ and $\hat{\beta}_2$ in Table 1 imply that $\rho_1 > \hat{\rho}_1$ and $\hat{\rho}_2 > 0$, so that banks under-react to recent realizations, and over-react to past realizations. Tables 1 (Panel B, Row H) and A.4 provides supporting evidence for these two conditions. This reasoning informs our modeling choice of the bank belief process in the next section.

# 3 Model

## 3.1 Environment

**Time and agents** Time is discrete. There is a continuum of heterogeneous banks and an infinitely-lived representative investor, who owns all banks. A bank is defined as a company that finances risky projects by equity and deposits. Both entities share a common exposure to an extreme economic adverse event ("crisis") that occurs with a time-varying probability. In order to focus solely and squarely on the impact of forecasting biases, we start from a partial equilibrium analysis: consumption and deposit growth follows exogenous processes and the deposit rate is fixed. In Section 5.2, we extend the model to general equilibrium, and endogenize the deposit rate.

**Consumption and disaster risk** In the baseline partial equilibrium model, we assume the following process for the investor's consumption (Gomes, Grotteria, and Wachter, 2023):

$$C_{t+1} = C_t e^{\mu_c + \sigma_c \varepsilon_{c,t+1} + \xi x_{t+1}}, \tag{5}$$

where $\mu_c$ represents the mean growth in consumption in normal times. We allow for the possibility of a rare "disaster" when consumption falls by a large fraction $\xi$, as in Rietz (1988) and Barro (2006). With probability $p_t$, a disaster realizes in $t+1$, and we set $x_{t+1} = 1$. Otherwise $x_{t+1} = 0$. Following Gourio (2012, 2013), the probability $p_t$ is time-varying and follows a Markov process:

$$\log p_{t+1} = (1 - \rho_p) \log \bar{p} + \rho_p \log p_t + \varepsilon_{p,t+1}, \tag{6}$$

with persistence $\rho_p$ and mean log $\bar{p}$.[26] $\varepsilon_{p,t+1} \sim iidN(0,\sigma_p^2)$. $\varepsilon_{ct}$ is a standard normal random variable that is i.i.d. over time. $\varepsilon_{pt}$, $\varepsilon_{ct}$ and $x_t$ are independent.

**Preferences** The representative investor who consumes endowment $C_t$ has Epstein and Zin (1989) preferences with time preference $\beta \in (0,1)$, relative risk aversion $\gamma$, and elasticity of intertemporal substitution $\psi$. Hence the stochastic discount factor (SDF) of the investor is given by:

$$M_{t,t+1} = \beta^{\theta} \left( \frac{C_{t+1}}{C_t} \right)^{-\gamma} \left( \frac{S_{t+1} + 1}{S_t} \right)^{-1+\theta} \tag{7}$$

where $\theta = \frac{1-\gamma}{1-1/\psi}$ and $S_t$ denotes the ratio of wealth to consumption as determined by:

$$\mathbb{E}_t^{\mathcal{P}} \left[ \beta^{\theta} \left( \frac{C_{t+1}}{C_t} \right)^{1-\gamma} \left( S_{t+1} + 1 \right)^{\theta} \right] = S_t^{\theta}. \tag{8}$$

## 3.2 Loan Portfolios and Uncertainty

In modeling the uncertainty on banks' balance sheets, we follow Gomes et al. (2023). Each bank has a portfolio of risky private sector loans ($j = 1,2,...,n$). There is uncertainty about the collateral value for loan $j$ of bank $i$, $W_{ijt}$, which is a random variable:

$$W_{ijt} = e^{\sigma_c \varepsilon_{ct} + \xi x_t + \omega_{it} + \sigma_j \varepsilon_{jt}}. \tag{9}$$

The collateral value is subject to three sources of uncertainty: $(\varepsilon_{ct}, x_t)$ are the aggregate shocks discussed above; $\omega_{it}$ is a bank-specific shock; $\varepsilon_{jt}$ is a borrower-specific shock. $\varepsilon_{ct}$ and $\varepsilon_{jt}$ are standard normal random variables that are i.i.d. over time. $\omega_{it}$ follows the Markov process:

$$\omega_{i,t+1} = \rho_{\omega} \omega_{it} + \varepsilon_{\omega i,t+1}, \tag{10}$$

where $\varepsilon_{\omega i,t+1} \sim iidN(0,\sigma_{\omega}^2)$. A persistent bank-specific shock ensures that the cross-section of banks remains non-trivial, and as we show later, bias about its persistence is important for matching the forecast error dynamics at the bank-level. $\varepsilon_{ct}$, $\varepsilon_{jt}$, $\varepsilon_{\omega it}$ and $\varepsilon_{pt}$ are independent of each other and also of $x_t$. Each of the four shocks can change the value of an individual loan and its default probability.

A borrower $j$ defaults at time $t$ if $W_{ijt} < \kappa$, and $\kappa$ is common across all borrowers. When a borrower defaults, the bank can recover a fraction $1 - \mathscr{L}$ of the collateral value,

[26] In our simulations, we discretize the process (6) so that $p_t < 1$.

where $\mathscr{L}$ is the loss given default. The ex-post return on the portfolio of loans equals

$$r^L(\mathbf{s}_{it}, \varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}) = \frac{\pi^L(\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1})}{P^L(\mathbf{s}_{it})} - 1, \tag{11}$$

where $\pi^L(\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1})$ is the payoff of the loan portfolio for bank $i$ at $t+1$, which we specify in Appendix A.1, and $P^L(\mathbf{s}_{it})$ is the price of the loan at $t$:

$$P^L(\mathbf{s}_{it}) = \mathbb{E}_t^{\mathcal{P}}\left[M_{t,t+1}\pi^L_{i,t+1}(\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1})\right]. \tag{12}$$

$\mathbf{s}_{it}$ denotes the exogenous state variables for bank $i$, which we specify below. $\mathrm{E}_t^{\mathcal{P}}(\cdot)$ captures the expectation formation process, which we now turn to.

## 3.3 Incorporating Beliefs

Agents (both bank managers and investors) have distorted expectations about future loan performances.[27] Since our measure of loan performances, the loan default rate, is endogenously determined, we introduce bias to the determinants of loan performance – that is, to the perceived aggregate and bank-specific shock processes. While the true processes of $p_t$ and $\omega_{it}$ follow (6) and (10), agents perceive the processes to be:

$$\omega_{i,t+1} = \hat{\rho}_{1\omega}\omega_{it} + \hat{\rho}_{2\omega}\omega_{i,t-1} + \varepsilon_{\omega i,t+1} \tag{13}$$

$$\log p_{t+1} = (1 - \hat{\rho}_{1p} - \hat{\rho}_{2p})\log \bar{p} + \hat{\rho}_{1p}\log p_t + \hat{\rho}_{2p}\log p_{t-1} + \varepsilon_{p,t+1}. \tag{14}$$

Rearranging (13)-(14) shows that expectations are influenced by not only the current outcome ($p_t$ and $\omega_{it}$) but also the recent trend ($\Delta p_t$ and $\Delta\omega_{it}$). Later in the paper, we explore the implications of having only biased beliefs about the aggregate shock, and show that for matching bank beliefs at the micro level, it is crucial to have biased beliefs about both aggregate and idiosyncratic shocks (see Table A.9).

Our specification of beliefs is a parsimonious way to capture the delayed extrapolation behavior observed in the data (see Section 4.1).[28] Ideally, one would prefer to model the bank belief formation process (say, due to limited memory as, for example, in

[27]By assuming that both managers and investors have the same degree of bias, we do not take a stance on whether some agents are more rational than others. Moreover, this improving the matching of model-implied asset (loan) pricing moments with the data.

[28]Models of extrapolation typically inflate the persistence of an AR(1) process (Greenwood and Hanson, 2013; Hirshleifer, Li, and Yu, 2015; Angeletos, Huo, and Sastry, 2020), or allow agents to extrapolate from all past realizations with geometric discounting (Barberis, Greenwood, Jin, and Shleifer, 2015). We show from the data that banks extrapolate from current and last period's realizations (Table 1), and that their beliefs follow an AR(2) (Table A.4). Nonetheless, we explore the implications of alternative belief specifications in Section 5.1.

Bordalo, Gennaioli, and Shleifer, 2017) more endogenously. This approach, however, would require us to take a stand on a specific source of friction that leads to biased bank expectations. Since our main focus is on studying the effect of biased expectations on bank lending behavior, we choose to remain agnostic about the source of the bias and summarize beliefs with a simple functional form capturing the basic facts on bank expectations that we documented earlier. The advantage of this approach is that the quantitative results will not be limited to a specific theory of the belief formation process as our model can accommodate several alternative interpretations of the nature of the belief formation process (see below for more details).

Furthermore, while the true probability of a disaster realization in the next period is $\text{Prob}[x_{t+1} = 1] = p_t$, agents extrapolate from the past and perceive this probability to depend on both $p_t$ and $p_{t-1}$:

$$\text{Prob}^{\mathcal{P}}[x_{t+1} = 1] = p_t^{\chi} p_{t-1}^{1-\chi}. \tag{15}$$

Unlike the beliefs about the shock processes (13)-(14), this assumption is not crucial for matching the forecast errors and lending dynamics at the bank level (see Table A.7 and Figure A.8 in Appendix). Nonetheless, this assumption helps matching the dynamics of loan rates $r_t^L$ (Table A.6) and generates an amplification effect through asset prices.

Our specification of beliefs is consistent with evidence across a variety of settings that expectations of financial markets outcomes are extrapolative (e.g. Greenwood and Shleifer, 2014). As in Barberis, Greenwood, Jin, and Shleifer (2015), we do not take a stand on the source of banks' extrapolative expectations, which could be driven by representativeness heuristic (Barberis, Shleifer, and Vishny, 1998; Rabin, 2002) or by experience effects (Malmendier and Nagel, 2011) or by limited memory as in the diagnostic expectations framework (Bordalo, Gennaioli, and Shleifer, 2017).[29] Sung (2024) shows that combining imperfect attention with noisy memory generates underreaction in the near term and overreaction for longer terms.

An alternative and related approach to model expectation errors that leads to excessively extrapolative beliefs is natural expectations (Fuster, Laibson, and Mendel, 2010), where forecasters neglect deeper lags of a shock process. While our model shares some predictions with natural expectations – such as overstating the long-run persistence of shocks – it makes distinctive predictions about delayed extrapolation that more closely describe the data on bank expectations.

[29] Bordalo, Gennaioli, La Porta, Matthew, and Shleifer (2023) explore a special case of the diagnostic expectations model, where the fundamental follows an AR(1) while beliefs follow an ARMA(2,1). We share the feature that agents overreact to past shocks.

### 3.4 The Bank's Balance Sheet

Each bank $i$ enters period $t$ with loan portfolio $L_{i,t-1}$, deposits $D_{i,t-1}$, and equity $E_{i,t-1}$. Then all aggregate and idiosyncratic shocks to loan returns are realized, and the bank decides whether to continue or default. If the bank continues, its net profit $\Pi_{it}$ depends on the rates of return on the bank's assets $r^L_{it}$ and liabilities $r^D$, any non-interest income $c^L$, and other cost of funding $c^D$, which captures overhead costs and the FDIC surcharge to fund deposit insurance:

$$\Pi_{it} = \left(r^L_{it} + c^L\right) L_{i,t-1} - \underbrace{\left(r^D + c^D\right)}_{\equiv \tilde{r}^D} D_{i,t-1}. \tag{16}$$

The bank chooses dividends $Div_{it}$ and new loans $L_{it}$. For now, we follow Merton (1978) and assume $D_{it} = e^g D_{i,t-1}$ – in other words, deposits grow at a constant rate $g$ – and we relax this assumption in the general equilibrium model (Section 5.2).[30] Equity is accumulated retained profits over time, i.e. after dividends and adjustment costs have been paid. Thus at the end of period $t$, each bank has a new equity level $E_{it}$, which is equal to the equity at the beginning of the period $t$ net of current dividends $Div_{it}$ and adjustment costs $\Phi_{it}$, plus current profit $\Pi_t$:

$$E_{it} = E_{it-1} - Div_{it} - \Phi_{it} + \Pi_{it}. \tag{17}$$

In choosing its investment in loans, each bank faces the balance sheet equation:

$$L_{it} = D_{it} + E_{it}, \tag{18}$$

as well as a quadratic loan adjustment cost:

$$\Phi_{it} = \eta^L L_{i,t-1} \left( \frac{L_{it} - L_{i,t-1}}{L_{i,t-1}} \right)^2. \tag{19}$$

Banks also face a regulatory capital requirement, consisting of a maximum ratio of total assets to equity captured by $\lambda$:

$$\frac{L_{it}}{E_{it}} \leq \lambda. \tag{20}$$

[30]Here the deposit rate $r^D$ is constant, and we calibrate $g$ to equal expected consumption growth:

$$g = \log\left( (1 - \mathrm{E}p_t) e^{\mu_c + \frac{\sigma_c^2}{2}} + \mathrm{E}p_t e^{\mu_c + \frac{\sigma_c^2}{2} + \xi} \right).$$

In the general equilibrium model (Section 5.2), $r^D$ becomes endogenous and time-varying.

### 3.5 The Bank's Problem

Banks are run by managers with limited liability that maximize the present discounted value of investor utility from dividends $Div_{it}$, and discount the future with the investor's SDF, $M_{t,t+1}$. Dividends represent equity payouts if $Div_{it} > 0$ and equity issuance if $Div_{it} < 0$. Equity issuance is costly due to asymmetric information and incentive issues. We capture this with a proportional equity issuance cost (Bolton, Li, Wang, and Yang, 2023):

$$\Lambda(Div_{it}) = \mathbb{1}_{Div_{it}<0}\eta^{E} Div_{it} \tag{21}$$

where $\mathbb{1}_{Div_{it}<0}$ is an indicator variable that is equal to 1 if $Div_{it} < 0$ and 0 otherwise.

We define a composite state variable $N_{it}$, that is the sum of the beginning-of-period equity and the current net profit:

$$N_{it} = E_{it-1} + \left(r^{L}_{it} + c^{L}\right) L_{i,t-1} - \tilde{r}^{D} D_{i,t-1}. \tag{22}$$

Conditional on not defaulting at time $t$, bank managers solve the following continuation problem: $V^{C}(L_{i,t-1}, D_{i,t-1}, N_{it}, \mathbf{s}_{it}) =$

$$\max_{Div_{it}, L_{it}} \left\{ Div_{it} + \Lambda(Div_{it}) + \mathbb{E}^{\mathcal{P}}_{it}\left[ M_{t,t+1} V(L_{it}, D_{it}, N_{i,t+1}, \mathbf{s}_{i,t+1}) \middle| \mathbf{s}_{it} \right] \right\}, \tag{23}$$

given the SDF (7), the return on risky loans (11), the current profit (16), the evolution of equity (17), the balance sheet constraint (18), asset adjustment costs (19), the capital requirement constraint (20), equity issuance costs (21), and the definition of $N_{i,t+1}$ (22). Limited liability implies that bank managers may choose an outside option $V^{D}$, which we normalize to zero, and the expected value in (23) is defined as the upper envelope:

$$V(L_{it}, D_{it}, N_{i,t+1}, \mathbf{s}_{i,t+1}) = \max\left[ V^{C}(L_{it}, D_{it}, N_{i,t+1}, \mathbf{s}_{i,t+1}),\ V^{D} \right]. \tag{24}$$

Default happens if a bank's continuation value $V^{C}$ falls below the threshold level $V^{D}$, which is normalized to zero. For tractability, we assume that in each period the exiting firms are replaced by identical new banks within the same period, so we maintain a stationary distribution of banks.

Since the constraints and cash flows are linear in $L_{it}$ and $D_{i,t-1}$, we can simplify the computation of the bank's problem by scaling the value of a bank by deposits $D_{it}$, as shown in Appendix A.2. As a result, the state variables in the model are lagged scaled assets ($l_{i,t-1} \equiv \frac{L_{i,t-1}}{D_{i,t-1}}$), equity before dividends and adjustment costs ($n_{it} \equiv \frac{N_{it}}{D_{it}}$), and the exogenous states $\mathbf{s}_{it}$. With rational expectations, $\mathbf{s}_{it}$ only include the current crisis probability $p_t$ and bank-specific conditions $\omega_{it}$, but with extrapolative beliefs, $\mathbf{s}_{it} = [p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1}]$.

# 4 Quantitative Analysis

This section first discusses the calibration. Next we explore the disaster dynamics in the model, with a joint focus on bank lending and expectations. Then we show that the model generates business cycle dynamics as well as bank-level dynamics for beliefs and lending that mimic the data. Finally, we study the effectiveness of quantitative easing through the lens of the model.

## 4.1 Parameterization

We solve and calibrate two variants of the model at an annual frequency:

1. Rational model: Agents believe that the aggregate shock $p_t$ and idiosyncratic shock $w_t$ follow the true processes, (6) and (10), and that the probability of a disaster in $t+1$ is $\text{Prob}[x_{t+1} = 1] = p_t$.

2. Delayed extrapolation model: Agents believe that $p_t$ and $w_t$ follow (13) and (14), and that the probability of a disaster in $t+1$ is (15).

There are two groups of parameters in each model: the first group is exogenously calibrated; the second group is calibrated in a moment-matching exercise. We calibrate the model parameters to best match moments for each version of the model, thus giving each model the best chance to represent the data. When we simulate the model with behavioral bias, all shocks and distributional dynamics are determined according to their true processes, even though the asset prices and bank polices involve distorted expectations.

**Assigned Parameters** A list of the exogenously calibrated parameters are shown in Table 6. For most of them, we take their values from existing models with disaster risk (Gourio, 2012; Gomes et al., 2023), to facilitate the comparison of models with and without belief distortions. Specifically, the values for $\beta$, $\mu_c$ and $\sigma_c$ follow the standard values in the business cycle literature (e.g. Cooley and Prescott, 1995), while the values for $\psi$ and $\gamma$ follow the literature on asset pricing with rare events (e.g. Gourio, 2012). We follow the estimates of an average probability of disaster on OECD countries by Barro and Ursúa (2008) and set the average probability of an economic collapse to be

2 percent per year and an associated drop in consumption of $\xi$ to be 30%. For parameters governing the disaster probability process, we set $\rho_p$ and $\sigma_p$ to be 0.8 and 0.42, respectively, which are within the range of values explored by Gourio (2012, 2013). For parameters governing the bank-specific shock process, we follow Gomes et al. (2023) and set $\rho_\omega$ and $\sigma_\omega$ to be 0.9 and 0.02, respectively. We fix the loan-to-value ratio at loan origination at 0.66, following Nagel and Purnanandam (2020). The loss given default on loans, $\mathcal{L}$, is calibrated to match the observed average recovery rate on loans. The regulatory capital requirement parameter $\lambda$ is 12.5, corresponding to an 8% equity to asset ratio in accordance with the Basel rules. Lastly, we follow Bolton et al. (2023) and calibrate the proportional equity issuance cost $\eta^E$ to 5%. For the return on deposits $r^D$, we use the average interest on core deposits over the sample period.

**Parameters from Moment Matching** The rest of the parameters are jointly calibrated in a moment-matching exercise. In the rational model, there are 4 parameters $\{\sigma_j, \eta^L, c^L, \tilde{r}^D\}$, and we target 4 moments. In the delayed extrapolation model, we have 5 additional parameters governing bank beliefs $\{\hat{\rho}_{1p}, \hat{\rho}_{2p}, \hat{\rho}_{1\omega}, \hat{\rho}_{2\omega}, \chi\}$, and we target 5 additional moments. All targeted moments are computed from our sample in Section 2.

The four common targeted moments are the mean and standard deviation of bank leverage, the mean profit-to-equity ratio and the mean bank default rate. The model is nonlinear, and all parameters affect all the moments. Nevertheless, some parameters are more important for certain statistics. The mean and the cross-sectional dispersion in bank leverage (assets over equity) $\frac{L_{it}}{E_{it}}$ are affected by the volatility of loan-specific shock $\sigma_j$ and the asset adjustment cost parameter $\eta^L$. The mean profit-to-equity ratio $\frac{\Pi_{it}}{E_{it}}$ and the mean bank default rate are largely driven by the non-interest income parameter $c^L$ and cost of funding $c^D$, respectively.

The additional parameters in the delayed extrapolation model are calibrated to target the coefficient estimates on current and lagged lending from our key regression (1) on delayed extrapolation. Specifically, we use the coefficient estimates for the full sample (see Table 1) to calibrate the belief parameters for the aggregate shock $\{\hat{\rho}_{1p}, \hat{\rho}_{2p}\}$, and the coefficient estimates from a subsample excluding banks in the bottom quartile (in terms of total loans) to calibrate the belief parameters for the bank-specific shock $\{\hat{\omega}_{1p}, \hat{\omega}_{2p}\}$. A comparison of the coefficient estimates in Table A.1 suggests that an average bank above the bottom quartile under-reacts less to the current realization and over-reacts more to the past realization, compared to an average bank in the full sample. We calibrate the model to match this feature. In these regressions, we define the model variables as closely as possible to their data counterparts. Thus, forecast errors are the difference between the actual and the expected change in loan performance over the next year, and the change in loan performance $I_{it}$ is the negative of the annual change in the loan default rate, so that $I_{it} > 0$ indicates an improvement in loan performance (or a reduction in default rate), to be consistent with the sign in the data.

