Expectations and Credit Slumps[*]

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Abstract

Since the 2008-09 financial crisis, U.S. bank lending has been slow to recover, despite the period of very low interest rates. We show that banks do not process information efficiently, and this is a quantitatively important explanation for credit slumps after 2008. Using a new dataset of bank expectations, we find that banks over-extrapolate the past, and their lending decisions are sensitive to beliefs. The behavioral bias is stronger for large banks, whose loan portfolios are also more sensitive to beliefs. To quantify the economic significance of imperfect expectations, we build a dynamic model with heterogeneous banks that are over-extrapolative and face a small risk of economic disaster. We show that a realistic degree of over-extrapolation estimated from the data generates the pace of credit and real recovery observed after the crisis. Banks' distorted beliefs hamper the effectiveness of policy tools, such as quantitative easing (QE) programs.

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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 during the crisis, and the Federal Reserve responded quickly by cutting interest rates and aggressively expanding the monetary base. One puzzling aspect of the recovery is why bank lending failed to recover, even after most measures of economic activity have improved.[1]

We propose one potential explanation for the puzzle: banks over-extrapolate the past, and their lending decisions are sensitive to beliefs. As banks have been over-pessimistic about the economic outlook and their loan performance since 2008, the growth in lending remained subdued long after the crisis.

We offer the explanation in two steps. First and foremost, we construct a new data set to study bank expectations, using the recently available *bank-level* responses on expected changes in loan performance over the next year, as reported on the Federal Reserve Board's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOOS). Since 2004, the survey began to include a list of special questions that inquire, among others, about banks' expectations for changes in lending standards, loan demand, and loan performance as measured by delinquencies and charge-offs, assuming that economic activity would evolve in line with consensus forecasts. We merge this sample with bank-level data on actual loan performance and loan growth, and the resulting data set allows us to analyze the properties of bank expectations and their connection with actual lending decisions. We find that banks' forecast errors are positively and significantly autocorrelated, and that banks are more likely to reduce lending if they had been over-pessimistic in past years. Second, to quantify the economic significance of imperfect expectations, we build a dynamic model with heterogeneous banks that are over-extrapolative and face a small risk of economic disaster. We show that a realistic degree of over-extrapolation estimated from the data generates the pace of credit and real recovery observed after the crisis. Banks' distorted beliefs also hamper the effectiveness of policy tools, such as quantitative easing (QE) programs.

Our analysis starts with the reduced-form evidence of systematic biases in banks' forecasts. In a similar approach to recent contributions in the macroeconomics and finance literature using survey data, we show that forecast errors from banks are highly persistent, with both the first- and second-order autocorrelation coefficients positively

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[1]Figure A.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.

and significantly significant.[2] This result rejects the rational expectations hypothesis, under which banks' forecast errors should not be predictable using variables in their information set, which includes past forecasts and past loans. Moreover, we show that forecast errors have significant predictive power for future loan growth, after controlling for loan demand, regulatory requirements, and other factors that can potentially influence banks' lending decisions. If a bank had been too pessimistic about its loan performance in the past, its current lending is also likely to be lower than the pre-crisis average. Notably, the persistence of forecast errors is stronger for large banks than small banks, and ceteris paribus, large banks' loan portfolios are more sensitive to their forecast errors in the past. Taking together, large banks appear to be slower at incorporating new information into their lending decisions and their loan portfolio is plausibly more susceptible to fluctuations in beliefs.

We then develop a framework to quantify the impact of imperfect expectations on the slow recovery in bank credit after 2008. 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 loan portfolios by equity and deposits. All agents share a common exposure to an extreme economic adverse event (such as the financial crisis), that occurs with a time-varying probability (Barro, 2006; Gourio, 2012). Banks have limited liability, and face a regulatory capital requirement. Defaults occur endogenously, if a bank's continuation value becomes too low. Importantly, all agents have full information, but they are not fully rational. Instead, they over-extrapolate past information when they make forecasts, which is consistent with the micro evidence.

Our modeling choice for over-extrapolation is disciplined by the empirical evidence: in matching the dynamics of forecast errors, we show that agents perceive the fundamentals to evolve according to AR(2), while the actual processes follow AR(1). If beliefs follow AR(1), only the current state the economy matters for expectation formation, even if the perceived degree of persistence is higher than the actual persistence. However, the current state does not necessarily indicate the trajectory of the economy, which is captured by AR(2). We show that by incorporating information on the trajectory in forming expectations, agents tend to be overly pessimistic as the economy recovers from a crisis, and overly optimistic at the end of a boom.

For a realistic parametrization that is calibrated to match the mean and standard deviation of leverage, the mean profit-to-equity, bank default rate and the dynamics of bank forecast errors, we show that the model with over-extrapolation outperforms the rational

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[2]See, for example, the recent works by Coibion and Gorodnichenko (2015), Bordalo, Gennaioli, and Shleifer (2017), Ma, Ropele, Sraer, and Thesmar (2020), which find the persistence in forecast errors using firm survey data.

expectations benchmark in terms of matching the time-series properties of bank performance, expectations, and asset prices simultaneously.