The last targeted moment in the delayed extrapolation model is the serial correlation of loan rate growth, which is the change in the ex-post return on loans $r_t^L$ in the model. This is closely related to the loan price, which is largely affected by $\chi$, the weight on $p_t$ in agents' perceived disaster probability at $t+1$. In Table 7, we report the target moments in the data and each model. Overall, both the rational and behavioral models produce similar statistics as the data moments.

## 4.2 Impulse Response Functions

### 4.2.1 An Increase in Disaster Probability

The main experiment is an increase in the disaster probability $p_t$. We independently simulate 3,000 economies, where each simulation is of 300 years for 1,000 banks. The first 250 years are simulated unconditionally, so all exogenous processes evolve normally. Then for each economy, after 250 years, we introduce two positive disaster probability shocks consecutively, which mimic the 2008-09 financial crisis. Figure 3 presents the impulse response functions of bank variables when the probability of disaster increases from the long-run average of 2 percent per year to 8.1 percent in two years. Then the probability of disaster mean-reverts to its long-run average according to equation (6).

**Slow Recovery in Lending and Bank Equity** Figure 3 show that an increase in disaster risk leads to a credit crunch. The key difference between the two models is that the delayed extrapolation model generates a much slower recovery in lending than the rational model. Relative to a rational expectations benchmark, extrapolative bias induces sizable aggregate credit losses of 1.5%-1.8% five to seven years after the crisis. In addition, the model also generates a slump in bank equity values (Sarin and Summers, 2016) and a larger increase in risk premia relative to the rational benchmark, consistent with the evidence in Muir (2017) that risk premia increase substantially in financial crises.

There is some persistence in banks' asset growth in the rational model, but, for realistic parameter values, this is not sufficient to match the slow credit growth after the crisis. Specifically, in the rational model, it only takes three years for the annual loan growth rate to return to the pre-crisis level, and the impulse response of loan growth does not exhibit any hump-shape. By contrast, in the delayed extrapolation model, it takes seven years for the loan growth rate to recover, which resembles the slow recovery in the data, as the annual growth rate only returned to the pre-crisis level after 2014 (Figure A.3). To facilitate inspecting the mechanism, we plot the policy functions in Figures A.4 and A.5 in the appendix.

In both models, two related forces lead to a reduction in lending upon impact of the shock. First, lending is decreasing in the disaster probability, until it hits the capital requirement constraint (Figure A.4, Panel A). This is because as at a higher $p_t$, investment in assets becomes less profitable (Figure A.5, Panel B). Second, given the balance sheet constraint (18), lending is increasing in the current net worth of a bank $n_{it}$ (Figure A.4, Panels C and D). Recall that the current net worth includes banks' beginning-of-period equity and the current net profit. As a higher disaster probability reduces realized loan returns, banks' current profit and net worth take a hit. Since external financing (both debt and equity) is costly for banks, banks deleverage in response to a reduction in net worth.

The persistence in the rational model comes from two sources: asset growth is costly and the net worth takes time to build. The additional persistence in the delayed model arises due to two effects. The first effect is the expectation channel: banks' expected continuation value is not only decreasing in $p_t$, but also in $p_{t-1}$ (Figure A.4, Panel B), so even when the disaster probability starts to revert back to the long-run mean, banks' lending decisions respond with a lag. The second effect is an interaction of expectations with the bank balance sheet. As shown in Figure 3, realized loan returns increases more slowly in the delayed extrapolation model, and thus banks' current profit and net worth also recover more slowly. This in turn exacerbates the slow recovery: lending policies of banks with lower net worth increase more slowly as disaster probability reverts to the steady state level. Intuitively, banks are more cautious about lending risky loans when their net worth is low and the disaster probability was high in the last period (Figure A.4, Panel C). As a result, we get a hump-shaped impulse response function for the loan growth rate in the delayed extrapolation model.

**Forecast Errors** Figure 3 also shows the impact of higher disaster probabilities on bank expectations. We plot the mean forecast error across banks and the net fraction of banks that expect a worsening of loan performance, respectively, for each year. To facilitate comparison, we construct these variables as closely as possible to the data definition. Forecast errors are the difference between the actual and expected change in loan performance, which is computed as the negative of the change in loan default rates (compared to the previous year), so that a positive forecast error indicates that the bank has been too pessimistic about its loan performance in the coming year, in line with the data definition. We compute forecast errors for each bank over time, and average them across banks for each year. The net fraction of banks expecting a worsening of loan performance is the fraction of banks that expect higher loan default rates in the coming year minus the fraction that expect lower default rates.

The main takeaway here is that the delayed extrapolation model replicates two important features of forecast errors in the data (Figure A.2): first, forecast errors switch signs during the crisis: they are initially negative (over-optimistic), but later turn positive (over-pessimistic); second, forecast errors remain positive long after the crisis. Both features are present in the delayed extrapolation model, whereas in the rational model, forecast errors fluctuate randomly.

Finally, the net fraction of banks expecting a worsening of loan performance in the delayed extrapolation model also follows the data more closely than in the rational model, especially in terms of timing. Immediately after the shocks, banks have not adjusted their expectations fully, so we see a short period with more banks (irrationally) expecting improvement than worsening, as in the data (Figure 2). As the disaster probability begins to revert to the long-run mean, more banks expect further worsening rather than improvement. Quantitatively, the model matches the fact that it took seven years since the first shock for bank expectations to be "neutral," or to have the same number of banks expecting worsening and improvement. While the rational model also generates an increase in the net fraction of banks expecting worsening, the timing and duration of the increase do not match with the data.

**Bank Heterogeneity** To examine the cross-sectional implications, we split our simulated sample into two groups, "large" and "small" banks, according to the size of their loan portfolios (above or below the median) before disaster probability shocks hit. All banks are subject to the same sequential shocks as in Figure 3. The main takeaway from Figure A.7 is that disaster probability shocks have a deeper and longer-lasting impact on larger banks' lending decisions, especially in the delayed extrapolation model.

In both models, large banks' lending falls by more. This is because small banks are closer to the capital requirement constraint than large banks in the steady state, so they hit the capital requirement constraint quickly, as disaster probability increases. Despite the steeper fall, the rate of recovery in lending (as well as bank net worth) is similar for large and small banks in the rational model.

The key difference in the delayed extrapolation model is that the rate of recovery is notably slower for large banks than for small banks. Recall that we calibrate the model to match the evidence on forecast error dynamics in the cross-section, which shows that large banks over-react more to past outcomes (Table A.1). In other words, large banks were more over-pessimistic than small banks during the recovery period, and thus their loan growth was more affected. Nonetheless, both types of banks exhibit a hump-shaped path for loan growth, which is missing in the rational model.

### 4.2.2 Disaster Realization

Figure 4 illustrates the response of the economy to a typical disaster that lasts for two years ($x_t = 1$ for $t = 1,2$), with the realizations of $p_t$ and $\omega_{it}$ equal to the mean of their distributions. This triggers a large reduction in consumption (5) and collateral values for loans (9), resulting in a sharp fall in loan returns. Consequently, bank net worth, lending, and continuation value fall in both models. Lending takes much longer to recover in the delayed extrapolation model, which again, exhibits a hump-shaped response in loan growth. Unlike the main experiment in Figure 3, disaster realization $x_t$ is not a state variable. Instead, the net worth of banks $n_{it}$ plays an important role in the propagation of a disaster. As explained above, banks downsize their loan portfolios in response to a reduction in net worth. The longer it takes to rebuild their net worth, the slower the recovery in bank lending.

## 4.3 Model Fit

In this section, we highlight that the delayed extrapolation model outperforms the rational model in terms of matching both the aggregate and bank-level evidence on lending dynamics and expectations.

**Business Cycle Statistics** Table 8 reports business cycle moments from model simulations for the key variables on both bank performance and expectations. As we seek to explain the stylized facts documented in Section 2, our main variables of interest are loan growth, changes in expected loan performance, changes in realized loan performance, and the growth of loan rates. Since the focus of the model is to explain the slow recovery, we examine the autocorrelations and cross-correlations of each variable with GDP, which is proxied by consumption for the model moments.

Overall the delayed extrapolation model is significantly closer to the data than the rational model. Loan growth and changes in expected loan performance (measured by changes in expected loan default) both follow AR(2) in the data, but the rational model does not generate enough persistence (despite the asset adjustment cost and the slow-moving bank equity). Notably, the correlation of lending growth and *lagged* GDP growth is positive in the data, implying that GDP growth leads bank lending growth by two years. This explains the slower recovery of lending compared to GDP after the crisis (see Figure A.1.B), but cannot be captured by the rational model.

To examine the model predictions on asset prices, we look at changes in loan rates. Similar to lending growth, loan rate growth is procyclical, and GDP growth leads loan rate growth by two years in the data, which is only captured by the delayed extrapolation model. Moreover, loan rate growth exhibits persistence in the data, while the rational model gives the counterfactual prediction of negative serial correlation.

Lastly, both models generate quantitatively similar time-series properties of realized loan performance (measured by realized loan default), and these are qualitatively similar to the data. The similarity between the two models for this variable is unsurprising, since loan default decisions depend on the true shock processes, which are drawn according to the rational representation for both models.

**Model-Implied Regressions** Next, we assess the explanatory power of the model for the bank-level belief and lending dynamics documented in Section 2. We repeat the panel regressions in Tables 1 (Panel A) and 3 (Panel A) on simulated data from each model. Table 9 reports the results. First, we regress forecast errors on current and lagged change in loan performance (Panel A). Recall that the coefficients from data are used as targeted moments for calibrating the delayed extrapolation model (columns 3-4). Unsurprisingly, the rational model fails to generate predictable forecast errors from current and past realizations (columns 5-6).[31]

As untargeted moments, we also examine whether bank beliefs predict future lending growth (Panel B). The delayed extrapolation model produces the correct sign of the estimates (columns 3-4): if a bank is pessimistic today, that would predict lower future lending relative to the pre-shock level, which is consistent with the data. This is because bank expectations of future loan performance adjusts slowly – as shown by the negative correlation between the expected change in future loan defaults and lagged GDP growth (Table 8) – and this, in turn, affects their lending decisions. Moreover, this direct effect from bank expectations is amplified by their impact on bank balance sheets (as bank profits remain low when they are over-pessimistic), which further suppress the recovery in lending. By contrast, random forecast errors in the rational model do not predict future bank lending (columns 5-6).

[31] We conduct a counterfactual experiment in which we remove the bias on the idiosyncratic shock process $\omega_{it}$, so agents make the rational forecast on $\omega_{i,t+1}$ according to (10). Notably, forecast errors are no longer predictable in our fixed effects regression (Table A.9), as the time fixed effects have absorbed the aggregate bias across banks. Thus, it is important to have biased beliefs about both aggregate and idiosyncratic shocks for matching forecast dynamics at the micro level.

### 4.4 Policy Implications

During the financial crisis and the subsequent recovery, many central banks around the world turned to quantitative easing (QE) as a monetary policy tool. These policies effectively subsidized the banking sector by providing banks with funding at favorable terms. We use our structural model to examine the effectiveness of this government intervention that reduces banks' cost of debt below its current value ($c^D_{QE} < c^D$) during and after the credit crunch. More specifically, for the first 250 periods in our simulation, we use the $c^D$ specified in Table 6; from $t = 251$, we lower $c^D$ (hence $\tilde{r}^D$) by 30 basis points in each model.

Figure 5 shows that reducing banks' cost of funding assists the recovery from a credit crisis in both models with a lag, but the policy appears to be much less effective when agents are biased. For instance, in the rational model (Panel B), lending returns to the pre-crisis level after five years of QE, whereas the policy only starts to have noticeable impact on lending after five years in the delayed extrapolation model (Panel A). To help inspecting the mechanism, we plot the lending policy functions under different values for $c^D$ in Appendix Figure A.6.

In the rational model, when the disaster probability $p_t$ is high, lending policies are not responsive to a reduction in bank funding cost $c^D$ if banks' current loan portfolios are relatively small (Panel B, Figure A.6). However, as $p_t$ decreases, the impact of lowering $c^D$ becomes more significant for a wider cross section of banks, especially those with larger portfolios. This explains why, in the rational model, the impulse response functions in the baseline (no QE) are very close to those in the policy experiment during and immediately after the crisis when banks have deleveraged, but as the disaster probability gradually decreases and banks build up their portfolios and net worth, the impulse response functions in the policy experiment diverge quickly from those in the baseline (Panel B, Figure 5). Intuitively, at high $p_t$, investment opportunities are less favorable, especially for banks with small existing portfolios, so banks prefer to return capital to their equity holders.[32]

In the delayed extrapolation model, bank lending is also a function of the past disaster probability $p_{t-1}$ as well as the current probability $p_t$. When $p_{t-1}$ is high, the pattern is similar to the high $p_t$ scenario: lending policies are not responsive to a reduction in bank funding cost $c^D$ if banks' current loan portfolios are relatively small (Panel A, Figure A.6). The dependence on $p_{t-1}$ explains why it takes three years in the rational

[32] When returns on loans $r^L_{it}$ are low, banks would need to further expand their loan portfolios to make profit from lending. To have a large portfolio expansion, banks with small existing portfolios have to pay more adjustment costs. Therefore, their lending is much less responsive to a reduction in the cost of funding when $p_t$ is high.

model, but five years in the delayed extrapolation model, for QE to have noticeable impact on lending (Figure 5). Moreover, even after five years, the speed of recovery is much slower in the delayed extrapolation model. With a sluggish recovery in lending, banks also build up their net worth more slowly in the delayed extrapolation model, which widens the differential impact of lowering $c^D$ in the two models after five years. This is again the interaction effect of expectations with bank balance sheets.

# 5 Extensions

## 5.1 Other Types of Behavioral Bias

We use our model framework as a laboratory to conduct counterfactual experiments with other types of behavioral bias, namely overextrapolation and diagnostic expectations. For overextrapolation, agents believe that $p_t$ and $\omega_{it}$ follow an AR(1) each, as in the true processes, but they perceive the persistence to be higher than in the true processes, i.e. $\hat{\rho}_p > \rho_p$, and $\hat{\rho}_\omega > \rho_\omega$ (e.g. Greenwood and Hanson, 2013; Angeletos et al., 2020). Unlike our baseline model, here agents only extrapolate from the current outcome but not from the recent growth. As a result, this model has the same exogenous state vector as the rational model, $\mathbf{s}_t = [p_t, \omega_t]$. For diagnostic expectations, we explore two slightly different formulations. The first one follows Bordalo et al. (2021), where agents believe that $p_t$ and $\omega_{it}$ follow an ARMA(1,1) each; in other words, the exogenous state vector becomes $\mathbf{s}_t = [p_t, \omega_t, \epsilon_{p,t}, \epsilon_{\omega,t}]$. The second formulation is a long-memory form of diagnostic expectations that takes into account the history of all shocks. We follow the discrete-time specification of Maxted (2023), which preserves the tractability by summarizing the history of all past shocks into a single state $\mathcal{I}_t$, so the exogenous state vector is $\mathbf{s}_t = [p_t, \omega_t, \mathcal{I}_{p,t}, \mathcal{I}_{\omega,t}]$.

We plot the impulse response function for lending in each alternative model in Figure A.9.[33] Both OE-AR(1) and DE-ARMA(1,1) generate a steeper decline in lending but a faster recovery than our baseline model. The long-memory diagnostic model generates a steeper decline and a relatively slower reversal. Otherwise, as shown in Table 10, some of the other models we consider can account for over-reaction but generally predict less delayed over-reaction than in our data, and some can account for under-reaction but do not simultaneously generate under-reaction at shorter horizons and over-reaction at longer horizons as in our data. That said, combining either OE-AR(1)

[33] In the overextrapolation model, we calibrate $\hat{\rho}_p = 0.9$ and $\hat{\rho}_\omega = 0.95$, similar to the degree of overextrapolation in Angeletos et al. (2020). In the ARMA(1,1) model, we take the estimate for the diagnostic parameter from Bordalo et al. (2021) and set it to 0.99. In the long-memory model, we set the rate of information decay to be 0.9.

or diagnostic expectations with information frictions in a richer model may potentially generate also the initial underreaction, at least in the aggregate (Angeletos et al., 2020; Bordalo et al., 2020).

## 5.2 General Equilibrium

We now extend the model to general equilibrium by endogenizing the deposit rate $r^D$, in order to examine the question: do movements in the deposit rate dampen the impact of bias? As in our baseline model, we continue to assume that the household has recursive preferences (Epstein and Zin, 1989). Now the household chooses consumption $C_t$ and savings $D_t^h$ subject to: $C_t + D_t^h = (1 + r_{t-1}^D)D_{t-1}^h + \Pi_t$, where $\Pi_t$ denotes aggregate payouts from banks. Banks are owned by households and maximize shareholder value by generating cash flows that are discounted using the SDF of households. We introduce a production sector, but for simplicity, we assume that this sector faces no frictions. The firm produces output $Y_t$ using capital $K_t$ with a decreasing returns to scale technology: $Y_t = z_t K_t^\alpha$. For tractability, we assume the following process for the technology shock: $z_t = \exp(\sigma_z \varepsilon_{z,t} + \phi\xi x_t)$, such that it is negatively impacted by a disaster $x_t = 1$. Capital accumulation follows: $K_{t+1} = [(1-\delta)K_t + I_t]\exp(\phi\xi x_{t+1})$, where $\phi$ is the firm's sensitivity to crises. Firms' investment at $t$ comes from the sum of new loans: $I_t = \int L_{it} d\mu_t$, subject to a convex adjustment cost $\lambda(I_t, K_t) = \eta_f \left(\frac{I_t}{K_t}\right)^2 K_t$. We now have the following market clearing conditions:

$$C_t + I_t = Y_t$$

for goods market clearing, and

$$\int (L_{it} - E_{it}) d\mu_t = D_t^h$$

for deposit-market clearing, where the left-hand side denotes total deposits in the banking sector.[34] This pins down the equilibrium deposit-rate $r_t^D$. $\mu_t = \mu(\omega_t, \omega_{t-1}, L_{t-1}, N_t)$ denotes the cross sectional distribution of micro states $(\omega_t, \omega_{t-1})$, lending $L_{t-1}$ and net worth $N_t$. Following the Krusell and Smith (1998) algorithm, we approximate the cross-sectional distribution $\mu$ by a low-dimensional state vector, including the mean bank net worth $\mathcal{N}_t = \int N_{it} d\mu_t$, and the current and lagged aggregate states $(p_t, p_{t-1})$, which summarize the relevant information in $\mu$.

To facilitate comparison, we parameterize the model using the baseline calibration

[34]See Appendix A.4 for a definition of general equilibrium.

(Table 6).[35] After the disaster probability shocks, households desire to save more, leading to a fall in the deposit rate $r_t^D$, which in turn lowers banks' funding cost. As a result, bank lending falls by less compared to the baseline model (Figure A.10). Nonetheless, comparing to the rational model, we see that the impact of bias remains significant. Furthermore, the model-implied regressions in Table A.8 suggest that forecast error dynamics at the bank-level are similar to those in the baseline model and in line with the data, and that their predictability for future lending remains significant.

# 6 Conclusion

This paper uses a unique survey data on banks' forecasts to explore the transmission of forecasting bias to bank lending, and offers one potential explanation for the slow recovery in bank credit after the 2008-09 financial crisis. We make two contributions. First, we document delayed extrapolation in forecast errors, suggesting that banks process information inefficiently. Moreover, we find that over-pessimistic banks are more likely to subsequently cut their lending in the recovery period. Second, we build a quantitative model that jointly explains: (a) the dynamics of beliefs, (b) the dynamics of loan growth, and (c) the link between beliefs and lending in the post-crisis period. Finally, we show that biased beliefs dampen the effectiveness of stimulative policies.

Our analysis opens up several potentially fruitful venues for future research. First, can bank expectations help to explain any other important stylized features of credit cycles, such as, the fact that lending decisions tend to be correlated across banks? While we have focused primarily on credit aggregates, exploring more in depth the microeconomics of credit cycles warrants additional research, Second, did bank pessimism over the recovery period affect all borrowers equally or rather did it have an asymmetric impact on borrowers? For example, did riskier growth firms bear the brunt of the expectations-driven crunch? Analyzing the distributional impacts would help to further clarify the transmission of bank expectations to the real economy. Finally, what are the implications of expectations for bank regulation overall and over the business cycle? While we have taken a first step toward examining the policy implications, clearly more can be done to examine the consequences of our stylized facts on bank expectations for optimal capital and macro-prudential regulation of banks.

[35]For the additional parameters, we set $\phi$ to 0.2, $\alpha$ to 0.6, $\delta$ to 0.1, and $\eta_f$ to 5.

# References


Angeletos, George-Marios, Zhen Huo, and Karthik A. Sastry (2020). Imperfect Macroeconomic Expectations: Evidence and Theory. *NBER Macro Annual 2020*.

Angeletos, George-Marios and Chen Lian (2022). Confidence and the Propagation of Demand Shocks. *Review of Economic Studies 89*(3), 1085–1119.

Barberis, Nicholas, Robin Greenwood, Lawrence Jin, and Andrei Shleifer (2015). X-CAPM: An Extrapolative Capital Asset Pricing Model. *Journal of Financial Economics 115*, 1–24.

Barberis, Nicholas, Andrei Shleifer, and Robert Vishny (1998). A Model of Investment Sentiment. *Journal of Financial Economics 49*, 307–343.

Barrero, Jose Maria (2022). The micro and macro of managerial beliefs. *Journal of Financial Economics 143*(2), 640–667.

Barro, Robert J. (2006). Rare Disasters and Asset Markets in the Twentieth Century. *Quarterly Journal of Economics 121*, 823–866.

Barro, Robert J. and José. F. Ursúa (2008). Macroeconomic Crises Since 1870. *Brookings Papers on Economic Activity 39*, 255–350.

Bassett, William F., Mary Beth Chosak, John C. Driscoll, and Egon Zakrajšek (2014). Changes in bank lending standards and the macroeconomy. *Journal of Monetary Economics 62*, 23–40.

Begenau, Juliane and Tim Landvoigt (2022). Financial Regulation in a Quantitative Model of the Modern Banking System. *Review of Economic Studies 89*(4), 1748–1784.

Bernanke, Ben (2012). Banks and Bank Lending: The State of Play. Speech at the 48th Annual Conference on Bank Structure and Competition.

Bernanke, Ben (2023). Nobel Lecture: Banking, Credit, and Economic Fluctuations. *American Economic Review 113*(5), 1143–1169.

Bernanke, Ben S. (2018). The Real Effects of Disrupted Credit: Evidence from the Global Financial Crisis. *Brookings Papers on Economic Activity*, 251–322.

Bertrand, Marianne (2004). From the Invisible Handshake to the Invisible Hand? How Import Competition Changes the Employment Relationship. *Journal of labor Economics 22*(4), 723–765.

Bianchi, Francesco, Cosmin Ilut, and Hikaru Saijo (2023). Diagnostic Business Cycles. *Review of Economic Studies. Forthcoming*.

Bolton, Patrick, Ye Li, Neng Wang, and Jinqiang Yang (2023). Dynamic Banking and the Value of Deposits. *Journal of Finance. Forthcoming*.

Bordalo, Pedro, Nicola Gennaioli, Rafael La Porta, O'Brien Matthew, and Andrei Shleifer (2023). Long Term Expectations and Aggregate Fluctuations. *NBER Macro Annual 2023*.

Bordalo, Pedro, Nicola Gennaioli, Yueran Ma, and Andrei Shleifer (2020). Overreaction in Macroeconomic Expectations. *American Economic Review 110*(9), 2748–82.

Bordalo, Pedro, Nicola Gennaioli, and Andrei Shleifer (2017). Diagnostic Expectations and Credit Cycles. *Journal of Finance 73*(1), 199–227.

Bordalo, Pedro, Nicola Gennaioli, Andrei Shleifer, and Stephen Terry (2021). Real Credit Cycles. Working Paper, Harvard University.

Borusyak, Kirill, Peter Hull, and Xavier Jaravel (2022). Quasi-Experimental Shift-Share Research Designs. *Review of Economic Studies 89*(1), 181–213.

Bouchaud, Jean-Philippe, Philipp Krueger, Augustin Landier, and David Thesmar (2019). Sticky Expectations and the Profitability Anomaly. *Journal of Finance 74*(2), 639–674.

Cavallo, Michele, Juan Morelli, Rebecca Zarutskie, and Solveig Baylor (2024). Measuring Bank Credit Supply Shocks Using the Senior Loan Officer Survey.

Chodorow-Reich, Gabriel (2014). The Employment Effects of Credit Market Disruptions: Firm-level Evidence from the 2008–9 Financial Crisis. *Quarterly Journal of Economics 129*(1), 1–59.

Chodorow-Reich, Gabriel and Antonio Falato (2022). The Loan Covenant Channel: How Bank Health Transmits to the Real Economy. *Journal of Finance 77*(1), 85–128.

Chodorow-Reich, Gabriel, Plamen T Nenov, and Alp Simsek (2021). Stock Market Wealth and the Real Economy: A Local Labor Market Approach. *American Economic Review 111*(5), 1613–1657.

Coibion, O. and Y. Gorodnichenko (2015). Information Rigidity and the Expectations Formation Process: A Simple Framework and New Facts. *American Economic Review 105*, 2644–2678.

Cooley, Thomas F. and Edward C. Prescott (1995). Economic growth and business cycles. In Thomas F. Cooley (Ed.), *Frontiers of Business Cycle Research*, pp. 1–38. Princeton University Press.

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

Dessaint, Olivier, Thierry Foucault, Laurent Frésard, and Adrien Matray (2019). Noisy stock prices and corporate investment. *Review of Financial Studies 32*(7), 2625–2672.

Egan, Mark, Ali Hortaçsu, and Gregor Matvos (2017). Deposit Competition and Financial Fragility: Evidence from the US Banking Sector. *American Economic Review 107*(1), 169–216.

Elenev, Vadim, Tim Landvoigt, and Stijn Van Nieuwerburgh (2021). A Macroeconomic Model with Financially Constrained Producers and Intermediaries. *Econometrica 89*(3), 361–1418.

Epstein, Larry G. and Stanley E. Zin (1989). Substitution, Risk Aversion, and the Temporal Behavior of Consumption and Asset Returns: A Theoretical Framework. *Econometrica 57*(4), 937–969.

Farmer, Leland, Emi Nakamura, and Jón Steinsson (2023). Learning About the Long Run. *Journal of Political Economy. Forthcoming*.

Fuster, Andreas, David Laibson, and Brock Mendel (2010). Natural Expectations and Macroeconomic Fluctuations. *Journal of Economic Perspectives 24*(4), 67–84.

Gertler, Mark and Simon Gilchrist (2018). What Happened: Financial Factors in the Great Recession. *Journal of Economic Perspectives 32*(3), 3–30.

Gertler, Mark and Nobuhiro Kiyotaki (2011). Financial intermediation and credit policy in business cycle analysis. In Benjamin Benjamin M. Friedman and Michael Woodford (Eds.), *Handbook of Monetary Economics*, pp. 547–599. Elsevier Science.

Gertler, Mark and Nobuhiro Kiyotaki (2015). Banking, Liquidity, and Bank Runs in an Infinite Horizon Economy. *American Economic Review 105*(7), 2011–2043.

Giglio, Stefano, Matteo Maggiori, Johannes Stroebel, and Steven Utkus (2021). Five Facts About Beliefs and Portfolios. *American Economic Review 111*(5), 1481–1522.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020). Bartik Instruments: What, When, Why, and How. *American Economic Review 110*(8), 2586–2624.

Gomes, João. F., Marco Grotteria, and Jessica A. Wachter (2023). Foreseen Risks. *Journal of Economic Theory 212*.

Gourio, François (2012). Disaster Risk and Business Cycles. *American Economic Review 102*(6), 2734–2766.

Gourio, Francois (2013). Credit Risk and Disaster Risk. *American Economic Journal: Macroeconomics 5*, 1–34.

Gourio, Francois, A. K. Kashyap, and Jae W. Sim (2018). The Tradeoffs in Leaning Against the Wind. *IMF Economic Review 66*, 70–115.

Greenwood, Robin and Samuel Hanson (2013). Issuer Quality and Corporate Bond Returns. *Review of Financial Studies 26*, 1483–1525.

Greenwood, Robin and Stefan Nagel (2009). Inexperienced investors and bubbles. *Journal of Financial Economics 93*(2), 239–258.

Greenwood, Robin and Andrei Shleifer (2014). Expectations of Returns and Expected Returns. *Review of Financial Studies 27*(3), 714–746.

Haruvy, Ernan, Yaron Lahav, and Charles N Noussair (2007). Traders' Expectations in Asset Markets: Experimental Evidence. *American Economic Review 97*(5), 1901–1920.

Hirshleifer, David, Jun Li, and Jianfeng Yu (2015). Asset pricing in production economies with extrapolative expectations. *Journal of Monetary Economics 76*, 87–106.

Ivashina, Victoria and David Scharfstein (2010). Bank lending during the financial crisis of 2008. *Journal of Financial Economics 97*(3), 319–338.

Jermann, Urban and Haotian Xiang (2023). Dynamic banking with non-maturing deposits. *Journal of Economic Theory 209*, 105644.

Kiyotaki, Nobuhiro (2011). A Perspective on Modern Business Cycle Theory. *Economic Quarterly 97*(3), 195–208.

Kohlhas, Alexandre N. and Ansgar Walther (2021). Asymmetric Attention. *American Economic Review 110*(9), 2879–2925.

Kozlowski, Julian, Laura Veldkamp, and Venky Venkateswaran (2020). The Tail That Wags the Economy: Beliefs and Persistent Stagnation. *Journal of Political Economy 128*(8), 2839–2879.

Krishnamurthy, Arvind and Wenhao Li (2020). Dissecting Mechanisms of Financial Crises: Intermediation and Sentiment. NBER Working Paper No.27088.

Krusell, Per and Anthony A. Smith (1998). Income and Wealth Heterogeneity in the Macroeconomy. *Journal of Political Economy 106*(5), 867–896.

Leary, Mark T and Michael R Roberts (2014). Do Peer Firms Affect Corporate Financial Policy? *Journal of Finance 69*(1), 139–178.

Ma, Yueran, Teodora Paligorova, and José-Luis Peydró (2022). Expectations and Bank Lending. Working Paper.

Malmendier, Ulrike and Stefan Nagel (2011). Depression-babies: Do Macroeconomic Experiences Affect Risk-taking? *Quarterly Journal of Economics 126*, 373–416.

Malmendier, Ulrike and Geoffrey Tate (2005). CEO Overconfidence and Corporate Investment. *Journal of Finance 60*(6), 2661–2700.

Maxted, Peter (2023). A Macro-Finance Model with Sentiment. *Review of Economic Studies 90*(5), 1–38.

McAndrews, James J. (2015). Credit growth and economic activity after the Great Recession. Speech 165, Federal Reserve Bank of New York.

Meeuwis, Maarten, Jonathan A Parker, Antoinette Schoar, and Duncan Simester (2022). Belief disagreement and portfolio choice. *Journal of Finance 77*(6), 3191–3247.

Merton, Robert (1978). On the Cost of Deposit Insurance When There Are Surveillance Costs. *The Journal of Business 51*(3), 439–52.

Muir, Tyler (2017). Financial Crises and Risk Premia. *Quarterly Journal of Economics 132*(2), 765–809.

Nagel, Stefan and Amiyatosh Purnanandam (2020). Banks' Risk Dynamics and Distance to Default. *Review of Financial Studies 33*(6), 2421–2467.

Rabin, Matthew (2002). Inference by Believers in the Law of Small Numbers. *Quarterly Journal of Economics 117*, 775–816.

Rietz, Thomas A. (1988). The equity risk premium a solution. *Journal of Monetary Economics 22*(1), 117–131.

Rozsypal, Filip and Kathrin Schlafmann (2020). Overpersistence Bias in Individual Income Expectations and its Aggregate Implications. *American Economic Journal: Macroeconomics. Forthcoming*.

Sarin, Natasha and Lawrence H. Summers (2016). Understanding Bank Risk through Market Measures. Brookings Papers on Economic Activity. *47*, 57–127.

Sung, Yeji (2024). Macroeconomic Expectations and Cognitive Noise. Federal Reserve Bank of San Francisco Working Paper Series 2024-19.

Tauchen, George (1986). Finite State Markov-Chain Approximations to Univariate and Vector Autoregressions. *Economic Letters 20*(177-181), 704–719.

**Figure 1:** Total Bank Loans in the U.S.

This figure plots total loans and leases in bank credit by all commercial banks in the U.S. in real terms from 2000 to 2020. The dashed line is a linear trend that fits the data from 2000 to 2008. Source: Assets and Liabilities of Commercial Banks in the U.S. (H.8), Federal Reserve Board.

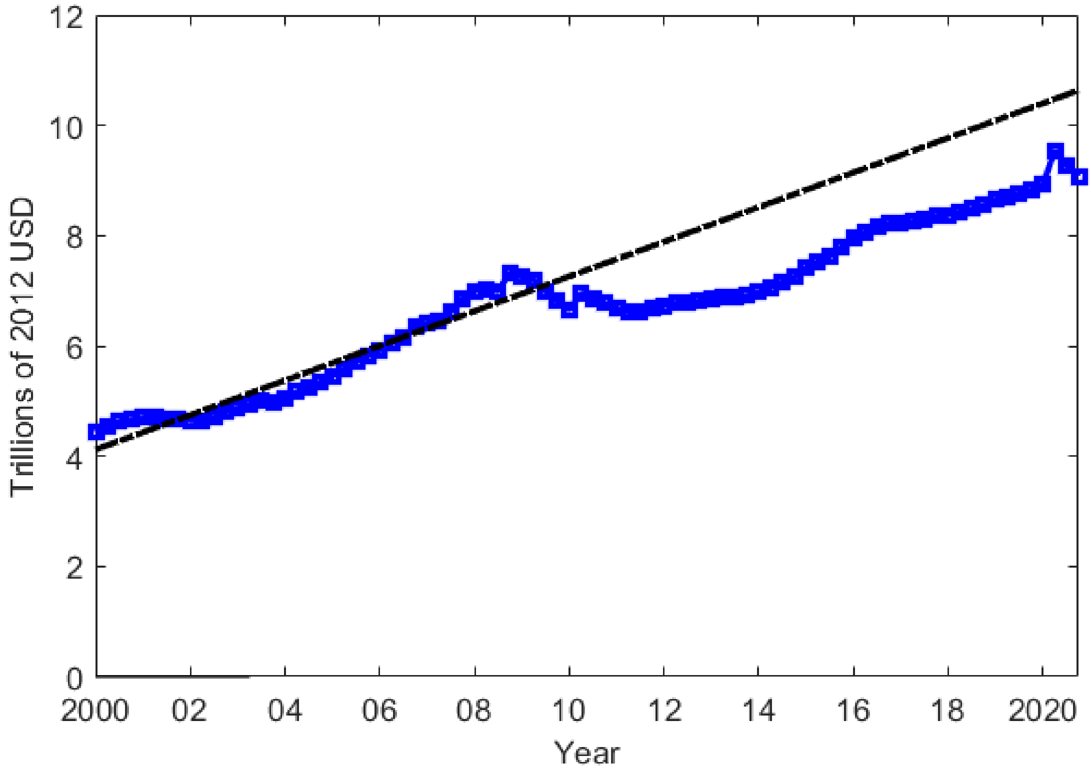


**Figure 2:** Bank Expectations versus Actual Loan Performance

This figure compares the net fraction of banks that expected (at year $t-1$) a worsening of loan performance for year $t$ (solid line) with the net fraction of banks that experienced an actual worsening of loan performance in $t$ (dashed line). The net fraction is computed as the number of banks that expected (or experienced) a worsening of loan performance minus the number of banks that expected (or experienced) an improvement, divided by the total number of banks. The shaded area indicates the NBER recession dates. Sources: Senior Loan Officer Opinion Survey on Bank Lending Practices (for bank expectations); Call Reports (for actual loan performance).

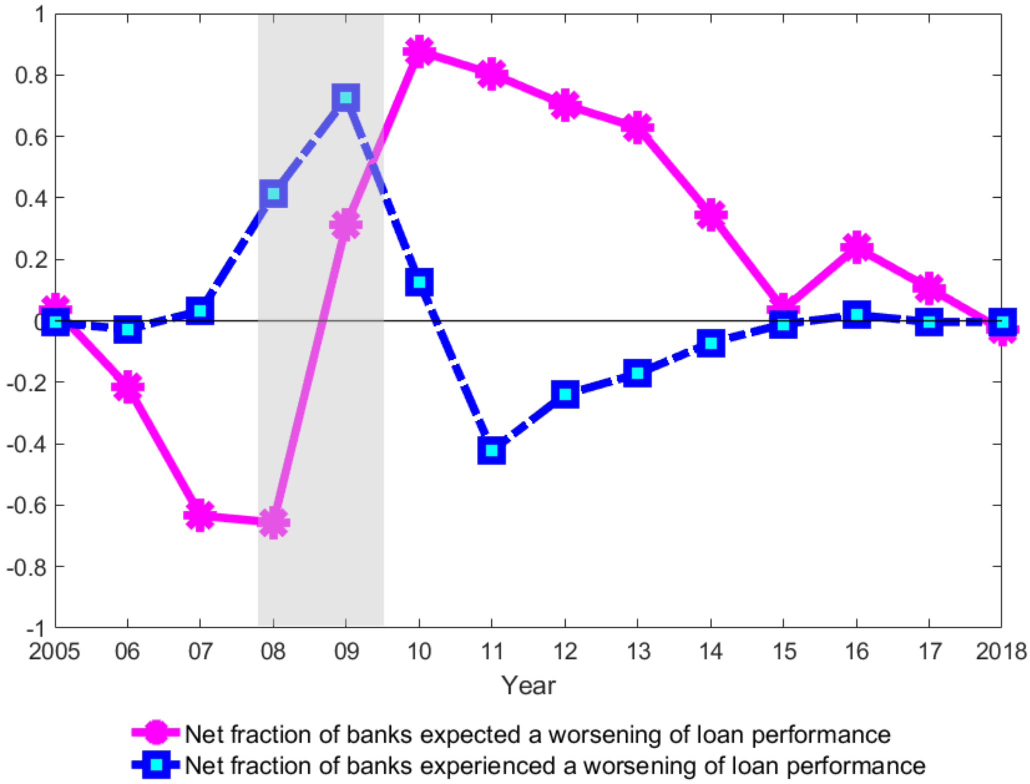


**Figure 3:** Impulse Response Functions to An Increase in Disaster Probability

The impulse response functions are averages of 3,000 simulations, where each simulation is of 300 years for 1,000 banks. For each simulation, we impose two consecutive disaster probability shocks in years 1 and 2, allowing normal evolution of the economy afterwards.

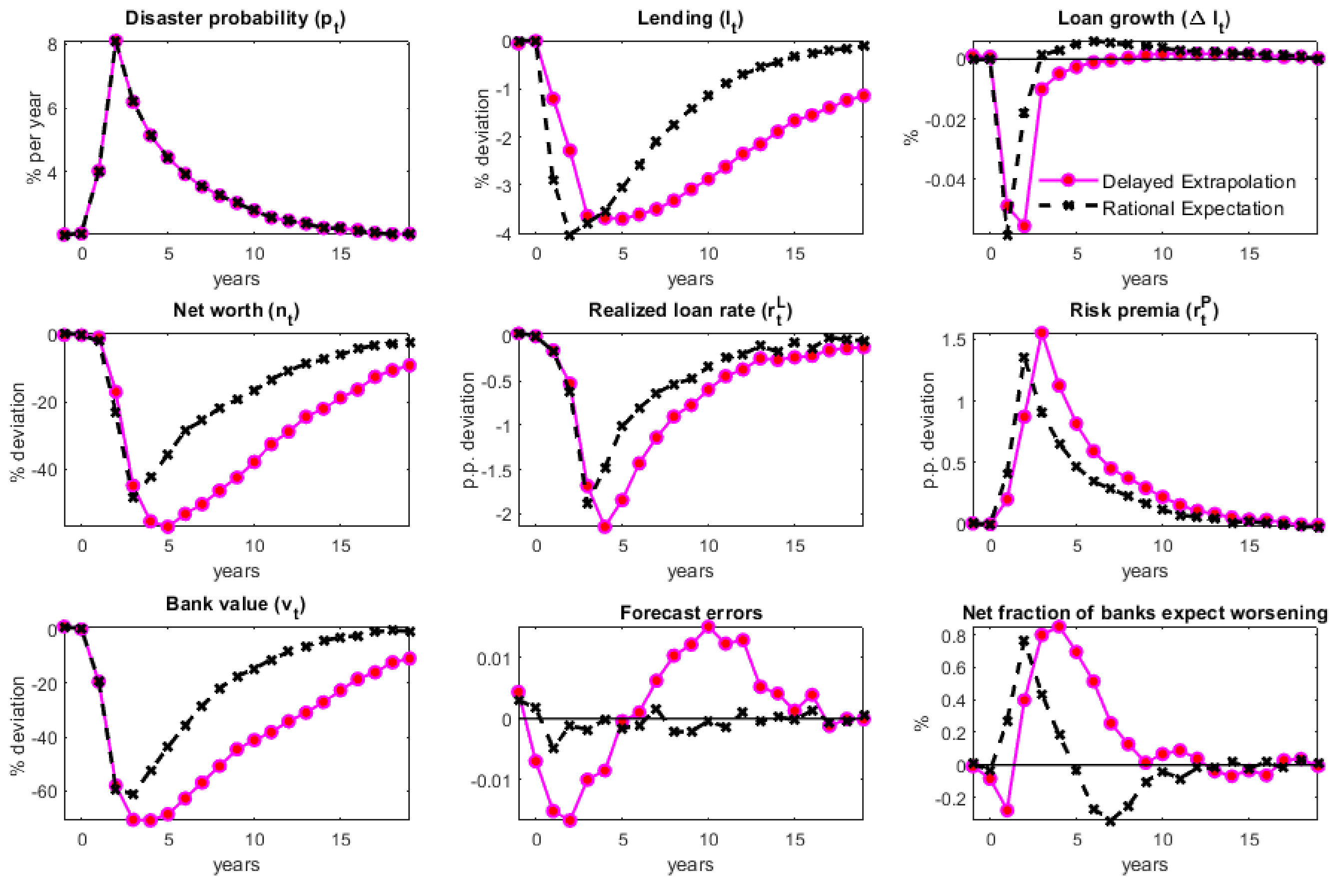


**Figure 4:** Disaster in the Model

The impulse response functions are averages of 3,000 simulations, where each simulation is of 300 years for 1,000 banks. For each simulation, we impose two disaster realizations ($x_t = 1$) in years 1 and 2, allowing normal evolution of the economy afterwards.