We model the 2008-09 financial crisis as two consecutive positive shocks to the disaster probability. In terms of matching the post-crisis dynamics, the model with over-extrapolation significantly outperforms its rational expectations counterpart: the OE model generates a much slower recovery in the *level* of lending and hence a hump-shaped response in the loan *growth* rate. There is some persistence in banks' asset growth in the RE model since net worth takes time to build, but for realistic parameter values this is not sufficient to match the slow credit growth after the crisis. The additional persistence in the OE model comes from two sources. First, lending is not only decreasing in the current disaster probability, but also last period's probability, so even when the disaster probability starts to revert back to the long-run mean, bank lending continues to decline. Second, the realized loan return increases more slowly in the OE model as disaster probability decreases. Since both lending and realized loan return recover more slowly, banks' current profit and hence net worth also recover more slowly. This in turn exacerbates the slow recovery in lending, which is a function of net worth. In other words, the slow recovery in the OE model comes both the over-extrapolative beliefs matched to the data and its interactions with the evolution of net worth. Finally, we use the framework as a laboratory to study the impact of policy, such as quantitative easing. By subsidizing bank equity holders, these policies have some positive effects on lending and bank value, but they are significantly hampered by the presence of forecasting bias.

Related Literature   We build upon an influential and expanding literature on expectations and real outcomes, which has focused on professional forecasters, firms, households, and financial market investors (see, for example, Greenwood and Schleifer, 2014; Coibion and Gorodnichenko, 2015; Bordalo, Gennaioli, and Shleifer, 2017 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, Farmer, Nakamura, and Steinsson, 2021). Until recently, there has been little data that measures banks' expectations. Ma, Paligorova, and Peydró (2021) use a new dataset on banks' economic projections about all metropolitan statistical areas in the U.S. to study the impact of lenders' expectations on credit supply. We offer a complementary angle on credit slumps after the 2007-09 crisis using a different dataset and quantify the economic impact in a structural model.

Our paper also speaks to a growing theoretical literature on the role of expectations in explaining credit cycles. For instance, Bordalo, Gennaioli, Shleifer, and Terry (2021) quantify the business cycle implications of diagnostic expectations in a heterogeneous-firm

model; Krishnamurthy and Li (2020) and Maxted (2022) consider the impact of imperfect expectations in models with financial intermediation. We complement this theoretical literature in two ways. First, we build a heterogeneous-bank model and examine how imperfect expectations propagate to the economy via changes in bank balance sheets. Second, while models of diagnostic expectations focus on explaining the frothy pre-crisis behavior and sudden reversals, our model focuses primarily on the recovery from a crisis.

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; Mankart, Michaelides, and Pagratis, 2018; Gomes, Grotteria, and Wachter, 2019; Corbae and D'Erasmo, 2021; Begenau and Landvoigt, 2021; Elenev, Landvoigt, and Van Nieuwerburgh, 2021).[3] 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 (2019). 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.

The rest of the paper is organized as follows. Section 2 presents reduced-form evidence of systematic biases in banks' forecasts and their predictability for future lending decisions. Section 3 builds a dynamic model with heterogeneous banks and over-expectations. Section 4 provides an explanation for the calibration. Section 5 compares the model fit under rational expectations versus over-extrapolation, and studies the impact of the 2008 financial crisis. Section 6 conducts policy analysis. Section 7 concludes.

2 Stylized Facts

2.1 Data Sources

Bank Expectations   The key source of data used in the analysis comes from the Federal Reserve's Senior Loan Officer Opinion Survey of Bank Lending Practices. Since the early 1990s, the survey has queried 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

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[3]The financial crisis of 2008 renewed interest in banking theories, particularly the role of intermediaries in financial crises (see, for example, Farhi and Tirole, 2012; Adrian and Shin, 2013; He and Krishnamurthy, 2013; Brunnermeier and Sannikov, 2014; Sarin and Summers, 2016; Dang, Gorton, Hölmstrom, and Ordoñez, 2017; Rampini and Viswanathan, 2019.)

domestically chartered commercial banks and up to 24 large U.S. branches and agencies of foreign banks. In 2004, the survey began to include a list of special questions that inquire, among others, about banks' expectations for changes in lending standards, loan demand, and loan performance as measured by delinquencies and charge-offs, assuming that economic activity would evolve in line with consensus forecasts. Our sample period is from 2005 and 2020.

Specifically, these annual special questions ask about banks' expectations for the behavior of loan delinquencies and charge-offs on selected categories of C&I, 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?*

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 a similar fashion to Bassett, Chosak, Driscoll, and Zakrajšek (2014), we use these responses to create categorical variables, $E_t[I_{i,t+1}^k]$, defined as $E_t[I_{i,t+1}^k] =$

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

In our baseline analysis, we construct an index of expectations of future loan performance, aggregated across loan types, for each bank i in year t. To this end, we use data from the Call Reports about the amount of outstanding loans each respondent bank has in each loan category and we compute the following weighted average for each bank:

$$
E_t[I_{i,t+1}] = \sum_k \omega_{it}^k \times E_t[I_{i,t+1}^k],
$$

where ω_{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 pessimistic a bank is about loan performance in the following year.