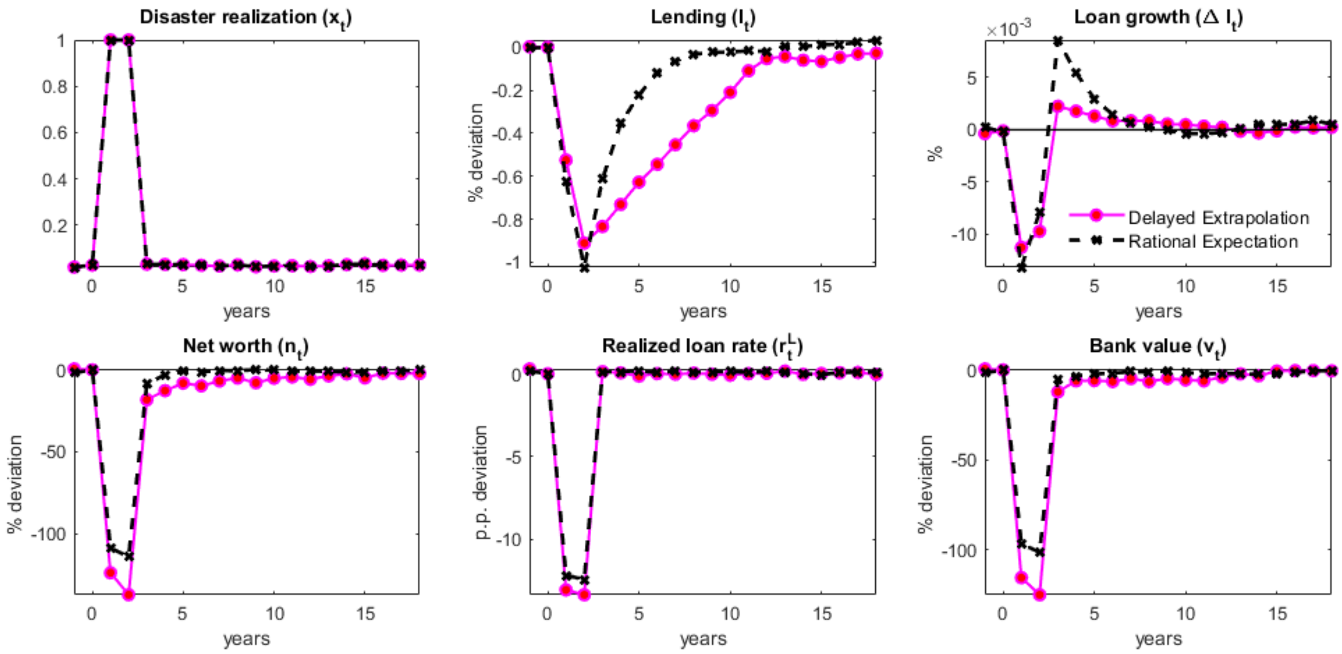
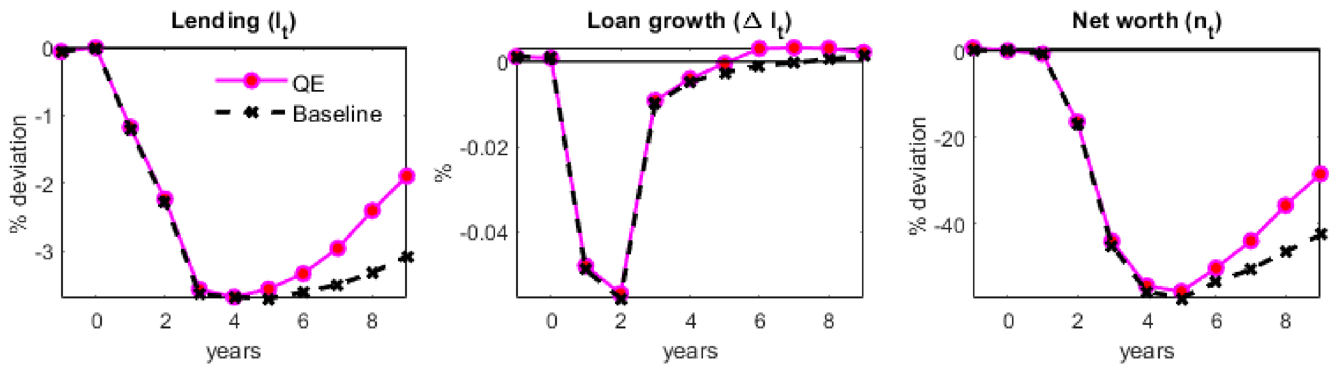


**Figure 5:** Impact of Reducing Banks' Cost of Funding

The impulse response functions are averages of 3,000 simulations, where each simulation is of 300 years for 1,000 banks. For each simulation, we impose two consecutive disaster probability shocks in years 1 and 2, allowing normal evolution of the shock process afterwards. For the policy experiment, we lower the cost of funding for banks $c^D$ (hence $\tilde{r}^D$) by 30 basis points from year 1 in each simulation.

**(a)** Delayed Extrapolation Model




**(b)** Rational Model

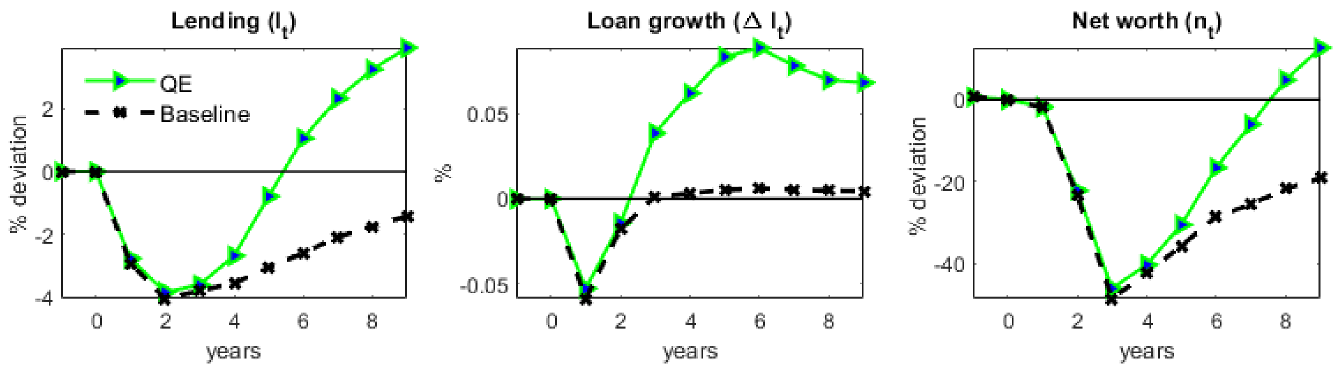


**Table 1:** Delayed Extrapolation

This table summarizes results of time-series regressions of bank expectation errors:

$$FE_{i,t+1|t} = \alpha_i + \sum_{k=0}^{K} \beta_k I_{it-k} + \gamma Z_{it} + \tau_t + u_{it}$$

We measure bank expectation errors, $FE_{i,t+1|t}$, as the difference between the actual and the expected change in loan performance over the next year, $FE_{i,t+1|t} = I_{i,t+1} - \mathrm{E}_{it}[I_{i,t+1}]$, and regress it on the actual change in loan performance at different lags, $I_{it-k}$ for $k = 0, 1, ..., K$. $I_{it} > 0$ indicates an improvement in loan performance. We include bank size measured as the logarithm of total assets as control, $Z_{it}$. Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). In Panel A, we report results for the baseline specification. In Panel B, we report results of specification checks, which include: dropping the bank size control (Row A), dropping time fixed effects (Row B), dropping bank fixed effects (Row C), dropping time and bank fixed effects (Row D), running a univariate regression with just 1-year lag (Row E), running a univariate regression with just 2-year lag (Row F), adding 3-year lag (Row G), trimming the extreme tails of the expected change in loan performance (survey responses equal to 1 or 5, Row H), and using bank forecasts instead of forecast errors as dependent variable (Row I). t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| | | |
|---|---|---|
| **Panel A: Baseline Estimates** | | |
| | $k=0$ | $k=1$ |
| | (1) | (2) |
| $\beta_k$ | 0.123** | -0.194*** |
| [t] | [2.32] | [-4.13] |
| Time FE | Yes | |
| Bank FE | Yes | |
| N | 3,232 | |
| $R^2$ | 0.65 | |
| within $R^2$ | 0.03 | |
| **Panel B: Sensitivity Checks** | | |
| [A] Drop size control | 0.147** | -0.171*** |
| [within $R^2$ =0.02] | [2.56] | [-3.60] |
| [B] Drop time FEs | 0.616*** | -0.387*** |
| [within $R^2$ =0.10] | [7.69] | [-8.76] |
| [C] Drop banks FEs | 0.193*** | -0.127** |
| [within $R^2$ =0.02] | [3.45] | [-2.58] |
| [D] Drop time & bank FEs | 0.654*** | -0.361*** |
| [within $R^2$ =0.10] | [8.53] | [-7.67] |
| [E] 1-year lag only | 0.102* | |
| [within $R^2$ =0.00] | [1.98] | |
| [F] 2-year lag only | | -0.160*** |
| [within $R^2$ =0.01] | | [-3.33] |
| [G] Trim extreme tails | 0.120** | -0.184*** |
| [within $R^2$ =0.03] | [2.22] | [-3.88] |
| [H] Forecasts as dep var | -0.252*** | 0.189*** |
| [within $R^2$ =0.10] | [-6.26] | [5.64] |
| [I] Add 3-year lag | 0.102* | -0.165*** |
| [within $R^2$ =0.04] | [1.97] | [-3.49] |

**Table 2:** Delayed Extrapolation: Cross-Sectional Heterogeneity by CEO Characteristics

This table summarizes results of cross-sectional heterogeneity tests on the baseline time-series regressions of Table 1. The tests repeat the main analysis for the following sub-sample splits based on bank CEO characteristics: young vs. old CEOs (bottom and top terciles of CEO age, Row A), CEOs with short vs. long tenure (bottom vs. top tercile, Row B), CEOs who were young vs. old in 2007 (above vs. below median age, Row C), overconfident CEOs based on the proxy by Malmendier and Tate (2005) (Row D), CEOs with a "golden parachute" defined as compensation in the event of forced termination or change in control (Row E). Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). We retrieve information on CEO characteristics from ExecuComp, which is available for most of our banks (N=2,523). t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| Panel A: Bank-Level Estimates of Forecast Errors | | | | | | |
|---|---|---|---|---|---|---|
| | Yes | | | No | | |
| | $k=0$ | $k=1$ | within $R^2$ | $k=0$ | $k=1$ | within $R^2$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| [A] CEO is young | 0.230* | -0.358*** | 0.06 | 0.077 | -0.152 | 0.01 |
| | [1.85] | [-3.08] | | [0.75] | [-1.29] | |
| [B] CEO has short tenure | 0.175** | -0.328*** | 0.13 | 0.016 | -0.167** | 0.10 |
| | [2.51] | [-3.15] | | [0.17] | [-2.23] | |
| [C] CEO was young in the GFC | 0.053 | -0.300*** | 0.04 | 0.145** | -0.201*** | 0.04 |
| | [0.59] | [-3.04] | | [2.51] | [-3.42] | |
| [D] CEO is overconfident | 0.032 | -0.110 | 0.01 | 0.142** | -0.261*** | 0.04 |
| | [0.36] | [-1.15] | | [2.13] | [-3.26] | |
| [E] CEO has golden parachute | 0.223** | -0.129 | 0.02 | 0.046 | -0.352*** | 0.08 |
| | [2.56] | [-1.66] | | [0.50] | [-3.19] | |

**Table 3:** Bank Expectations and Lending Dynamics

This table summarizes results of bank-level regressions of bank loans on bank expectations of loan performance:

$$\Delta Loans_{i,t+k} = \alpha_i + \delta_k FE_{i,t+1|t} + \gamma Z_{it-1} + \tau_t + u_{it}$$

where $k$ is the predictive horizon of 1-, 2-, 3-, or 4-years ahead, $\Delta Loans_{i,t+k}$ is the change in bank loans measured as the logarithmic change of total bank loans relative to pre-crisis, and $FE_{i,t+1|t} = I_{i,t+1} - \mathrm{E}_{it}[I_{i,t+1}]$ is the bank expectation error measured as the difference between the actual and the expected change in loan performance over the next year. Time $\tau_t$ and bank $\alpha_i$ fixed effects are included in all specification. We do not include additional controls in the baseline but consider more saturated specifications with additional controls in robustness analysis (Panel D). We consider two sample periods: full sample (Columns 1-4) and the recovery period after the Great Recession (2010-, Columns 5-8). Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). In Panel A, we report ordinary least square (OLS) estimates. In Panel B, we report OLS estimates for an alternative specification that replaces the (potentially endogenous) bank expectation errors with a Bartik instrument, $S_{it-1}\overline{FE}_{it+1|t}$, which is defined as the product of a shift variable, $\overline{FE}_{it+1|t}$, equal to the "consensus" forecast error for other banks measured as the mean of their forecast error in each period ($\overline{FE}_{it+1|t} = \sum_{j \neq i} \frac{FE_{jt+1|t}}{n-1}$), times a share variable, $S_{it-1}$, equal to the lagged ratio of total loans to total assets. In Panel C, we report results of a 2SLS-IV specification that instruments for bank expectation errors using the Bartik instrument. See Appendix Table A.2 for details of the first-stage. In Panel D, we add to the 2SLS-IV specification the control set, $Z_{it-1}$, which includes controls for the interaction of the share variable with other shocks that includes GDP growth, the change in the Federal Funds Rate and the VIX, as well as average changes in other bank characteristics (profitability as measured by the ratio of total income to assets, loan performance, bank capital and liquidity as measured by tier 1 capital and cash ratios, respectively). In Panel E, we report results for the 2SLS-IV specification and the shift variable defined as the mean of idiosyncratic forecast errors of other banks. The idiosyncratic forecast errors are the estimated residuals from a regression of forecast errors for each type of loan (C&I, CRE, RRE, and Consumer) on the consensus forecast error, which is defined above. The shift variable is then constructed using for each bank the idiosyncratic forecast error in the primary loan type, which is assigned based on the largest share of loan type (C&I, CRE, RRE, and Consumer) relative to total assets. The share variable is constructed as the lagged ratio of the primary loan type to total assets. To ease interpretation and comparison across specifications, the main explanatory variables are expressed in standard deviation units. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| | Full Sample (2005-2020) | | | | Recovery Period (2010-2020) | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 year | 2 year | 3 year | 4 year | 1 year | 2 year | 3 year | 4 year |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: OLS | | | | | | | | |
| $\delta_k$ | -0.032*** | -0.032*** | -0.030** | -0.026* | -0.029** | -0.036*** | -0.034** | -0.035* |
| [t] | [-2.83] | [-2.91] | [-2.64] | [-1.98] | [-2.34] | [-2.66] | [-2.17] | [-1.78] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,222 | 2,856 | 2,549 | 2,274 | 2,486 | 2,174 | 1,899 | 1,641 |
| within $R^2$ | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 | 0.01 |

(To be continued)

| | Full Sample (2005-2020) | | | | Recovery Period (2010-2020) | | | |
|---|---|---|---|---|---|---|---|---|
| | 1 year | 2 year | 3 year | 4 year | 1 year | 2 year | 3 year | 4 year |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel B: Bartik | | | | | | | | |
| $\delta_k$ | -0.041* | -0.044** | -0.041** | -0.023 | -0.082** | -0.086** | -0.075* | -0.045 |
| [t] | [-1.95] | [-2.13] | [-2.17] | [-1.10] | [-2.58] | [-2.39] | [-1.98] | [-1.10] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,173 | 2,825 | 2,523 | 2,252 | 2,460 | 2,156 | 1,885 | 1,630 |
| within $R^2$ | 0.01 | 0.02 | 0.01 | 0.00 | 0.04 | 0.04 | 0.03 | 0.01 |
| Panel C: 2SLS-IV | | | | | | | | |
| $\delta_k$ | -0.157* | -0.164** | -0.164** | -0.097 | -0.315** | -0.317** | -0.293* | -0.184 |
| [t] | [-1.90] | [-2.01] | [-2.05] | [-1.09] | [-2.33] | [-2.13] | [-1.80] | [-1.07] |
| 1st stage $F$-stat | 225.74 | 190.57 | 135.19 | 111.95 | 131.32 | 107.64 | 78.25 | 62.73 |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,173 | 2,825 | 2,523 | 2,252 | 2,460 | 2,156 | 1,885 | 1,630 |
| Panel D: 2SLS-IV with controls for other shocks | | | | | | | | |
| $\delta_k$ | -0.149** | -0.163** | -0.196** | -0.213*** | -0.271** | -0.288** | -0.304** | -0.313** |
| [t] | [-2.16] | [-2.30] | [-2.49] | [-2.43] | [-2.42] | [-2.46] | [-2.29] | [-2.43] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,087 | 2,758 | 2,464 | 2,194 | 2,417 | 2,126 | 1,857 | 1,600 |
| Panel E: 2SLS-IV with Bartik from idiosyncratic forecast errors | | | | | | | | |
| $\delta_k$ | -0.178** | -0.168** | -0.144** | -0.078 | -0.327** | -0.309** | -0.265* | -0.163 |
| [t] | [-2.35] | [-2.26] | [-2.12] | [-1.14] | [-2.56] | [-2.32] | [-1.92] | [-1.13] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,173 | 2,825 | 2,523 | 2,252 | 2,460 | 2,156 | 1,885 | 1,630 |
| Economic Significance (within time, bank) | | | | | | | | |
| Mean LHS | -0.082 | | | | -0.081 | | | |
| Sdev LHS | 0.342 | | | | 0.351 | | | |
| IQR LHS | 0.397 | | | | 0.421 | | | |

**Table 4:** Heterogeneity Analysis by Loan Type

This table repeats the OLS analysis of Table 3 (Panel A) separately for each loan type regressed on its respective forecast error, in turn. Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). To ease interpretation and comparison across specifications, the main explanatory variables are expressed in standard deviation units. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| Panel A: C&I and RRE Loan Dynamics | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| | Commercial & Industrial Loans | | | | Residential Real Estate Loans | | | |
| | 1 year | 2 year | 3 year | 4 year | 1 year | 2 year | 3 year | 4 year |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta_k$ | -0.043*** | -0.032*** | -0.010 | -0.011 | -0.059*** | -0.052** | -0.054** | -0.048** |
| [t] | [-3.32] | [-2.44] | [-0.77] | [-0.69] | [-2.99] | [-2.36] | [-2.39] | [-2.51] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,849 | 2,814 | 2,509 | 2,233 | 2,580 | 2,551 | 2,270 | 2,020 |
| within $R^2$ | 0.01 | 0.01 | 0.00 | 0.00 | 0.02 | 0.01 | 0.01 | 0.01 |
| **Panel B: CRE and Consumer Loan Dynamics** | | | | | | | | |
| | Commercial Real Estate Loans | | | | Consumer Loans | | | |
| | 1 year | 2 year | 3 year | 4 year | 1 year | 2 year | 3 year | 4 year |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta_k$ | -0.025** | -0.029** | -0.031** | -0.025** | -0.030 | -0.001 | -0.014 | -0.021 |
| [t] | [-2.02] | [-2.37] | [-2.24] | [-2.26] | [-1.66] | [-0.57] | [-0.73] | [-0.97] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,837 | 2,808 | 2,506 | 2,235 | 2,625 | 2,596 | 2,309 | 2,051 |
| within $R^2$ | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 | 0.00 |

**Table 5:** Bank Expectations and Borrower Outcomes

This table summarizes results of bank-firm level regressions of borrower outcomes on bank expectations of loan performance:

$$\Delta Y_{ijt+k} = \alpha_i + \alpha_j + \delta_k FE_{i,t+1|t} + \gamma Z_{ijt-1} + \tau_t + u_{ijt}$$

where $k$ is the predictive horizon of 1-, 2-, 3-, or 4-years ahead, $\Delta Y_{ijt+k}$ is the change in borrower outcomes measured as the logarithmic change in outcomes relative to prior year, and $FE_{i,t+1|t}$ is the bank C&I loan expectation error measured as the difference between the actual and the expected change in C&I loan performance over the next year. The control set includes firm size as measured by the logarithm of total assets. We report results for the full sample period and a 2SLS-IV specification that instruments for bank expectation errors using a Bartik instrument, $S_{it-1}\overline{FE}_{it+1|t}$, which is defined as the product of a shift variable, $\overline{FE}_{it+1|t}$, equal to the "consensus" forecast error for other banks measured as the mean of their C&I loans forecast error ($\overline{FE}_{it+1|t} = \sum_{k \neq i} \frac{FE_{kt+1|t}}{n-1}$), times a share variable, $S_{it-1}$, equal to the lagged ratio of C&I loans to total assets. We report results for the following borrower outcomes, in turn: debt financing as measured by total debt and investment as measured by capital expenditures (Panel A), human capital investment as measured by the sum of research and development (R&D) expenditures and selling, general, and administrative (SGA) expenditures and employment as measured by the number of employees (Panel B), sales as measured by total sales and total assets (Panel C), and profits as measured by earnings before interest and taxes (EBITDA) and exit as measured by an indicator for whether the firm ceases to be active (Panel D). To ease interpretation and comparison across specifications, the main explanatory variables are expressed in standard deviation units. Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). Information on lender-borrower links is from SNC and on borrower balance sheets is from Compustat. t-statistics are based on standard errors clustered at the borrower level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| | 1 year | 2 year | 3 year | 4 year | 1 year | 2 year | 3 year | 4 year |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: Borrower Debt Financing and Investment | | | | | | | | |
| | $\Delta Debt_{jt+k}$ | | | | $\Delta Capex_{jt+k}$ | | | |
| $\delta_k$ | -0.050* | -0.071** | -0.037 | 0.015 | -0.081*** | -0.074*** | 0.006 | 0.018 |
| [t] | [-1.66] | [-2.37] | [-1.24] | [0.50] | [-2.64] | [-2.69] | [0.24] | [0.72] |
| Time, Bank, Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 15,528 | 15,204 | 14,109 | 13,258 | 14,704 | 14,346 | 13,186 | 12,326 |
| Panel B: Borrower Human Capital Investment and Employment | | | | | | | | |
| | $\Delta(R\&R + SG\&A)_{jt+k}$ | | | | $\Delta Employment_{jt+k}$ | | | |
| $\delta_k$ | -0.020* | -0.020* | -0.010 | -0.004 | -0.027*** | -0.025*** | -0.010 | -0.001 |
| [t] | [-1.82] | [-1.86] | [-0.90] | [-0.36] | [-2.75] | [-2.70] | [-1.07] | [-0.10] |
| Time, Bank, Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 7,472 | 7,390 | 6,913 | 6,541 | 15,463 | 15,128 | 14,020 | 13,158 |
| Panel C: Borrower Sales and Total Assets | | | | | | | | |
| | $\Delta Sales_{jt+k}$ | | | | $\Delta Total\ Assets_{jt+k}$ | | | |
| $\delta_k$ | -0.035*** | -0.036*** | -0.024** | -0.012 | -0.036*** | -0.043*** | -0.021* | 0.007 |
| [t] | [-2.72] | [-3.15] | [-2.07] | [-1.01] | [-2.96] | [-3.47] | [-1.77] | [0.64] |
| Time, Bank, Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 15,695 | 15,299 | 14,072 | 13,157 | 16,206 | 15,836 | 14,611 | 13,693 |
| Panel D: Borrower Profits and Exit | | | | | | | | |
| | $\Delta EBITDA_{jt+k}$ | | | | $Exit_{jt+k}$ | | | |
| $\delta_k$ | -0.018 | -0.044** | -0.025 | -0.002 | 0.078*** | 0.095*** | 0.097*** | 0.103*** |
| [t] | [-0.74] | [-2.03] | [-1.17] | [-0.13] | [7.22] | [7.65] | [8.13] | [8.13] |
| Time, Bank, Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 14,413 | 14,008 | 12,841 | 12,018 | 17,235 | 15,851 | 14,773 | 13,882 |

**Table 6:** Parameterization

| Panel A: Assigned Parameters | | |
|---|---|---|
| Parameter | Description | Value |
| $\beta$ | Rate of time preference | 0.987 |
| $\psi$ | Elasticity of intertemporal substitution | 2 |
| $\gamma$ | Relative risk aversion | 3 |
| $\bar{p}$ | Average probability of crisis | 0.02 |
| $\sigma_p$ | Volatility of crisis probability | 0.42 |
| $\rho_p$ | Persistence in crisis probability | 0.80 |
| $\sigma_\omega$ | Volatility of bank-specific shock | 0.02 |
| $\rho_\omega$ | Persistence in bank-specific shock | 0.90 |
| $\xi$ | Impact of crisis on endowment | $\log(1-0.3)$ |
| $\mu_c$ | Mean growth in consumption (normal times) | 0.01 |
| $\sigma_c$ | Volatility of aggregate shock (normal times) | 0.015 |
| $\mathscr{L}$ | Loss given default on loans | 0.40 |
| $\kappa$ | Loan-to-value ratio | 0.66 |
| $r^D$ | Return on deposits | 0.0043 |
| $\lambda$ | Capital requirement | 12.5 |
| $\eta^E$ | Equity issuance cost | 0.05 |

| Panel B: Parameters from Moment Matching | | | |
|---|---|---|---|
| Parameter | Description | Delayed extrapolation | Rational |
| $\sigma_j$ | Volatility of loan-specific shock | 0.13 | 0.12 |
| $\eta^L$ | Asset adjustment cost | 0.59 | 0.62 |
| $c^L$ | Non-interest income | 0.005 | 0.006 |
| $c^D$ | Other cost of funding | 0.0069 | 0.0073 |
| $\hat{\rho}_{1p}$ | Overextrapolation of crisis probability | 0.294 | – |
| $\hat{\rho}_{2p}$ | Overextrapolation of crisis probability | 0.645 | – |
| $\hat{\rho}_{1\omega}$ | Overextrapolation of bank-specific shock | 0.307 | – |
| $\hat{\rho}_{2\omega}$ | Overextrapolation of bank-specific shock | 0.618 | – |
| $\chi$ | Weight of $p_t$ in subjective disaster prob. | 0.315 | – |

*Note*: "–" indicates that the parameter is absent in the model.

**Table 7:** Moment Matching Exercise

| Description | Data | Delayed extrapolation | Rational |
|---|---|---|---|
| Leverage (mean) | 8.50 | 8.52 | 8.69 |
| Leverage (std) | 2.95 | 3.10 | 2.50 |
| Profit-to-equity (mean) | 0.169 | 0.137 | 0.149 |
| Bank default rate (mean) | 0.041 | 0.062 | 0.053 |
| Delayed extrapolation full sample (Table 1) | | | |
| Coefficient on current realization $I_{it}$ | 0.123 | 0.129 | – |
| Coefficient on lagged realization $I_{i,t-1}$ | -0.194 | -0.205 | – |
| Delayed extrapolation excluding bottom quartile banks (Table A.1) | | | |
| Coefficient on current realization $I_{it}$ | 0.115 | 0.114 | – |
| Coefficient on lagged realization $I_{i,t-1}$ | -0.230 | -0.236 | – |
| Serial correlation of loan rate growth | 0.179 | 0.195 | – |

**Table 8:** Business Cycle Statistics

| Description | Data | Delayed extrapolation | Rational |
|---|---|---|---|
| Annual loan growth ($\Delta l_t$) | | | |
| $\text{Corr}(\Delta l_t, \Delta\text{GDP}_t)$ | 0.134 | 0.235 | 0.133 |
| $\text{Corr}(\Delta l_t, \Delta\text{GDP}_{t-1})$ | 0.239 | 0.164 | -0.012 |
| $\text{Corr}(\Delta l_t, \Delta\text{GDP}_{t-2})$ | 0.218 | 0.058 | -0.126 |
| $\text{Corr}(\Delta l_t, \Delta l_{t-1})$ | 0.207 | 0.597 | 0.128 |
| $\text{Corr}(\Delta l_t, \Delta l_{t-2})$ | 0.118 | 0.128 | -0.017 |
| | | | |
| Annual change in expected loan performance ($\Delta\text{E}_t[\text{LoanDefault}_{t+1}]$) | | | |
| $\text{Corr}\big(\Delta\text{E}_t[\text{LoanDefault}_{t+1}], \Delta\text{GDP}_t\big)$ | -0.354 | -0.226 | -0.165 |
| $\text{Corr}(\Delta\text{E}_t[\text{LoanDefault}_{t+1}], \Delta\text{GDP}_{t-1})$ | -0.023 | -0.075 | 0.169 |
| $\text{Corr}(\Delta\text{E}_t[\text{LoanDefault}_{t+1}], \Delta\text{GDP}_{t-2})$ | 0.295 | 0.237 | 0.123 |
| $\text{Corr}\big(\Delta\text{E}_t[\text{LoanDefault}_{t+1}], \Delta\text{E}_{t-1}[\text{LoanDefault}_t]\big)$ | 0.465 | 0.254 | -0.176 |
| $\text{Corr}\big(\Delta\text{E}_t[\text{LoanDefault}_{t+1}], \Delta\text{E}_{t-2}[\text{LoanDefault}_{t-1}]\big)$ | 0.153 | 0.063 | -0.092 |
| | | | |
| Annual change in realized loan performance ($\Delta\text{LoanDefault}_{t+1}$) | | | |
| $\text{Corr}\big(\Delta\text{LoanDefault}_{t+1}, \Delta\text{GDP}_t\big)$ | -0.110 | -0.022 | -0.021 |
| $\text{Corr}(\Delta\text{LoanDefault}_{t+1}, \Delta\text{GDP}_{t-1})$ | -0.064 | -0.026 | -0.026 |
| $\text{Corr}(\Delta\text{LoanDefault}_{t+1}, \Delta\text{GDP}_{t-2})$ | 0.023 | 0.010 | 0.010 |
| $\text{Corr}\big(\Delta\text{LoanDefault}_{t+1}, \Delta\text{LoanDefault}_t\big)$ | -0.195 | -0.499 | -0.498 |
| $\text{Corr}\big(\Delta\text{LoanDefault}_{t+1}, \Delta\text{LoanDefault}_{t-1}\big)$ | -0.083 | -0.003 | -0.003 |
| | | | |
| Annual loan rate growth ($\Delta r^L_t$) | | | |
| $\text{Corr}(\Delta r^L_t, \Delta\text{GDP}_t)$ | 0.194 | 0.375 | 0.393 |
| $\text{Corr}(\Delta r^L_t, \Delta\text{GDP}_{t-1})$ | 0.154 | 0.110 | -0.191 |
| $\text{Corr}(\Delta r^L_t, \Delta\text{GDP}_{t-2})$ | 0.148 | 0.009 | -0.026 |
| $\text{Corr}(\Delta r^L_t, \Delta r^L_{t-1})$ | 0.179 | 0.195 | -0.174 |
| $\text{Corr}(\Delta r^L_t, \Delta r^L_{t-2})$ | -0.103 | -0.171 | -0.049 |

*Note*: The empirical sample is 2005-2020 at annual frequency. The model moments are computed from an unconditional simulation of 2,000 periods for 1,000 banks. We use consumption to proxy for GDP for the model moments.

**Table 9:** Model-Implied Regressions

We repeat the regressions in Tables 1 (Panel A) and 3 (Panel A), respectively, on simulated data for 2,000 periods and 1,000 banks. Forecast errors $FE_{i,t+1|t}$ are the difference between the actual and the expected change in loan performance over the next year. The change in loan performance $I_{it}$ is the negative of the annual change in the loan default rate, so that $I_{it} > 0$ indicates an improvement in loan performance (or a reduction in default rate), and $FE_{i,t+1|t} > 0$ indicates that bank $i$ has been too pessimistic in year $t$ about the performance of its loan portfolio in $t+1$, as in the data. $\Delta Loans_{i,t+1}$ is the change in lending compared to the steady state. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Forecast Error Dynamics

$$FE_{i,t+1|t} = \alpha_i + \beta_1 I_{it} + \beta_2 I_{i,t-1} + \gamma Z_{it} + \tau_t + u_{it}$$

| | Data | | Delayed extrapolation | | Rational | |
|---|---|---|---|---|---|---|
| | $I_{it}$ | $I_{i,t-1}$ | $I_{it}$ | $I_{i,t-1}$ | $I_{it}$ | $I_{i,t-1}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | 0.123** | -0.194*** | 0.129** | -0.205** | -0.026 | 0.009 |
| [t] | [2.32] | [-4.13] | [2.08] | [-2.16] | [-0.57] | [0.19] |
| Time FE | Yes | | Yes | | Yes | |
| Bank FE | Yes | | Yes | | Yes | |

**(b)** Bank Expectations and Lending Dynamics

$$\Delta Loans_{i,t+k} = \alpha_i + \delta_k FE_{i,t+1|t} + \tau_t + u_{it}$$

| | Data | | Delayed extrapolation | | Rational | |
|---|---|---|---|---|---|---|
| | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\delta$ | -0.032*** | -0.032*** | -0.043*** | -0.068*** | -0.008 | 0.005 |
| [t] | [-2.83] | [-2.91] | [-6.15] | [-8.78] | [-0.42] | [0.23] |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Table 10:** Model-Implied Regressions:
A Comparison Different Types of Behavioral Bias

We repeat the regression in Table 1, respectively, on simulated data for 2,000 periods and 1,000 banks. Forecast errors $FE_{i,t+1|t}$ are the difference between the actual and the expected change in loan performance over the next year. The change in loan performance $I_{it}$ is the negative of the annual change in the loan default rate, so that $I_{it} > 0$ indicates an improvement in loan performance (or a reduction in default rate), as in the data. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Forecast Error Dynamics

$$FE_{i,t+1|t} = \alpha_i + \beta_1 I_{it} + \beta_2 I_{i,t-1} + \gamma Z_{it} + \tau_t + u_{it}$$

| | Data | Delayed Extrapolation | Diagnostic ARMA(1,1) | Diagnostic Long Memory | OE AR(1) |
|---|---|---|---|---|---|
| $I_{it}$ | 0.123$^{**}$ | 0.129$^{**}$ | -0.325$^{***}$ | -0.297$^{***}$ | -0.126$^{***}$ |
| [t] | [2.32] | [2.08] | [-3.72] | [-3.53] | [-2.81] |
| $I_{i,t-1}$ | -0.194$^{***}$ | -0.205$^{**}$ | 0.238$^{**}$ | -0.122$^{**}$ | 0.008 |
| [t] | [-4.13] | [-2.16] | [2.12] | [-2.24] | [0.20] |
| Time FE | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes |

# Internet Appendix
# Expectations and Credit Slumps

## A Model Appendix

### A.1 Loan Portfolio Payoffs

Assuming that each bank $i$ holds an equal-weighted portfolio of an arbitrarily large number of loans, then the payoff of the loan portfolio can be expressed as:

$$
\begin{aligned}
&\pi^L(\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}) \\
=&\underbrace{\kappa \mathrm{Prob}\Big(W_{ij,t+1} \geq \kappa \Big| \varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}\Big)}_{\text{Repay}} + \underbrace{(1-\mathscr{L})\mathrm{E}\Big[W_{ij,t+1}\mathbb{1}_{W_{ij,t+1}<\kappa}\Big|\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}\Big]}_{\text{Default}} \\
=&\begin{cases}
\kappa\Big(1-\Phi\big(\frac{1}{\sigma_j}(\log(\kappa)-\sigma_c\varepsilon_{c,t+1}-\omega_{i,t+1})\big)\Big) \\
\qquad +(1-\mathscr{L})e^{\sigma_c\varepsilon_{c,t+1}+\omega_{i,t+1}+\frac{\sigma_j^2}{2}}\int_{-\infty}^{\frac{1}{\sigma_j}(\log(\kappa)-\sigma_c\varepsilon_{c,t+1}-\omega_{i,t+1})}\frac{1}{\sqrt{2\pi}}e^{-\frac{(z-\sigma_j)^2}{2}}dz & \text{if } x_{t+1}=0 \\
\\
\kappa\Big(1-\Phi\big(\frac{1}{\sigma_j}(\log(\kappa)-\sigma_c\varepsilon_{c,t+1}-\xi-\omega_{i,t+1})\big)\Big) \\
\quad +(1-\mathscr{L})e^{\sigma_c\varepsilon_{c,t+1}+\omega_{i,t+1}+\xi+\frac{\sigma_j^2}{2}}\int_{-\infty}^{\frac{1}{\sigma_j}(\log(\kappa)-\sigma_c\varepsilon_{c,t+1}-\xi-\omega_{i,t+1})}\frac{1}{\sqrt{2\pi}}e^{-\frac{(z-\sigma_j)^2}{2}}dz & \text{if } x_{t+1}=1
\end{cases}
\end{aligned}
\tag{A.1}
$$

where $\Phi(\cdot)$ denotes the standard normal cdf.

### A.2 Normalization

We scale the market value of a bank by deposits, and conjecture that it is a function of $l_{i,t-1}$, $n_{it}$, and $\mathbf{s}_{it}$:

$$v^C(l_{i,t-1}, n_{it}, \mathbf{s}_{it}) = \frac{V_i^C(L_{i,t-1}, D_{i,t-1}, N_{it}, \mathbf{s}_{it})}{D_{it}}$$

where $l_{i,t-1} \equiv \frac{L_{i,t-1}}{D_{i,t-1}}$ and $n_{it} \equiv \frac{N_{it}}{D_{it}}$. We further define $div_{it} \equiv \frac{Div_{it}}{D_{it}} =$

$$\begin{aligned}
&\frac{1}{D_{it}}\Big(\underbrace{BE_{i,t-1} + (r_t^L + c)L_{i,t-1} - \tilde{r}^D D_{i,t-1}}_{\equiv N_{it}} - (L_{it} - D_{it}) - \Phi(L_{i,t-1}, L_{it})\Big) \\
=&n_{it} + 1 - l_{it} - \phi(l_{i,t-1}, l_{it})
\end{aligned}$$

which uses the evolution of equity (17), the balance sheet constraint (18), and $\phi(l_{i,t-1}, l_{it}) \equiv \frac{\Phi_{it}}{D_{it}} =$

$$\phi(l_{i,t-1}, l_{it}) = \eta^L l_{i,t-1} e^{-g} \left(\frac{l_{it} - l_{i,t-1}e^{-g}}{l_{i,t-1}e^{-g}}\right)^2.$$

Recursively define the bank's problem as

$$\begin{aligned}
v^C(l_{i,t-1}, n_{it}, \mathbf{s}_{it}) = \max_{l_{it}} \Bigg\{ & n_{it} + 1 - l_{it} - \phi(l_{i,t-1}, l_{it}) + \Lambda(div_{it}) \\
& + \mathbb{E}_{it}^{\mathcal{P}}\left[M_{t,t+1}e^{g} \max\left\{v^C(l_{it}, n_{i,t+1}, \mathbf{s}_{i,t+1}),\, 0\right\}\Big| \mathbf{s}_{it}\right]\Bigg\} \qquad \text{(A.2)}
\end{aligned}$$

subject to the evolution of $n_{i,t+1}$:

$$n_{i,t+1} = e^{-g}\Big(l_{it} - 1 + \big(r^L(\mathbf{s}_{it}, \varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}) + c\big)l_{it} - \tilde{r}^D\Big) \qquad \text{(A.3)}$$

the capital requirement constraint:

$$\frac{l_{it}}{l_{it} - 1} \leq \lambda \qquad \text{(A.4)}$$

and the equity issuance cost:

$$\Lambda(div_{it}) = \mathbb{1}_{div_{it}<0}\eta^E div_{it}, \qquad \text{(A.5)}$$

thus verifying the conjecture.