Loan Performance   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 charge-offs and delinquency rates on a particular type of loans, and define a categorical variable, I_{it}^k, such that:

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

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

$$
I_{it} = \sum_k \omega_{it}^k \times I_{it}^k,
$$

where ω_{it}^k is the same weight that is used to construct the expectation measure, $E_t[I_{i,t+1}]$.

Finally, we use the two categorical variables to compute each bank's forecast errors in each year, R_{it}^{FE}. Specifically, the forecast error is defined as the difference between the expected and the actual change in loan performance:

$$
R_{it}^{FE} = E_t[I_{i,t+1}] - I_{i,t+1}.
$$

For instance, if $R_{it}^{FE} < 0$, this indicates that the respondent bank is too pessimistic in year t about its loan performance in the coming year.

Bank Lending and Other Bank-Specific Information We use the bank-level data on outstanding loan balances in each year from the Call Reports to construct our measure of dependent variable, $\Delta Loan_{it}$, the logarithm change of total bank loans relative to the pre-crisis level. In addition, we also obtain other bank balance sheet data from the Call Reports, and use them to control bank characteristic variables, including size (the logarithm of total assets), the share of loans in assets, the ratio of common equity Tier 1 (CET1) capital to risk-weighted assets, and the cash ratio.

2.2 Persistence of Forecast Errors

Under rational expectations, banks' forecast errors should not be predictable using variables in their information set, which includes past forecasts and past loans. We document instead that banks' forecast errors are persistent, and positively predictable by lagged forecast errors.

We show this finding by estimating the following model:

$$R_{it}^{FE} = \alpha + \sum_{k=1}^{K} \beta_k R_{it-k}^{FE} + \sum_{k=1}^{K} g_k X_{it-k} + \tau_t + u_{it}, \quad k = 1, 2, 3 \tag{1}$$

where α is a constant, τ_t denotes year fixed effects. The vector X_{it} includes bank variables such as size, the share of loans in assets, the ratio of core deposits to assets, loan loss reserves, and loan performance. Standard errors are clustered at the bank level.

Table 1 reports the estimates of coefficients β_k, for $k = 1, 2, 3$. The estimated β_k is highly significant for the first- and second-year lags: on average, forecast errors exhibit a positive autocorrelation for two lags. Intuitively, a positive news at date t about date t loan performance – for example, a shock that increases house prices and hence the collateral value of a loan – implies a negative forecast error at date t, as the bank was too pessimistic at date $t-1$ about date t loan performance (i.e. expected delinquencies are higher than the actual rate). If the shock is persistent, and the bank is slow to incorporate the information from the latest shock into their forecast for date $t+1$, we end up with negative forecast errors at $t+1$ and beyond. Thus, the positive autocorrelation of forecast errors are consistent with a hypothesis that banks, on average, under-react to loan performance related news.

A possible concern about the relevance of this finding is that the persistence in forecast error might mostly be a phenomenon among small banks. To address this concern, we split the sample of banks into two groups, small and large, based on the bottom and top quartiles of bank total loans respectively. For each of the two groups, we re-run regression (1) separately. We report results in Table A.1. Across both groups, the estimates for β_1 and β_2 are strongly significant, and the degree of persistence increases with bank size. Overall, the results in Tables 1 and A.1 reject the hypothesis that banks process information efficiently.

2.3 Expectations and Lending Dynamics

We now show that banks' expectations are linked to their lending decisions. To this end, we regress the logarithmic change of total loans (relative to the pre-crisis level) in year t on their forecast errors in the past three years:

$$\Delta Loans_{it} = \alpha + \sum_{k=1}^{K} \beta_k R_{it-k}^{FE} + \sum_{k=1}^{K} g_k X_{it-k} + \tau_t + u_{it}, \quad k = 1, 2, 3 \tag{2}$$

where α is a constant, τ_t denotes year fixed effects, and X_{it} is a vector of bank controls including past loan performance. Standard errors are clustered at the bank level. Ta-

ble 2 reports estimates of coefficients on lagged forecast errors (columns (1)–(3)) and on past loan performance (columns (4)–(6)), respectively. The sample period is the recovery after the Great Recession (2010-2020). We find that forecast errors in year $t-2$ are positively and significantly related to banks' lending decisions in year t: if banks were too pessimistic in past ($R_{it-2}^{FE} < 0$), their lending in year t is likely to stay below the pre-crisis level (column (2)). We also find that the proxy for loan performance in years $t-2$ and $t-3$, the fraction of loan defaults, is negatively and significantly related to loan growth in year t: if loan default rates were high in the past, bank lending is still likely to stay below the pre-crisis level today (columns (5)-(6)).