### A.3 Computation

Before solving the model, we discretize the state space

$$(l_{i,t-1}, n_{it}, \mathbf{s}_{it}) = \begin{cases} (l_{i,t-1}, n_{it}, p_t, \omega_{it}) & \text{for rational beliefs} \\ (l_{i,t-1}, n_{it}, p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1}) & \text{for AR(2) beliefs} \end{cases}$$

into $n_l \times n_n \times n_p \times n_\omega$ grid points for rational beliefs, and $n_l \times n_n \times n_p \times n_p \times n_\omega \times n_\omega$ grid points for AR(2) beliefs, respectively. We discretize the rational and perceived transitions of the exogenous states $p_t$ and $\omega_{it}$ following a straightforward generalization of Tauchen (1986). We solve the fixed-point problem (8) to find the equilibrium wealth-consumption ratio $S_t$. Then the stochastic discount factor follows from (7), and the price of the loan portfolio $P^L(\mathbf{s}_t)$ and $r^L(\varepsilon_{c,t+1}, x_{t+1}, \omega_{t+1}, \mathbf{s}_t)$ are derived from (12) and (11), respectively. The bank takes these prices as given, and decides on its loan portfolio to maximize the sum of dividends and continuation value, subject to the regulation constraint. We solve the problem by iterating on the Bellman equation (A.2).

We obtain model-implied moments (Tables 7 and 8) by simulating 1,000 banks for 2,000 periods, discarding the first 200 years. Each bank starts with some specific initial values for $l_{i,t-1}$ and $n_{it}$. We simulate the series for the exogenous state variables $\omega_{it}$, $p_t$, $\omega_{i,t-1}$, and $p_{t-1}$, the endogenous state variables $a_{i,t-1}$ and $n_t$, and shocks $\varepsilon_{c,t+1}$ that determine the ex-post returns on loan portfolios. Using these series, we calculate the value of the bank as well as their forecast errors. If a bank defaults (when its continuation value $V^C$ falls below zero), an identical bank is created with the same state variables (for tractability). Hence we maintain a stationary distribution of banks. Importantly, in our simulations, all shocks are determined according to the true processes (i.e. the rational expectations representation), even though the asset prices and bank polices may involve distorted expectations.

### A.4 General Equilibrium Model

In Section 5.2, we introduce an extended model that endogenizes the deposit rate. Here, we elaborate on the household, firm and bank problems, and define the equilibrium.

**Households** The economy has a representative household that derives utility from consuming $C_t$. She maximizes the discounted value of future utility flows, defined through the Epstein and Zin (1989) recursive function:

$$U_t = \left[(1-\beta)u(C_t)^{1-\frac{1}{\psi}} + \beta \mathrm{E}_t^{\mathcal{P}}[U_{t+1}^{1-\gamma}]^{\frac{1}{\theta}}\right]^{\frac{1}{1-\frac{1}{\psi}}}$$

with time preference $\beta \in (0,1)$, relative risk aversion $\gamma$, and elasticity of intertemporal substitution $\psi$, and $\theta = \frac{1-\gamma}{1-1/\psi}$. The household states includes the distribution $\mu$ across banks, current and lagged aggregate shocks $p_t$ and $p_{t-1}$ and last period's deposit $D^h_{t-1}$.

The household budget constraint is given by:

$$C_t + D_t^h = (1 + r_{t-1}^D) D_{t-1}^h + \Pi_t$$

where $\Pi_t$ denotes aggregate payouts from banks.

**Firms** A representative firm produces output $Y_t$ using capital $K_t$ with a decreasing returns to scale technology $\alpha < 1$:

$$Y_t = z_t K_t^\alpha,$$

where the technology shock follows:

$$z_t = \exp(\sigma_z \varepsilon_{z,t} + \phi \xi x_t),$$

where $\phi$ is the firm's sensitivity to crises. Capital accumulation follows:

$$K_{t+1} = [(1-\delta)K_t + I_t] \exp(\phi \xi x_{t+1}).$$

Investment at $t$ comes from the sum of new loans made by banks:

$$I_t = \int L_{it} d\mu_t.$$

Finally, the firm faces a convex adjustment cost to capital:

$$\lambda(I_t, K_t) = \eta_f \left(\frac{I_t}{K_t}\right)^2 K_t.$$

Optimal investment decisions can then by constructed by computing the total value of the firm $V^f$, which satisfies the recursive problem: $V^f(K_t, \mu_t, p_t, p_{t-1}) =$

$$\max_{I_t, K_{t+1}} \left[ \exp(\sigma_z \varepsilon_{z,t} + \phi \xi x_t) - I_t - \lambda(I_t, K_t) + \mathbb{E}_{it}^{\mathcal{P}} \left[ M_{t,t+1} V^f(K_{t+1}, \mu_{t+1}, p_{t+1}, p_t) \right] \right]$$

subject to the capital accumulation and adjustment cost functions.

**Banks** Banks' problem remain more or less the same as in (23) and (24), with two differences: (i) deposit growth is no longer exogenous; and (ii) the state vector for each bank now includes the current cross-sectional distribution $\mu$, so it is now given by $(L_{it-1}, D_{it-1}, N_{it}, \mathrm{s}_{it}, \mu_t)$. As in the baseline model, we assume that all agents (banks, household, firm) have biased beliefs about the persistent shock processes (13) and (14), and that their perceived disaster probability follows (15).

**Equilibrium Definition** An equilibrium in this economy with behavioral bias is a collection including:

- a deposit rate $r^D(\mu_t, p_t, p_{t-1})$
- a loan pricing function $P^L(\mu_t, p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1})$
- household value $V^h(\mu_t, p_t, p_{t-1}, D^h_{t-1})$ and policy functions $C(\mu_t, p_t, p_{t-1}, D^h_{t-1})$ and $D^h(\mu_t, p_t, p_{t-1}, D^h_{t-1})$
- firm value $V^f(\mu_t, p_t, p_{t-1}, K_t)$ and policy function $I(\mu_t, p_t, p_{t-1}, K_t)$
- bank value $V^C(\mu_t, p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1}, L_{it-1}, D_{it-1}, N_{it})$ and policy functions $L(\mu_t, p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1}, L_{it-1}, D_{it-1}, N_{it})$, $D(\mu_t, p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1}, L_{it-1}, D_{it-1}, N_{it})$, and $Div(\mu_t, p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1}, L_{it-1}, D_{it-1}, N_{it})$
- a transition mapping
$$\mu_{t+1} = \Gamma(\mu_t, p_t, p_{t-1})$$
for the distribution $\mu(\omega_{it}, \omega_{it-1}, N_{it}, L_{i,t-1}, D_{i,t-1})$ across periods;

such that:

- household maximizes her utility under biased beliefs (13)-(15)
- firm maximizes its value under biased beliefs (13)-(15)
- each bank maximizes its value under biased beliefs (13)-(15)
- goods market clear: $C_t + I_t = Y_t$
- deposit market clear: $\int (L_{it} - E_{it}) d\mu_t = D^h_t$
- the transition mapping $\Gamma$ accurately reflects transitions of states given bank policies and biased beliefs.

**Table A.1:** Additional Heterogeneity

This table repeats the analysis of Table 1 by sub-sample based on bank size. In Panel A, we report the estimates for repeating the analysis of forecast error dynamics of Table 1 separately for two sub-samples of banks that exclude banks in the bottom quartile and below the median of bank size, in turn. Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| | Exclude Bottom Quartile Size Banks | | Exclude Below Median Size Banks | |
|---|---|---|---|---|
| | 1 year | 2 year | 1 year | 2 year |
| | (1) | (2) | (3) | (4) |
| $\beta_k$ | 0.115** | -0.230*** | 0.108** | -0.167** |
| [t] | [2.30] | [-4.36] | [1.75] | [-3.02] |
| Year FE | Yes | | Yes | |
| Bank FE | Yes | | Yes | |

**Table A.2:** First-Stage and Additional Robustness of Loan Dynamics

Panel A of this table reports first-stage results for the 2SLS-IV analysis of Table 3 (Panel C). Panel B of this table reports results of additional robustness for the 2SLS-IV analysis of Table 3 (Panel C, Columns 5-8) to using alternative definitions of the pre-crisis benchmark, in turn. In Panel C, we add to the 2SLS-IV specification the control set, $Z_{it-1}$, which includes controls for alternative explanations (loan demand as measured by the SLOOS response on loan demand, bank securitization as measured by securitization income to net interest income ratio and bank capital and liquidity as measured by tier 1 capital and cash ratios, respectively). Panel D repeats the 2SLS-IV analysis after excluding the largest banks (top quartile). Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level respectively.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel A: First-stage results for 2SLS-IV analysis | | | | | | | | |
| | Full Sample | | | | Recovery Period | | | |
| | 1 year | 2 year | 3 year | 4 year | 1 year | 2 year | 3 year | 4 year |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta_k$ | 0.263*** | 0.268*** | 0.248*** | 0.239*** | 0.261*** | 0.271*** | 0.254*** | 0.246*** |
| [t] | [15.02] | [13.80] | [11.63] | [10.58] | [11.46] | [10.38] | [8.85] | [7.92] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,173 | 2,825 | 2,523 | 2,252 | 2,460 | 2,156 | 1,885 | 1,630 |
| within $R^2$ | 0.07 | 0.06 | 0.05 | 0.05 | 0.05 | 0.05 | 0.04 | 0.04 |
| $F$-statistic | 225.74 | 190.57 | 135.19 | 111.95 | 131.32 | 107.64 | 78.25 | 62.73 |
| Panel B: 2SLS-IV robustness to using alternative benchmarks for pre-crisis | | | | | | | | |
| | Pre-Crisis is 2004-2006 | | | | Pre-Crisis is 2003-2005 | | | |
| | 1 year | 2 year | 3 year | 4 year | 1 year | 2 year | 3 year | 4 year |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| $\delta_k$ | -0.317** | -0.309** | -0.281* | -0.177 | -0.319** | -0.313** | -0.289** | -0.189 |
| [t] | [-2.47] | [-2.37] | [-1.99] | [-1.01] | [-2.46] | [-2.38] | [-2.03] | [-1.09] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,338 | 2,054 | 1,801 | 1,562 | 2,338 | 2,054 | 1,801 | 1,562 |
| Panel C: 2SLS-IV with controls for alternatives | | | | | | | | |
| | Full Sample | | | | Recovery Period | | | |
| $\delta_k$ | -0.151* | -0.187** | -0.168* | -0.048 | -0.237** | -0.245** | -0.217* | -0.117 |
| [t] | [-1.71] | [-2.13] | [-1.93] | [-0.34] | [-2.20] | [-2.20] | [-1.80] | [-0.73] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,480 | 2,206 | 1,972 | 1,752 | 2,042 | 1,792 | 1,570 | 1,355 |
| Panel D: 2SLS-IV excluding the largest banks | | | | | | | | |
| | Full Sample | | | | Recovery Period | | | |
| $\delta_k$ | -0.150** | -0.158** | -0.158** | -0.092 | -0.289*** | -0.299*** | -0.305*** | -0.224 |
| [t] | [-2.01] | [-2.18] | [-2.26] | [-1.01] | [-2.94] | [-2.84] | [-2.49] | [-1.36] |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,423 | 2,159 | 1,933 | 1,737 | 1,877 | 1,648 | 1,445 | 1,259 |

**Table A.2:** First-Stage and Additional Robustness of Loan Dynamics (Continued)

Panels E-F of this table report results of additional robustness for the 2SLS-IV analysis of Table 3 (Panel C, Columns 5-8) to adding the first or the first and second lags of Bartik, respectively. Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| | | | | | | | | |
|---|---|---|---|---|---|---|---|---|
| Panel E: 2SLS-IV adding the first lag of Bartik | | | | | | | | |
| $\delta_k$ | -0.163* | -0.167** | -0.170** | -0.080 | -0.322** | -0.322** | -0.281* | -0.160 |
| [t] | [-1.97] | [-2.02] | [-2.05] | [-0.79] | [-2.32] | [-2.11] | [-1.75] | [-0.96] |
| 1st stage $F$-stat | 103.37 | 86.06 | 60.84 | 52.00 | 62.82 | 50.91 | 37.36 | 30.44 |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 3,032 | 2,706 | 2,415 | 2,155 | 2,390 | 2,100 | 1,833 | 1,585 |
| Panel F: 2SLS-IV adding the first and second lags of Bartik | | | | | | | | |
| $\delta_k$ | -0.173** | -0.174** | -0.173* | -0.075 | -0.327** | -0.319** | -0.269* | -0.138 |
| [t] | [-1.90] | [-1.99] | [-1.96] | [-0.66] | [-2.31] | [-2.07] | [-1.69] | [-0.83] |
| 1st stage $F$-stat | 60.66 | 49.72 | 35.98 | 30.71 | 41.34 | 33.52 | 24.68 | 20.24 |
| Time, Bank FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 2,910 | 2,599 | 2,318 | 2,067 | 2,332 | 2,051 | 1,788 | 1,545 |

**Table A.3:** Additional Robustness on Delayed Overreaction – Placebo Test

This table summarizes results of additional analysis of Table 1. We repeat the analysis of Table 1 for pseudo bank beliefs that are generated randomly for each bank from a normal distribution. Panel (a) reports the estimates for the pseudo beliefs $E_{it}^{RE}(I_{i,t+1})$. Panel (b) reports estimates for pseudo beliefs after discretizing them to three categories as in the baseline analysis: 0 ("no change"), 1 ("improvement"), or -1 ("worsening") if $E_{it}^{RE}(I_{i,t+1})$ is within, above, or below one standard deviation from the median, respectively. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| Panel A: Dynamics of Random Beliefs | | |
|---|---|---|
| | $I_{it}$ | $I_{i,t-1}$ |
| $\beta$ | -0.088 | 0.050 |
| [t] | [-1.29] | [0.95] |

| Panel B: Dynamics of Discretized Random Beliefs | | |
|---|---|---|
| | $I_{it}$ | $I_{i,t-1}$ |
| $\beta$ | 0.073 | -0.014 |
| [t] | [1.38] | [-0.37] |

**Table A.4:** Additional Corroborating Evidence

This table summarizes results of time-series regressions of loan performance on its own lag(s):

$$I_{it} = \alpha_i + \rho_1 I_{i,t-1} + \rho_2 I_{i,t-2} + u_{it}$$

t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| Panel A: Dynamics of Loan Performance | | |
|---|---|---|
| | $I_{i,t-1}$ | $I_{i,t-2}$ |
| $\rho$ | 0.546** | -0.034 |
| [t] | [11.14] | [-1.13] |

**Table A.5:** Bank Expectations and Borrower Outcomes: Additional Outcomes

This table summarizes results for additional outcomes of bank-level regressions of borrower outcomes on bank expectations of loan performance (see Table 5). The additional outcomes considered include: property, plant and equipment (PPE) and payouts as measured by the sum of cash dividends and repurchase expenditures (Panel A). To ease interpretation and comparison across specifications, the main explanatory variables are expressed in standard deviation units. t-statistics are based on standard errors clustered at the borrower level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

| | 1 year | 2 year | 3 year | 4 year | 1 year | 2 year | 3 year | 4 year |
|---|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| Panel A: PPE and Payouts | | | | | | | | |
| | $\Delta PPE_{it+k}$ | | | | $\Delta Payouts_{it+k}$ | | | |
| $\delta_k$ | -0.021** | -0.028*** | -0.021** | -0.001 | 0.041 | -0.012 | -0.024 | -0.048 |
| [t] | [-2.45] | [-3.55] | [-2.40] | [-0.08] | [0.52] | [-0.16] | [-0.35] | [-0.79] |
| Time, Bank, Firm FE | Yes | Yes | Yes | Yes | Yes | Yes | Yes | Yes |
| N | 14,717 | 14,382 | 13,262 | 12,427 | 12,174 | 12,079 | 11,400 | 10,849 |

**Table A.6:** Business Cycle Statistics:
Delayed Extrapolation Model with $\chi = 1$

The empirical sample is 2005-2020 at annual frequency. The model moments are computed from an unconditional simulation of 2,000 periods for 1,000 banks. In the counterfactual model, we set $\chi = 1$ in (15); in other words, agents form the correct beliefs about the probability of disaster realization in $t+1$: $\text{Prob}[x_{t+1} = 1] = p_t$. Nonetheless, they still form biased beliefs about the evolution of $p_t$ and $\omega_{it}$, as in the baseline model.

| Description | Data | Delayed Extrapolation (Baseline) | ($\chi = 1$) |
|---|---|---|---|
| Annual loan growth ($\Delta l_t$) | | | |
| Corr($\Delta l_t$, $\Delta\text{GDP}_t$) | 0.134 | 0.235 | 0.198 |
| Corr($\Delta l_t$, $\Delta\text{GDP}_{t-1}$) | 0.239 | 0.164 | 0.102 |
| Corr($\Delta l_t$, $\Delta\text{GDP}_{t-2}$) | 0.218 | 0.058 | 0.037 |
| Corr($\Delta l_t$, $\Delta l_{t-1}$) | 0.207 | 0.597 | 0.573 |
| Corr($\Delta l_t$, $\Delta l_{t-2}$) | 0.118 | 0.128 | 0.110 |
| Annual change in expected loan performance ($\Delta\text{E}_t[\text{LoanDefault}_{t+1}]$) | | | |
| Corr$\left(\Delta\text{E}_t[\text{LoanDefault}_{t+1}], \Delta\text{GDP}_t\right)$ | -0.354 | -0.226 | -0.185 |
| Corr($\Delta\text{E}_t[\text{LoanDefault}_{t+1}]$, $\Delta\text{GDP}_{t-1}$) | -0.023 | -0.075 | -0.013 |
| Corr($\Delta\text{E}_t[\text{LoanDefault}_{t+1}]$, $\Delta\text{GDP}_{t-2}$) | 0.295 | 0.237 | 0.211 |
| Corr$\left(\Delta\text{E}_t[\text{LoanDefault}_{t+1}], \Delta\text{E}_{t-1}[\text{LoanDefault}_t]\right)$ | 0.465 | 0.254 | 0.125 |
| Corr$\left(\Delta\text{E}_t[\text{LoanDefault}_{t+1}], \Delta\text{E}_{t-2}[\text{LoanDefault}_{t-1}]\right)$ | 0.153 | 0.063 | 0.040 |
| Annual change in realized loan performance ($\Delta\text{LoanDefault}_{t+1}$) | | | |
| Corr$\left(\Delta\text{LoanDefault}_{t+1}, \Delta\text{GDP}_t\right)$ | -0.110 | -0.022 | -0.022 |
| Corr($\Delta\text{LoanDefault}_{t+1}$, $\Delta\text{GDP}_{t-1}$) | -0.064 | -0.026 | -0.026 |
| Corr($\Delta\text{LoanDefault}_{t+1}$, $\Delta\text{GDP}_{t-2}$) | 0.023 | 0.010 | 0.010 |
| Corr$\left(\Delta\text{LoanDefault}_{t+1}, \Delta\text{LoanDefault}_t\right)$ | -0.195 | -0.499 | -0.500 |
| Corr$\left(\Delta\text{LoanDefault}_{t+1}, \Delta\text{LoanDefault}_{t-1}\right)$ | -0.083 | -0.003 | -0.003 |
| Annual loan rate growth ($\Delta r^L_t$) | | | |
| Corr($\Delta r^L_t$, $\Delta\text{GDP}_t$) | 0.194 | 0.375 | 0.154 |
| Corr($\Delta r^L_t$, $\Delta\text{GDP}_{t-1}$) | 0.154 | 0.110 | -0.122 |
| Corr($\Delta r^L_t$, $\Delta\text{GDP}_{t-2}$) | 0.148 | 0.009 | -0.035 |
| Corr($\Delta r^L_t$, $\Delta r^L_{t-1}$) | 0.179 | 0.195 | 0.108 |
| Corr($\Delta r^L_t$, $\Delta r^L_{t-2}$) | -0.103 | -0.171 | -0.096 |

**Table A.7:** Model-Implied Regressions:
Delayed Extrapolation Model with $\chi = 1$

We repeat the regressions in Tables 1 (Panel A) and 3 (Panel A), respectively, on simulated data for 2,000 periods and 1,000 banks in each model. In the counterfactual model, we set $\chi = 1$ in (15); in other words, agents form the correct beliefs about the probability of disaster realization in $t+1$: $\text{Prob}[x_{t+1} = 1] = p_t$. Nonetheless, they still form biased beliefs about the evolution of $p_t$ and $\omega_{it}$, as in the baseline model. Forecast errors $FE_{i,t+1|t}$ are the difference between the actual and the expected change in loan performance over the next year. The change in loan performance $I_{it}$ is the negative of the annual change in the loan default rate, so that $I_{it} > 0$ indicates an improvement in loan performance (or a reduction in default rate), as in the data. $\Delta Loans_{i,t+1}$ is the change in lending compared to the steady state. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Forecast Error Dynamics

$$FE_{i,t+1|t} = \alpha_i + \beta_1 I_{it} + \beta_2 I_{i,t-1} + \gamma Z_{it} + \tau_t + u_{it}$$

| | Data | | Delayed extrapolation (Baseline) | | Delayed extrapolation ($\chi = 1$) | |
|---|---|---|---|---|---|---|
| | $I_{it}$ | $I_{i,t-1}$ | $I_{it}$ | $I_{i,t-1}$ | $I_{it}$ | $I_{i,t-1}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | 0.123** | -0.194*** | 0.129** | -0.205** | 0.142** | -0.186** |
| [t] | [2.32] | [-4.13] | [2.08] | [-2.16] | [2.33] | [-2.41] |
| Time FE | Yes | | Yes | | Yes | |
| Bank FE | Yes | | Yes | | Yes | |

Panel B: Bank Expectations and Lending Dynamics

$$\Delta Loans_{i,t+k} = \alpha_i + \delta_k FE_{i,t+1|t} + \tau_t + u_{it}$$

| | Data | | Delayed extrapolation (Baseline) | | Delayed extrapolation ($\chi = 1$) | |
|---|---|---|---|---|---|---|
| | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\delta$ | -0.032*** | -0.032*** | -0.043*** | -0.068*** | -0.038*** | -0.059*** |
| [t] | [-2.83] | [-2.91] | [-6.15] | [-8.78] | [-6.45] | [-7.92] |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Table A.8:** Model-Implied Regressions:
General Equilibrium Extension

We repeat the regressions in Tables 1 (Panel A) and 3 (Panel A), respectively, on simulated data for 2,000 periods and 1,000 banks in each model. Forecast errors $FE_{i,t+1|t}$ are the difference between the actual and the expected change in loan performance over the next year. The change in loan performance $I_{it}$ is the negative of the annual change in the loan default rate, so that $I_{it} > 0$ indicates an improvement in loan performance (or a reduction in default rate), as in the data. $\Delta Loans_{i,t+1}$ is the change in lending compared to the steady state. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Forecast Error Dynamics

$$FE_{i,t+1|t} = \alpha_i + \beta_1 I_{it} + \beta_2 I_{i,t-1} + \gamma Z_{it} + \tau_t + u_{it}$$

| | Data | | Delayed extrapolation (Baseline) | | Delayed extrapolation (General Equilibrium) | |
|---|---|---|---|---|---|---|
| | $I_{it}$ | $I_{i,t-1}$ | $I_{it}$ | $I_{i,t-1}$ | $I_{it}$ | $I_{i,t-1}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | 0.123** | -0.194*** | 0.129** | -0.205** | 0.158* | -0.167** |
| [t] | [2.32] | [-4.13] | [2.08] | [-2.16] | [1.59] | [-1.97] |
| Time FE | Yes | | Yes | | Yes | |
| Bank FE | Yes | | Yes | | Yes | |

Panel B: Bank Expectations and Lending Dynamics

$$\Delta Loans_{i,t+k} = \alpha_i + \delta_k FE_{i,t+1|t} + \tau_t + u_{it}$$

| | Data | | Delayed extrapolation (Baseline) | | Delayed extrapolation (General Equilibrium) | |
|---|---|---|---|---|---|---|
| | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\delta$ | -0.032*** | -0.032*** | -0.043*** | -0.068*** | -0.019* | -0.034** |
| [t] | [-2.83] | [-2.91] | [-6.15] | [-8.78] | [-1.65] | [-1.92] |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Table A.9:** Model-Implied Regressions:
Remove Bias on Idiosyncratic Shock $\omega_{it}$

We repeat the regressions in Tables 1 (Panel A) and 3 (Panel A), respectively, on simulated data for 2,000 periods and 1,000 banks in each model. The counterfactual model here is the an alternative version of the delayed extrapolation model, where we remove the bias on the bank-specific shock $\omega_{it}$, so agents make the rational forecast on $\omega_{i,t+1}$ according to (10), while they still form biased beliefs about the aggregate shock process $p_t$. Forecast errors $FE_{i,t+1|t}$ are the difference between the actual and the expected change in loan performance over the next year. The change in loan performance $I_{it}$ is the negative of the annual change in the loan default rate, so that $I_{it} > 0$ indicates an improvement in loan performance (or a reduction in default rate), as in the data. $\Delta Loans_{i,t+1}$ is the change in lending compared to the steady state. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

Panel A: Forecast Error Dynamics

$$FE_{i,t+1|t} = \alpha_i + \beta_1 I_{it} + \beta_2 I_{i,t-1} + \gamma Z_{it} + \tau_t + u_{it}$$

| | Data | | Delayed extrapolation (Baseline) | | Delayed extrapolation (Only Aggregate Bias) | |
|---|---|---|---|---|---|---|
| | $I_{it}$ | $I_{i,t-1}$ | $I_{it}$ | $I_{i,t-1}$ | $I_{it}$ | $I_{i,t-1}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\beta$ | 0.123** | -0.194*** | 0.129** | -0.205** | 0.073 | -0.091 |
| [t] | [2.32] | [-4.13] | [2.08] | [-2.16] | [0.93] | [-1.05] |
| Time FE | Yes | | Yes | | Yes | |
| Bank FE | Yes | | Yes | | Yes | |

Panel B: Bank Expectations and Lending Dynamics

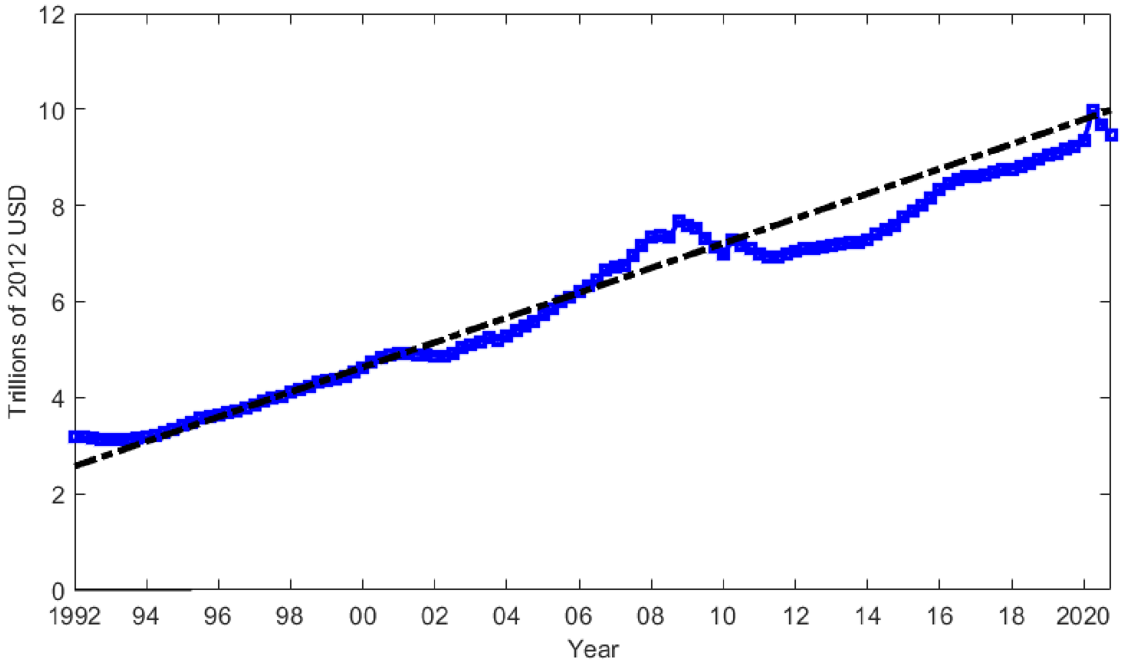
$$\Delta Loans_{i,t+k} = \alpha_i + \delta_k FE_{i,t+1|t} + \tau_t + u_{it}$$

| | Data | | Delayed extrapolation (Baseline) | | Delayed extrapolation (Only Aggregate Bias) | |
|---|---|---|---|---|---|---|
| | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ | $Loans_{i,t+1}$ | $Loans_{i,t+2}$ |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| $\delta$ | -0.032*** | -0.032*** | -0.043*** | -0.068*** | -0.011 | -0.014 |
| [t] | [-2.83] | [-2.91] | [-6.15] | [-8.78] | [-1.32] | [-1.27] |
| Time FE | Yes | Yes | Yes | Yes | Yes | Yes |
| Bank FE | Yes | Yes | Yes | Yes | Yes | Yes |

**Figure A.1:** Robustness to Aggregate Evidence on Bank Lending

Panel (a) plots total loans and leases in bank credit by all commercial banks in the U.S. in real terms from 1992 to 2020, and the dashed line is a linear trend that fits the data from 1992 to 2008. Panel (b) plots total loans to U.S. GDP ratio, and the dashed line is a linear trend that fits the data from 2000 and 2020. Source: Assets and Liabilities of Commercial Banks in the U.S. (H.8), Federal Reserve Board.

**(a)** Total bank loans in the U.S.




**(b)** Total bank loans as a fraction of U.S. GDP

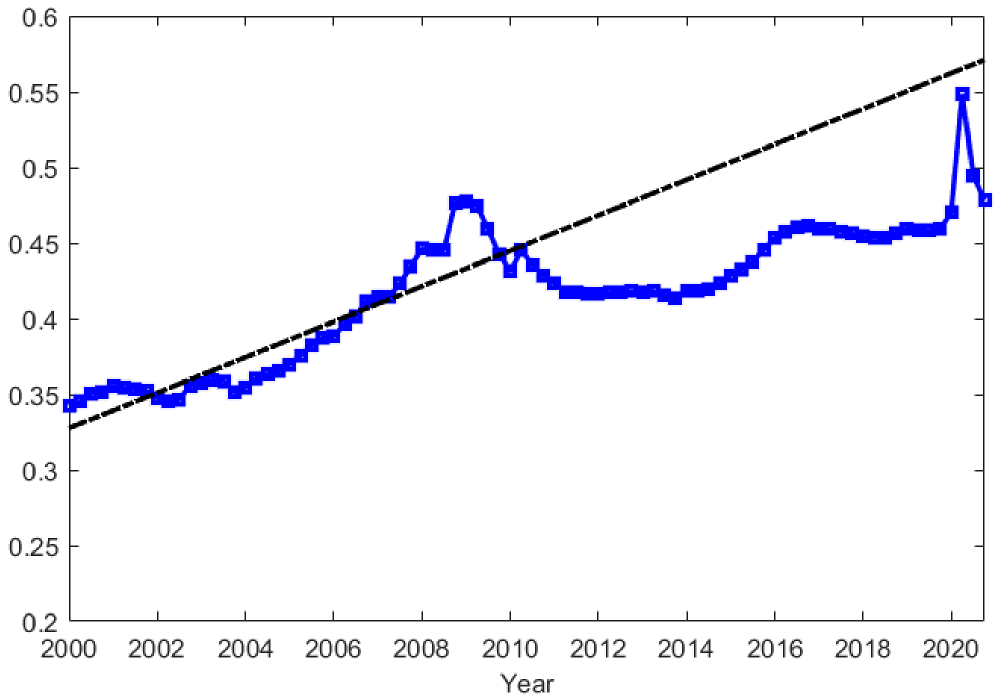


**Figure A.2:** Corroborating Evidence on Bank Forecast Errors

This figure shows the median of bank-level forecast errors for each year. This reflects the same sample of banks as in Figure 2. Bank forecast errors are defined as the difference between the actual and the expected change in loan performance over the next year. The shaded area indicates the NBER recession dates. Source: SLOOS.

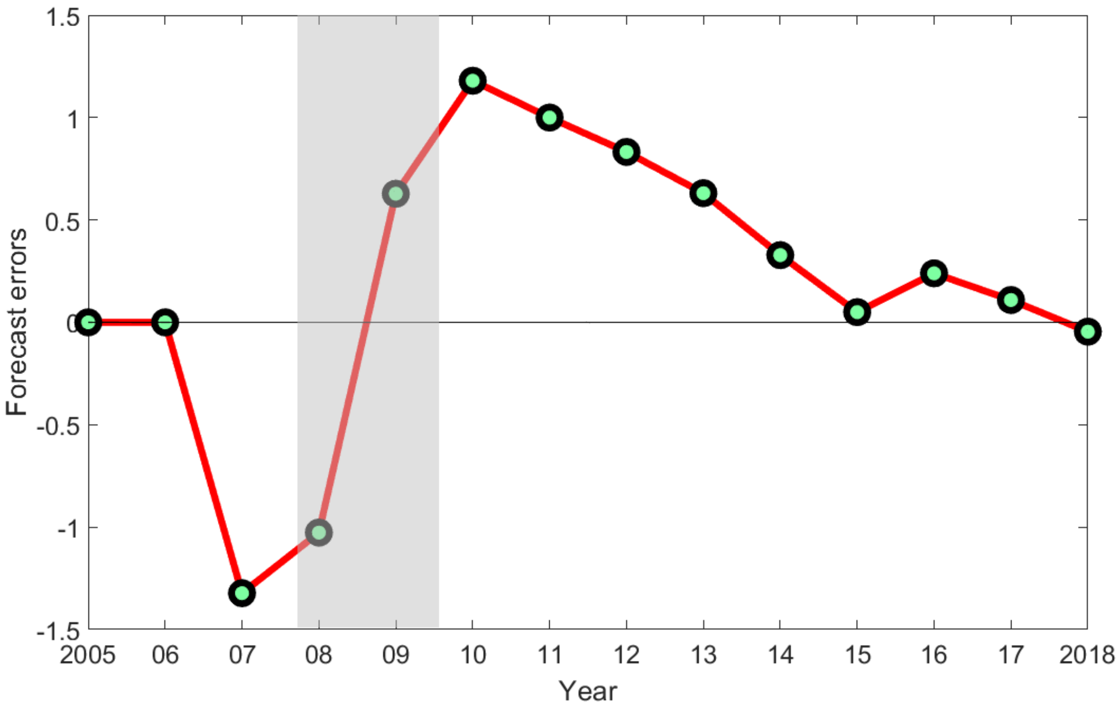


**Figure A.3:** Corroborating Evidence on Bank Lending

This figure shows the year-on-year average lending growth for banks in our full sample (after merging the expectations data in SLOOS with the Call Reports). This reflects the same sample of banks as in Figure 2. The shaded area indicates the NBER recession dates. Source: Call Reports.

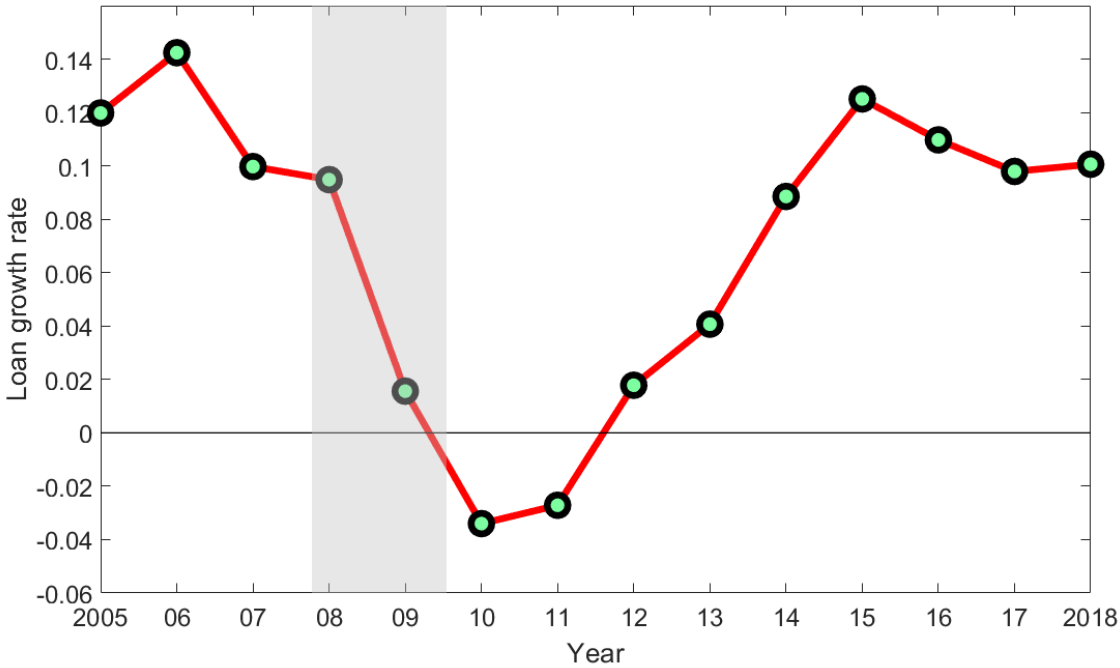


**Figure A.4:** Lending Policy Functions in Delayed Extrapolation Model

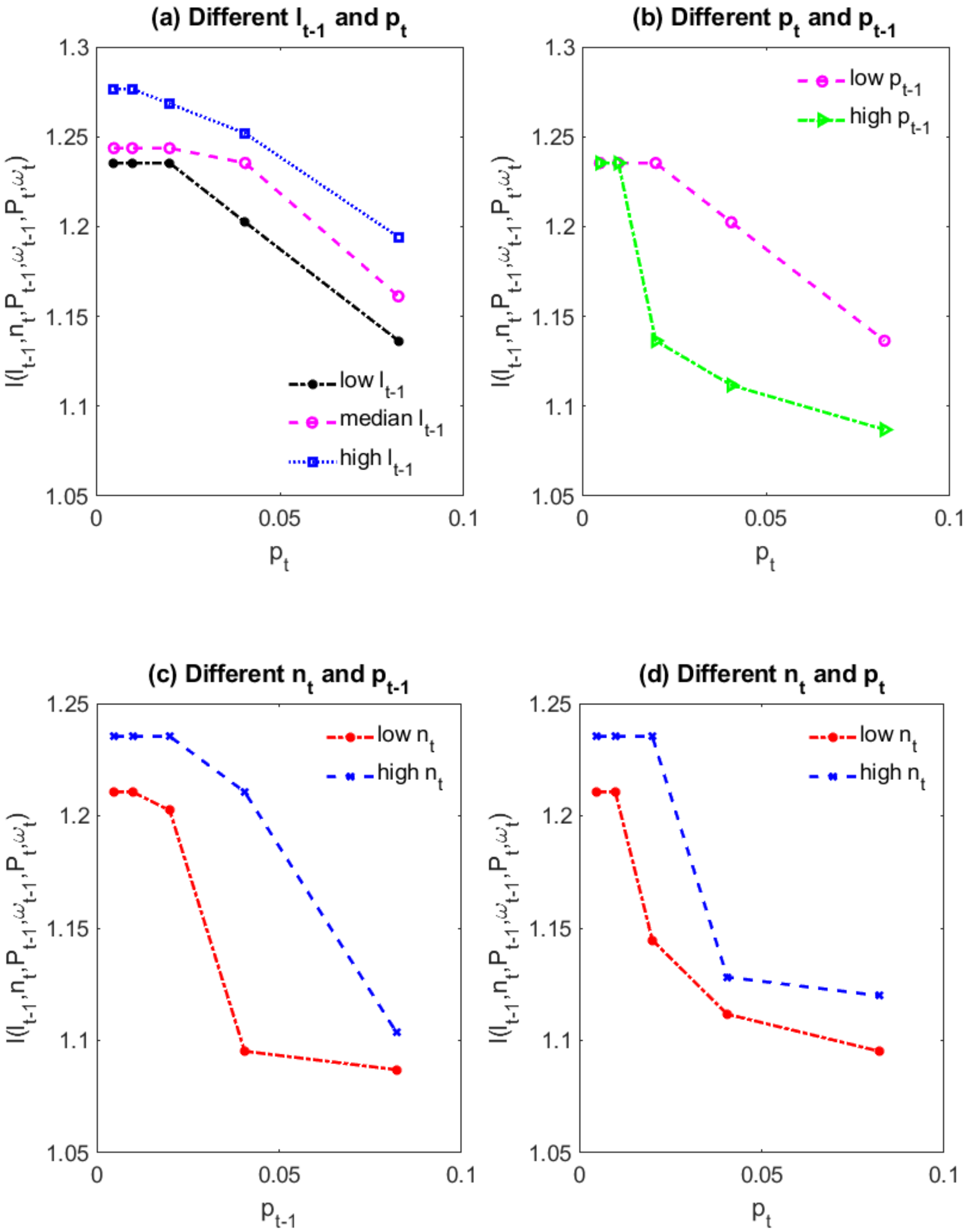
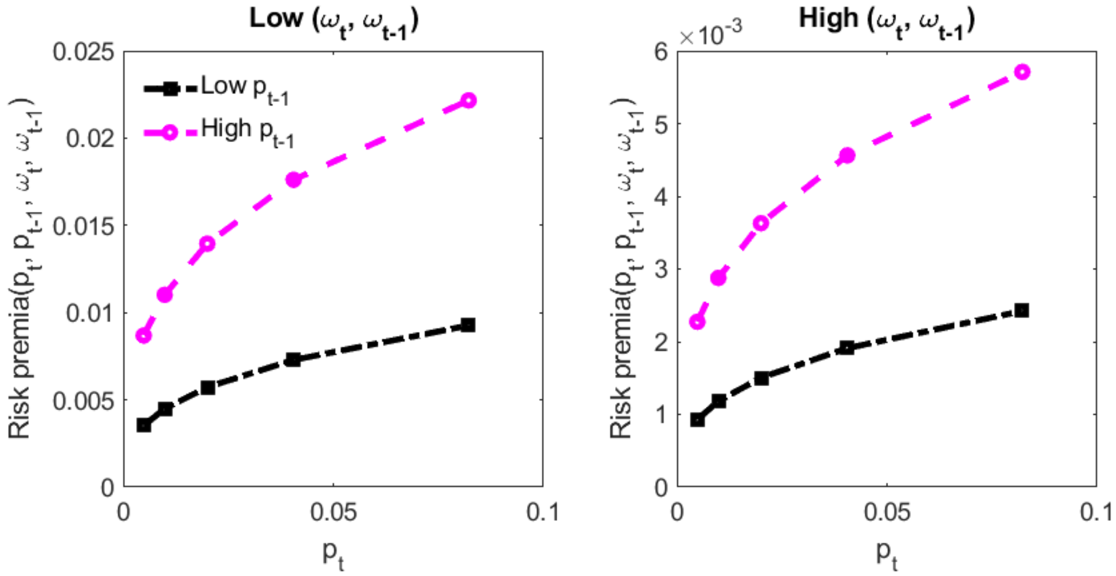