Alternative Hypotheses Our results so far indicate that there is a significant degree of "stickiness" in the post-crisis lending dynamics, and that bank expectations appear to play an important role in shaping the slow recovery in loan growth. Nonetheless, one possible concern with the findings in Table 2 is that there could be alternative hypotheses for the slow recovery in intermediated credit. For instance, one other potential explanation is the low level of economic growth and employment following the crisis. These factors could indicate that low rates of lending were due to a lack of loan demand. Another potential explanation is the tightened bank regulation in response to the financial crisis. To address these concerns, we repeat the same analysis as in Table 2 and add controls for loan demand, loan performance in the crisis, the ratio of CET1 capital to risk-weighted assets, and bank liquidity (measured by the cash ratio) in turn. We present the additional results in Table A.2. The key takeaway is that the estimate of β_2 – the coefficient on forecast errors in $t-2$ – is robustly and positively significant. The magnitude of the coefficient also remains stable across specifications. In other words, the bank expectation channel is still present, after controlling for alternative explanations for the persistent decline in bank lending in the post-crisis period.

2.4 Bank and Loan Heterogeneity

Next, we examine if the relation between bank expectations and their lending dynamics varies by bank size or loan types. To do so, we repeat the same analysis as in Table 2 and split the full sample according to bank size and loan types, in turn. As in Table A.1, we define "small" and "large" banks based on the bottom and top quartiles of bank total loans, respectively. Moreover, we also split the sample into four types of loans: commercial and industrial (C&I) loans, residential real estate (RRE) loans, commercial real estate (CRE) loans, and consumer Loans. For each loan type, we regress the current loan growth on the respective forecast error as well as on the average forecast error for

other loan types, in turn.

Table A.1 reports the estimates of coefficient β_k, for $k = 1, 2, 3$. We find that the estimated β_2 is positive and statistically significant for both small and large banks, with the estimate significantly higher for large banks. Moreover, bank lending in all but consumer loans is positively related to their forecast errors on that particular type of loans in the past, and unrelated to forecast errors for other loan types. In particular, the estimates are four times higher for real estate loans (both residential and commercial) than for C&I loans. This evidence suggests that on average, past beliefs play a more prominent role in influencing the current lending decisions of larger banks, and for real estate loans.

2.5 Key Takeaways

In this section, we document a set of new facts about bank expectations and lending dynamics in the post-crisis period (2010-2020) using a unique bank-level dataset:

1. Banks' forecast errors are positively and significantly autocorrelated.

2. Forecast errors have significant predictive power for future loan growth, even after controlling for loan demand, regulatory requirements, and other factors that can potentially influence banks' lending decisions. If a bank had been too pessimistic about its loan performance in the past, its current lending is also likely to be lower than the pre-crisis average.

3. The persistence of forecast errors is stronger for large banks than small banks, and ceteris paribus, large banks' loan portfolios are more sensitive to their forecast errors in the past. Taking together, large banks appear to be slower at incorporating new information into their lending decisions and their loan portfolio is plausibly more susceptible to fluctuations in beliefs.

4. The growth of real estate loans is more sensitive to fluctuations in bank beliefs than other loan types.

Figure 2 provides further demonstrative evidence from the micro data on the relevance of forecasting biases for bank lending in the post-crisis period. In particular, our goal here is to highlight the disconnect of loan growth from actual loan performance, and contrast it with the link between loan growth and expected loan performance. In Panel (a), we plot the net fraction of banks that experience an actual worsening of loan performance: it is the number of banks that experience worsening (defined by an increase in expected the loan default rate) minus the number of banks that experience improving, divided by the total number of banks. Panel (b) shows the net fraction of banks

that expect a worsening of loan performance. While actual loan performance appears to start improving, on average, from 2010 (with more banks experiencing an improvement in loan performance than worsening), most banks remained over-pessimistic about their loan portfolios well beyond 2010. This corroborates our evidence above that banks adjust their expectations slowly. Furthermore, not only is expectation slow to adjust, so is the rate of low growth. As shown in Panel (c), the average rate of loan growth only returned to the pre-crisis level approximately seven years after the crisis. In other words, the speed of recovery in bank lending appears to be much more correlated with the speed of recovery in expectations than in actual loan performance.

Taking together, the empirical evidence suggests that inefficient information processing by banks plays a potentially important role in the post-crisis decline in bank lending. In particular, the evidence suggests that banks overextrapolate the past in forming their expectations. Our next goal is to understand how overextrapolation affects banks' lending decisions, and quantify the economic significance of such behavioral bias. We do so through the lens of a structural model, which allows us to "shut down" the behavioral biases that we observe in the data and construct appropriate policy counterfactuals.

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 do not fully integrate these sectors into a general equilibrium setting.

Aggregate shocks   There are two aggregate shocks in the economy, denoted by ε_{ct} and x_t. ε_{ct} is a standard normal random variable that is i.i.d. over time. x_{t+1} is a Bernoulli random variable which takes on the value 1 with probability p_t and 0 otherwise. If $x_{t+1} = 1$, the economy experiences a "crisis" in period $t + 1$, and the investor's endowment falls by a large fraction ξ (see, for example, Rietz, 1988; Barro, 2006; Gourio, 2012, 2013; Gourio, Kashyap, and Sim, 2018). The probability p_t follows a Markov process:

$$\log p_{t+1} = (1 - \rho_p) \log \tilde{p} + \rho_p \log p_t + \varepsilon_{p,t+1}, \tag{3}$$

where $\varepsilon_{p,t+1} \sim iidN(0,\sigma_p)$. ε_{pt}, ε_{ct} and x_t are independent. Following Gomes et al. (2019), we assume the following process for the endowment of the investor:

$$C_{t+1} = C_t e^{\mu_c + \sigma_c \varepsilon_{c,t+1} + \xi x_{t+1}}, \tag{4}$$

where μ_c represents the mean growth in consumption in normal times.

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 γ, and elasticity of intertemporal substitution ψ. Hence the stochastic discount factor of the investor is given by:

$$M_{t,t+1} = \beta^\theta \left(\frac{C_{t+1}}{C_t} \right)^{-\gamma} \left(\frac{S_{t+1} + 1}{S_t} \right)^{-1+\theta} \tag{5}$$

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

$$E_t^{\mathcal{P}} \left[\beta^\theta \left(\frac{C_{t+1}}{C_t} \right)^{1-\gamma} \left(S_{t+1} + 1 \right)^\theta \right] = S_t^\theta. \tag{6}$$

where $\mathcal{P}$ denotes the subjective belief of the investor, which we specify below. To avoiding clouding on our key mechanism, we do not fully integrate the agents in a general equilibrium setting.

3.2 Loan Portfolios and Uncertainty

Each bank has a portfolio of risky private sector loans ($j = 1,2,...,n$) within a local economy. There is uncertainty about the collateral value for loan j of bank i, W_{ijt}, which is modeled as a random variable:

$$W_{ijt} = e^{\sigma_c \varepsilon_{ct} + \xi x_t + \omega_{it} + \sigma_j \varepsilon_{jt}}. \tag{7}$$

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

$$\omega_{i,t+1} = \rho_\omega \omega_{it} + \varepsilon_{\omega i,t+1}, \tag{8}$$

where $\varepsilon_{\omega i,t+1} \sim iidN(0,\sigma_\omega)$. ε_{ct}, ε_{jt}, $\varepsilon_{\omega it}$ and ε_{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.

We assume that borrower j defaults at time t if $W_{ijt} < \kappa$, and κ is common across all borrowers. When a borrower defaults, the bank can recover a fraction $1 - \mathscr{L}$ of the collateral value, where $\mathscr{L}$ is the loss given default. The ex-post return on the portfolio of loans equals

$$r^L_{i,t+1}(\mathbf{s}_{it}, \varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}) = \frac{\pi^L_{i,t+1}(\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1})}{P^L_{it}(\mathbf{s}_{it})} - 1, \tag{9}$$

where $\pi^L_{i,t+1}(\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1})$ is the payoff of the loan portfolio for bank i, and $P^L_{it}(\mathbf{s}_{it})$ is the price of the loan. $\mathbf{s}_{it}$ denotes the exogenous state variables for bank i, which we specify below.

Assuming that each bank i holds an equal-weighted portfolio of an arbitrarily large number of loans, then as shown in Gomes et al. (2019), the payoff of the loan portfolio can be expressed as:

$$\pi^L_{i,t+1}(\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1})$$

$$= \underbrace{\kappa \mathrm{Prob}\left(W_{ij,t+1} \geq \kappa \middle| \varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}\right)}_{\text{Repay}} + \underbrace{(1 - \mathscr{L})\mathrm{E}\left[W_{ij,t+1} \mathbb{1}_{W_{ij,t+1}<\kappa} \middle| \varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}\right]}_{\text{Default}}$$

$$= \begin{cases} \kappa\left(1 - \Phi\left(\frac{1}{\sigma_j}(\log(\kappa) - \sigma_c\varepsilon_{c,t+1} - \omega_{i,t+1})\right)\right) \\ \quad + (1 - \mathscr{L})e^{\sigma_c\varepsilon_{c,t+1}+\omega_{i,t+1}+\frac{\sigma_j^2}{2}} \int_{-\infty}^{\frac{1}{\sigma_j}(\log(\kappa)-\sigma_c\varepsilon_{c,t+1}-\omega_{i,t+1})} \frac{1}{\sqrt{2\pi}}e^{-\frac{(z-\sigma_j)^2}{2}} dz & \text{if } x_{t+1} = 0 \\[2em] \kappa\left(1 - \Phi\left(\frac{1}{\sigma_j}(\log(\kappa) - \sigma_c\varepsilon_{c,t+1} - \xi - \omega_{i,t+1})\right)\right) \\ \quad + (1 - \mathscr{L})e^{\sigma_c\varepsilon_{c,t+1}+\omega_{i,t+1}+\xi+\frac{\sigma_j^2}{2}} \int_{-\infty}^{\frac{1}{\sigma_j}(\log(\kappa)-\sigma_c\varepsilon_{c,t+1}-\xi-\omega_{i,t+1})} \frac{1}{\sqrt{2\pi}}e^{-\frac{(z-\sigma_j)^2}{2}} dz & \text{if } x_{t+1} = 1 \end{cases} \tag{10}$$

where $\Phi(\cdot)$ denotes the standard normal cdf. The price of the loan portfolio equals

$$P^L_{it}(\mathbf{s}_{it}) = \mathrm{E}^{\mathcal{P}}_t\left[M_{t,t+1}\pi^L_{i,t+1}(\varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1})\right]. \tag{11}$$