**Figure A.5:** Asset Prices in Delayed Extrapolation Model

**(a)** Risk premia




**(b)** Realized loan return

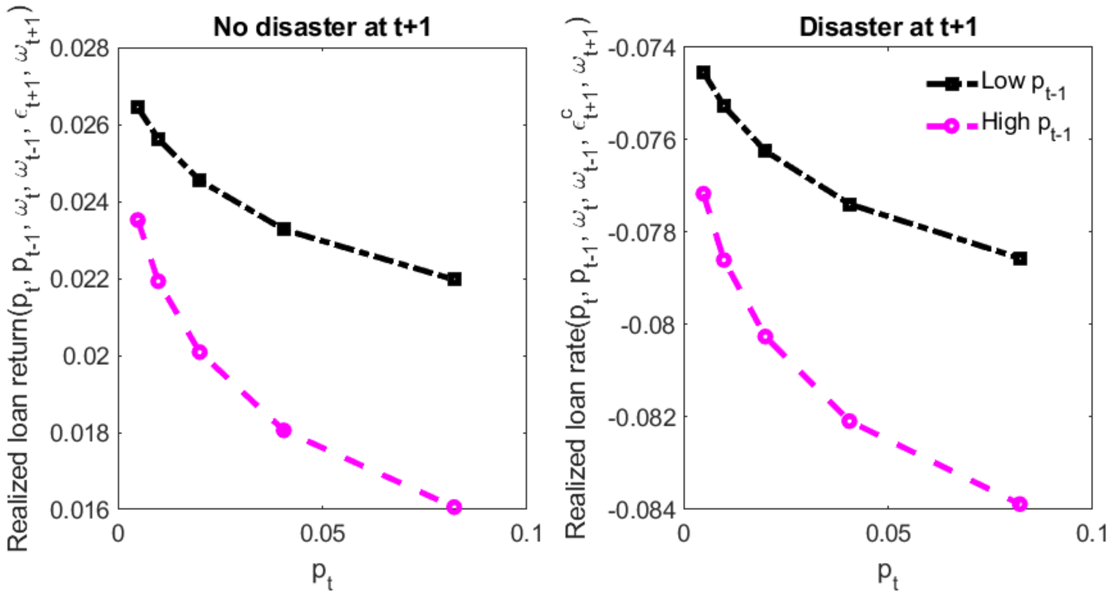
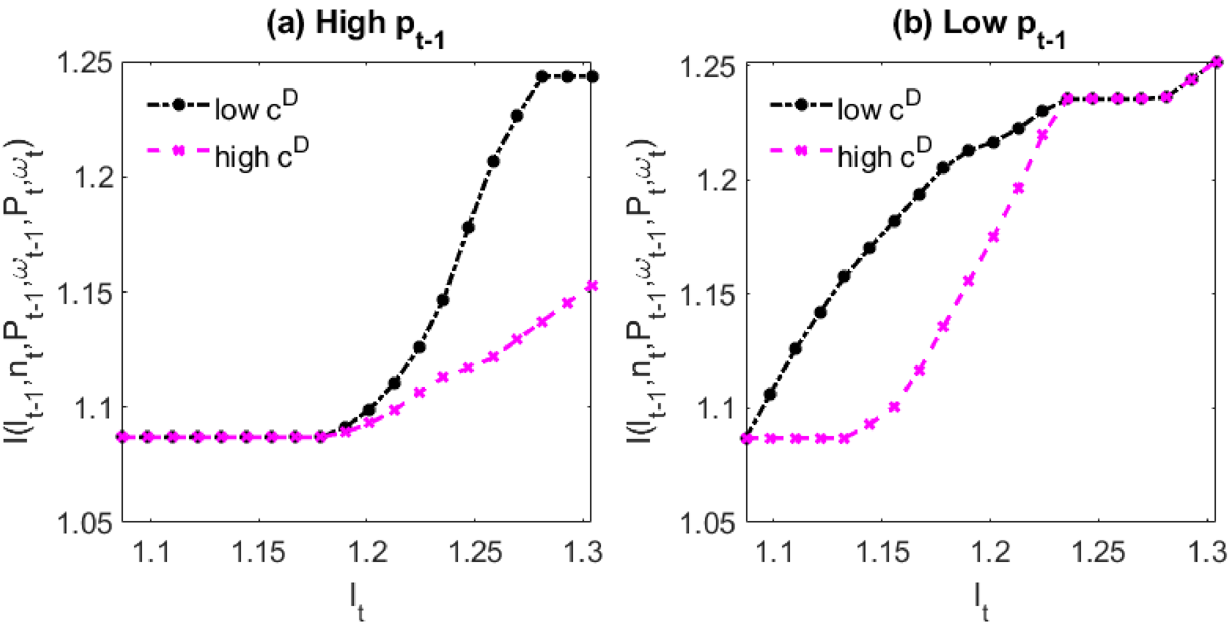


**Figure A.6:** Lending Policy Functions under different $c^D$

**(a)** Delayed Extrapolation Model




**(b)** Rational Model

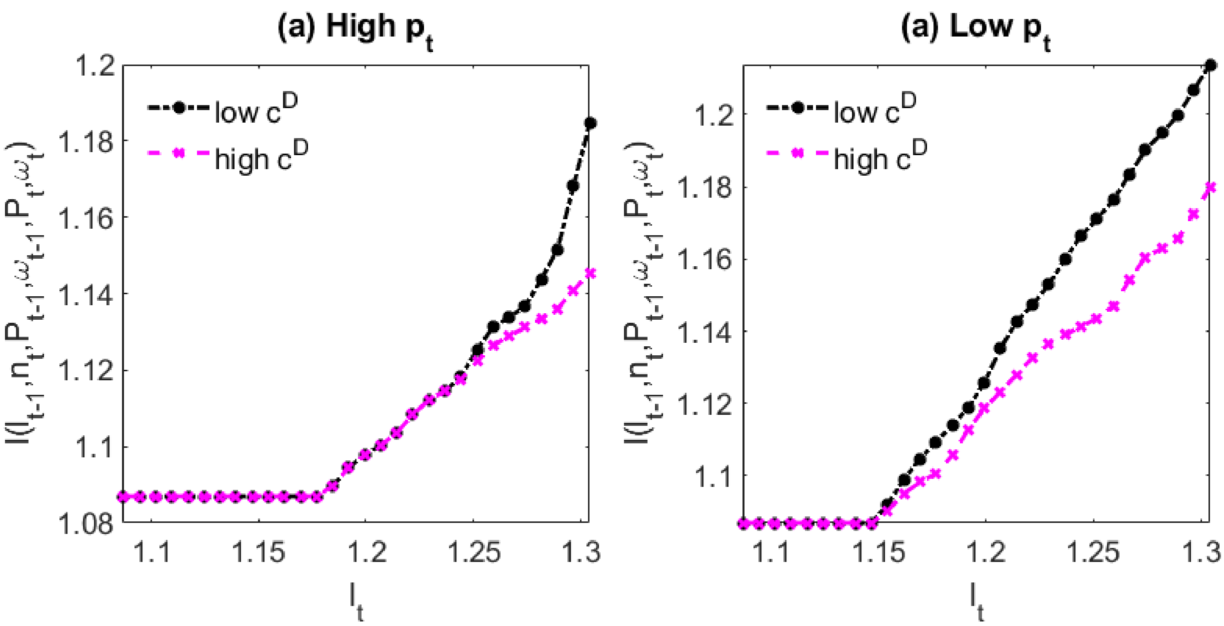
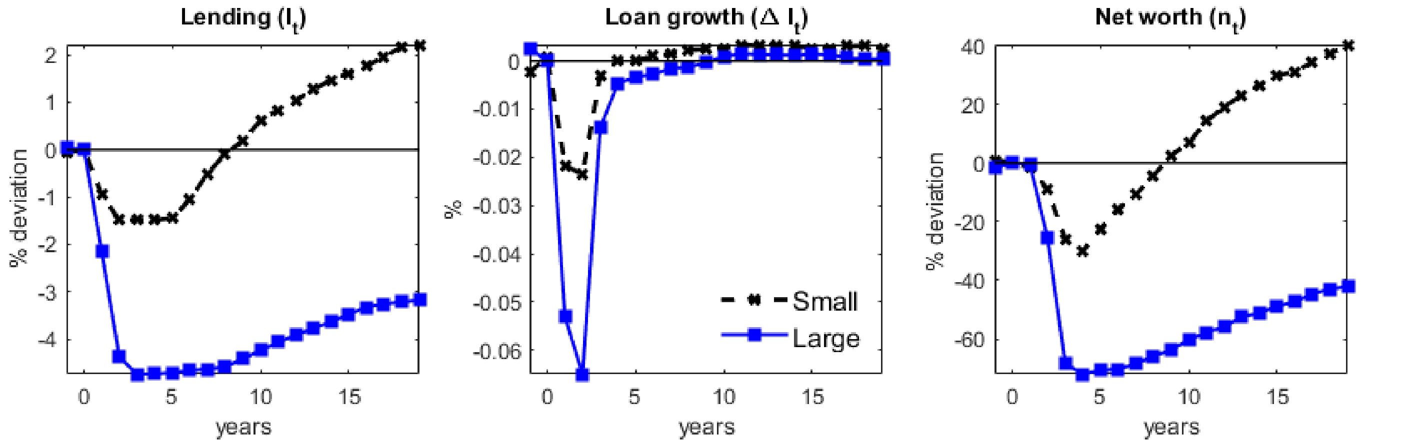


**Figure A.7:** Impulse Response Functions By Bank Size

In this figure, we disaggregate the impulse response functions in Figure 3 by bank size. Small and large banks are defined according to the size of their loan portfolios (below or above median) before the two consecutive disaster probability shocks in years 1 and 2.

**(a)** Delayed Extrapolation Model




**(b)** Rational Model

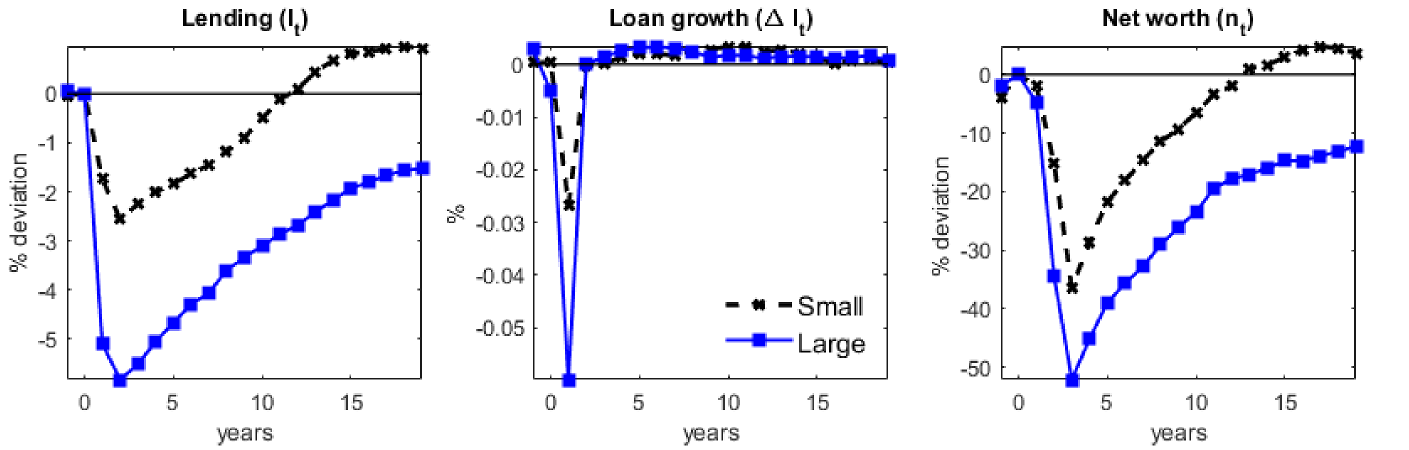


**Figure A.8:** Impulse Response Functions to An Increase in Disaster Probability: Delayed Extrapolation Model with $\chi = 1$

The impulse response functions are averages of 3,000 simulations, where each simulation is of 300 years for 1,000 banks. For each simulation, we impose two consecutive disaster probability shocks in years 1 and 2, allowing normal evolution of the economy afterwards. In the counterfactual model, we set $\chi = 1$ in (15), so they form the correct believe about the probability of disaster realization in $t+1$: $\text{Prob}[x_{t+1} = 1] = p_t$. Nonetheless, they still form biased beliefs about the evolution of $p_t$ and $\omega_{it}$, as in the baseline model.

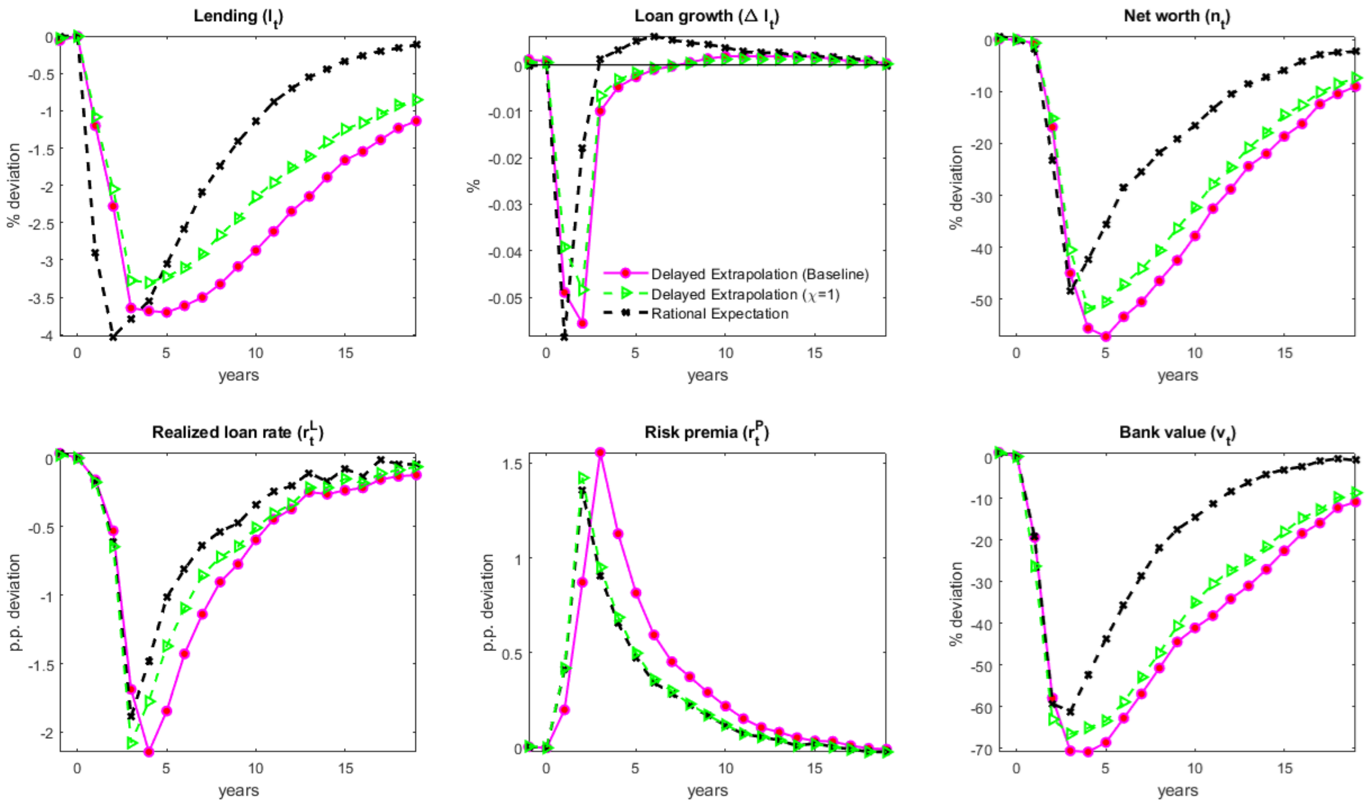


**Figure A.9:** Impulse Response Functions to An Increase in Disaster Probability: Other Types of Behavioral Bias

The impulse response functions are averages of 3,000 simulations, where each simulation is of 300 years for 1,000 banks. For each simulation, we impose two consecutive disaster probability shocks in years 1 and 2, allowing normal evolution of the economy afterwards. In all models, all shocks and distributional dynamics are determined according to their true processes, even though asset prices and bank policies involve distorted expectations. Besides our baseline model (delayed extrapolation), we consider three other forms of behavioral bias: (i) AR(1) Overextrapolation (agents perceive that $p_t$ and $\omega_{it}$ follow AR(1), but with a higher degree of persistence than the actual process); (ii) ARMA(1,1) Diagnostic Expectations (Bordalo et al., 2021); (iii) Long Memory Diagnostic Expectations (Maxted, 2023).

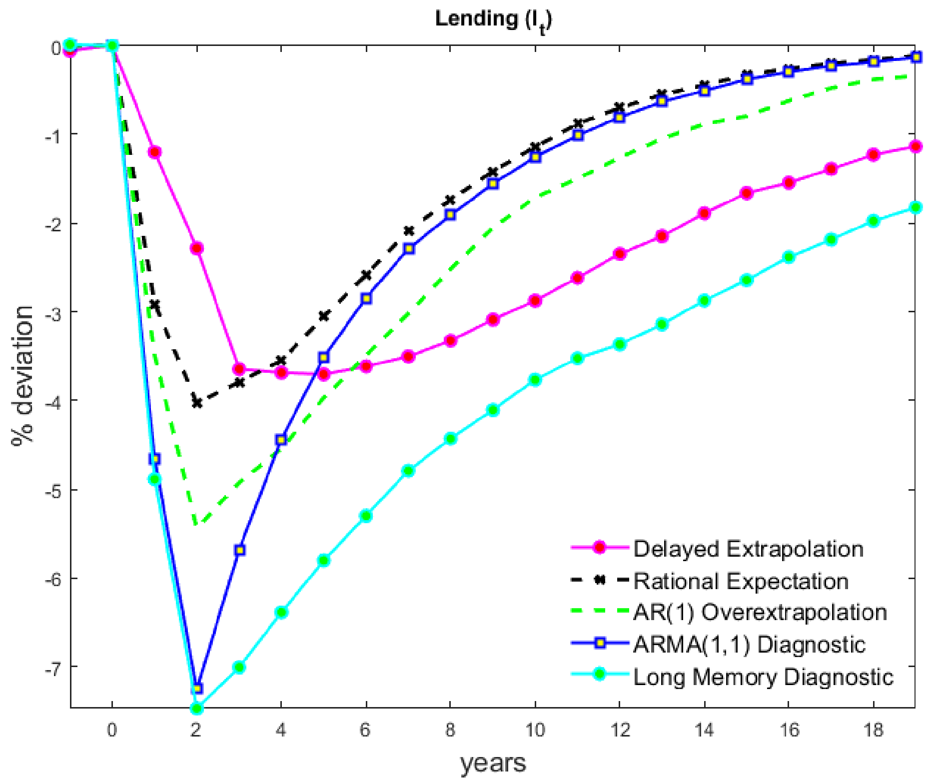


**Figure A.10:** Impulse Response Functions to An Increase in Disaster Probability: General Equilibrium Extension

The impulse response functions are averages of 3,000 simulations, where each simulation is of 300 years for 1,000 banks. For each simulation, we impose two consecutive disaster probability shocks in years 1 and 2, allowing normal evolution of the economy afterwards.