3.3 The Bank's Balance Sheet

Each bank i enters period t with loan portfolio $L_{i,t-1}$, deposits $D_{i,t-1}$, and book value of equity $BE_{i,t-1}$. 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 Π_{it} depends on the rates of return on the bank's assets r_{it}^L and liabilities (deposits) r^D, any non-interest income c_L, and operating expenses c_D, which captures overhead costs and the FDIC surcharge to fund deposit insurance:

$$\Pi_{it} = \left(r_{it}^L + c^L \right) L_{i,t-1} - \underbrace{\left(r^D + c^D \right)}_{\equiv \tilde{r}^D} D_{i,t-1}. \tag{12}$$

The bank chooses dividends Div_{it} and new loans L_{it}. 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 BE_{it}, which is equal to the equity at the beginning of the period t net of current dividends Div_{it} and adjustment costs Φ_{it}, plus current profit Π_t:

$$BE_{it} = BE_{it-1} - Div_{it} - \Phi_{it} + \Pi_{it}. \tag{13}$$

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

$$L_{it} = D_{it} + BE_{it}, \tag{14}$$

as well as a quadratic loan adjustment cost:

$$\Phi_{it} = \eta^L L_{i,t-1} \left(\frac{L_{it} - L_{i,t-1}}{L_{i,t-1}} \right)^2. \tag{15}$$

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

$$\frac{L_{it}}{BE_{it}} \leq \lambda. \tag{16}$$

Following Merton (1978), we assume $D_{it} = e^g D_{i,t-1}$; in other words, deposits grow at a constant rate g.[4]

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[4]We calibrate g to equal expected consumption growth:

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

3.4 Belief Distortions

Agents (both bank managers and investors) have distorted expectations about future loan performances. First, whereas the true processes of p_t and ω_{it} follow (3) and (8), agents perceive the processes to be:

$$\omega_{i,t+1} = \hat{\rho}_{1\omega}\omega_{it} + \hat{\rho}_{2\omega}\omega_{i,t-1} + \varepsilon_{\omega i,t+1}, \tag{17}$$

$$\log p_{t+1} = (1 - \hat{\rho}_{1p} - \hat{\rho}_{2p})\log\tilde{p} + \hat{\rho}_{1p}\log p_t + \hat{\rho}_{2p}\log p_{t-1} + \varepsilon_{p,t+1}. \tag{18}$$

This formulation is motivated by the empirical observation in Table 1: forecast errors are positively correlated up to a two-year lag. Secondly, while the true probability of $x_{t+1} = 1$ is p_t, the subjective probability of the occurrence of a disaster in $t+1$ depends on both p_t and p_{t-1}:

$$\text{Prob}^{\mathcal{P}}\left[x_{t+1} = 1\right] = p_t^{\chi} p_{t-1}^{1-\chi}. \tag{19}$$

As explained below (see Section 4), we calibrate the belief parameters $\{\hat{\rho}_{1p}, \hat{\rho}_{2p}, \hat{\rho}_{1\omega}, \hat{\rho}_{2\omega}, \chi\}$ to match the dynamics of bank forecast errors in Table 1.

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. Following Bolton et al. (2021), we adopt a reduced-form approach by choosing a proportional equity issuance cost:

$$\Lambda(Div_{it}) = \mathbb{1}_{Div_{it}<0}\eta^E Div_{it} \tag{20}$$

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:

$$N_{i,t+1} = BE_{it} + \left(r_{i,t+1}^L + c^L\right)L_{it} - \tilde{r}^D D_{it}. \tag{21}$$

Conditional on not defaulting at time t, bank managers solve the following continuation

problem:

$$V_i^C(L_{i,t-1}, D_{i,t-1}, N_{it}, \mathbf{s}_{it}) = \max_{Div_{it}, L_{it}} \left\{ Div_{it} + \Lambda(Div_{it}) + E_t^{\mathcal{P}} \left[M_{t,t+1} V_i(L_{it}, D_{it}, N_{i,t+1}, \mathbf{s}_{i,t+1}) \middle| \mathbf{s}_{it} \right] \right\},$$

(22)

subject to the return on risky loans (9), the current profit (12), the evolution of equity (13), the balance sheet constraint (14), asset adjustment costs (15), the capital requirement constraint (16), equity issuance costs (20), and the definition of $N_{i,t+1}$ (21). $E_t^{\mathcal{P}}(\cdot)$ captures the expectation formation process, which follows (17)-(19) with extrapolative beliefs. Limited liability implies that bank managers may choose an outside option V^D, which we normalize to zero, and the expected value in (22) is defined as the upper envelope:

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

(23)

Default happens if a bank's continuation value V^C falls below the threshold level V^D.[5]

A bank's states include last period's loan portfolio $L_{i,t-1}$, deposits $D_{i,t-1}$, the current net worth N_{it}, and exogenous states $\mathbf{s}_{it}$, which depend on the expectation formation process.[6] With rational expectations, $\mathbf{s}_{it}$ includes the persistent aggregate and idiosyncratic shocks $\mathbf{s}_{it} = [p_t, \omega_{it}]$; with overextrapolative expectations, $\mathbf{s}_{it}$ must also include last period's aggregate and idiosyncratic shocks, i.e. $\mathbf{s}_{it} = [p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1}]$.

4   Calibration

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

1. Model with rational expectations (RE): Agents believe that the aggregate shock p_t and idiosyncratic shock w_t follow (3) and (8), respectively, and that the probability of a disaster in $t+1$ is p_t.

2. Model with overextrapolative expectations (OE): Agents believe that p_t and w_t follow (18) and (17), and that the probability of a disaster in $t+1$ is (19).

There are two groups of parameters: the first group is exogenously calibrated; the second group is calibrated in a moment-matching exercise. We calibrate the model parameters

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[5]When a bank defaults, an identical bank is created with the same state variables, so we maintain a stationary distribution of banks.

[6]We simplify the computation of the problem by scaling the value of a bank by deposits. See Appendix A.1 for details.

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 overextrapolation, all shocks and distributional dynamics are determined according to their true processes, even though the asset prices and bank polices involve overextrapolative beliefs.

A list of the exogenously calibrated parameters are shown in Table 4. For most of them, we take their values from the literature, in order to facilitate comparison of models with and without belief distortions. More specifically, the values for β, μ_c and σ_c follow the standard values in the business cycle literature (e.g. Cooley and Prescott, 1995), while the values for ψ and γ 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 ξ to be 30%. For parameters governing the disaster probability process, we set ρ_p to be 0.8 and σ_p to be 0.42 (Gourio, 2012). For parameters governing the bank-specific shock process, we follow Gomes et al. (2019) and set ρ_ω to be 0.9 and σ_ω to be 0.02. 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 set to match the observed average recovery rate on loans. The regulatory capital requirement parameter λ is set to 12.5, corresponding to an 8% equity to asset ratio in accordance with the Basel rules. Lastly, we follow Bolton et al. (2021) and set the proportional equity issuance cost η^E to 5%.

The rest of the parameters are calibrated in a moment-matching exercise. All targeted moments are computed using our sample from Section 2, for the period 2005 and 2020. We calibrate the volatility of loan-specific shock σ_j and the asset adjustment cost parameter η^L to match the unconditional mean and the cross-sectional dispersion in bank leverage. Bank equity is defined as total bank assets minus total bank liabilities. Bank leverage is calculated as the sum of bank equity and liabilities to bank equity. The non-interest income parameter c^L and the cost of liabilities (including both interest expenses and operating expenses) $\tilde{r}^D$ are chosen to target the mean profit-to-equity ratio and the bank default rate.

Lastly, we calibrate the parameters governing distorted beliefs $\{\hat{\rho}_{1p}, \hat{\rho}_{2p}, \hat{\rho}_{1\omega}, \hat{\rho}_{2\omega}, \chi\}$ to match the dynamics of bank forecast errors in the data. We remain agnostic about whether it is more difficult to forecast aggregate or local conditions, and assume that banks have similar belief distortions when they are forecasting both the aggregate (p_{t+1}) and the local ($\omega_{i,t+1}$) conditions, i.e. $\hat{\rho}_{1p} = \hat{\rho}_{1\omega}$ and $\hat{\rho}_{2p} = \hat{\rho}_{2\omega}$. Moreover, we set $\chi = \frac{\hat{\rho}_{1p}}{\hat{\rho}_{1p} + \hat{\rho}_{1p}}$ and calibrate $\hat{\rho}_{1p}$ and $\hat{\rho}_{2p}$ to target the dynamics of bank forecast errors shown in Table 1. We measure bank forecast errors as the difference between the expected and the realized loan performance over the next year or two, and loan performance is defined as the loan

default rate.

We obtain model-implied moments by simulating 1,000 banks for 3,000 periods, discarding the first 300 observations. All shocks and distributional dynamics are determined according to the true process (i.e. the rational expectations representation), even though the asset prices and bank polices may involve distorted expectations. Table 5.A presents the targeted moments in each model.

5   Quantitative Results

5.1   Model Fit

Before using the model to study the impact of a credit crisis, we first examine the time-series statistical properties of the key variables on both bank performance and expectations. As we seek to explain the stylized facts in Figure 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. For untargeted moments, we examine their autocorrelations and correlations with the aggregate economic condition, both contemporaneously and with lags.[7]

Table 5.B reports the moments in each model. First, in the data, the annual loan *growth* is positively correlated with current and lagged GDP growth, and both the first and second order autocorrelations are positive. In the RE model, only the level of loans is positively correlated with lagged GDP growth and has a positive second order autocorrelation, but not the growth rate; in other words, the RE model does not generate enough persistence in the bank lending series that we observe in the data. As shown in the table, the OE model outperforms the RE model on the time-series statistics for loan growth rates.

Next, we turn to the annual change in expected loan performance, where loan performance is measured by loan defaults, so we look at the properties of changes in expected loan defaults. This is our main measure for bank expectations. These are highly counter-cyclical in the data: if the current GDP growth is low, banks' expected loan default rates increase at a faster rate. Moreover, if last year's GDP growth was low, banks' expectations today also worsen at a faster rate. While both models match the contemporaneous correlations with aggregate conditions, only the OE model can match the negative correlation with lagged GDP growth. In addition, the OE model also outperforms the RE model on

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[7]While the obvious candidate for measuring aggregate economic conditions is GDP growth, which is used to compute the data moments, we use one minus the disaster probability (i.e. the probability of not having a disaster in the next period) as a proxy for the aggregate condition.

the autocorrelations of bank expectations. Both AR(1) and AR(2) correlation coefficients are positive for changes in expectations in the data; in other words, bank expectations adjust slowly. We find positive correlations for the counterparts in the OE model, but they are counterfactually negative in the OE model.

We also examine the time-series properties of realized loan performance, or realized loan default rates. These have similar cyclical properties as the expected loan performance: changes in realized default rates are negatively correlated with current and one-year lagged GDP growth, but the autocorrelations are negative. Notably, both models generate the correct signs, and the magnitudes of coefficients are very similar in the two models. This is unsurprising since they only differ in terms of how expectations are computed, and loan default decisions depend on the true shock processes, which are drawn according to the RE representation in both models.

To examine the model prediction on asset prices, we look at changes in loan rates. The model counterparts are the changes in ex-post returns on loan portfolios r_{it}^L, which are affected by how expectations are computed, as shown in (9). In the data, changes in loan rates are positively correlated with GDP growth up to a two-year lag. In the RE model, the positive correlation only holds for contemporaneous GDP growth and not for either lag. The OE model outperforms the RE model on the cyclical properties, as changes in loan rates are also positively correlated with last year's aggregate conditions. Furthermore, the OE model generates positive first-order autocorrelation and negative second-order autocorrelation as shown in the data, whereas both autocorrelations are negative in the RE model.

Lastly, we compare the model-implied regression results with our findings in Tables 1 and 2. The RE model predicts that bank forecast errors follow an AR(1), with a strong reversal in expectations after one year: the coefficient estimate on the second lag is negative and strongly significant, contrary to the evidence. Moreover, forecast errors only predict loan growth for one year in the RE model, but the predictability remains positively significant beyond that in the data and the OE model.

Main Takeaways   The OE model outperforms the RE model on the time-series properties of key indicators of bank performance, expectations, and asset prices. Specifically, the OE model is successful on two fronts that the RE model fails at: one is the autocorrelations of both bank performance and expectation variables, and the other is their correlations with 1- and 2-year lagged aggregate economic conditions. The data counterparts indicate that banks exhibit strong sluggishness in adjusting their expectations, and therefore, performance. We show that the OE model can simultaneously account for both.

5.2 A Temporary Increase in Disaster Probability

The main experiment of the paper is an increase in disaster probability p_t. We mimic the financial crisis in 2008 and 2009 with two consecutive years of increase in disaster probability. Figures 3 and 4 present the impulse response functions of bank variables when the probability of disaster increases from the long-run average of 2.61 percent per year to 4.03 percent and 8.11 percent, respectively. Then the probability of disaster mean-reverts to its long-run average according to equation (3).

Impact on Bank Lending Figure 3 shows that an increase in disaster risk leads to a credit crisis. To inspect the mechanism, we plot the policy functions in Figures A.7–A.9. 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 (see Figure A.7). This is because as at a higher p_t, investment in assets becomes less profitable, as shown in Panel B of Figure A.6. Secondly, lending is increasing in the current net worth of a bank (n_{it}). 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 profits take a hit and hence their net worth decreases. Since external financing (both debt and equity) is costly for banks, they decrease their loan portfolios in response to a reduction in net worth.

The key difference between the two models is that the OE model generates a much slower recovery than the RE model. There is some persistence in banks' asset growth in the RE model, but, for realistic parameter values, this is not sufficient to match the slow credit growth after the crisis. The persistence in the RE model comes from two sources: asset growth is costly and the net worth takes time to build. Nonetheless, 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, it takes seven years for the loan growth rate to recover in the OE model, which resembles the slow recovery in the data, as the annual growth rate only returned to the pre-crisis level after 2014.

There is additional persistence in the OE model because lending is not only decreasing in P_t, but also in P_{t-1}, so even when the disaster probability starts to revert back to the long-run mean in $t = 3$, banks' lending decisions respond with a lag. Moreover, realized loan return increases more slowly in the OE model than in the RE model, as disaster probability returns to the steady state level (see Figure A.8). As both lending and realized loan return recover more slowly, banks' current profit and hence 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 decreases. As we illustrate in Panel B of Figure A.9, the slope of the policy function is flatter for banks with low net worth, at each level of P_t. In particular, when P_{t-1} is high, the capital requirement only becomes non-binding when P_t falls to the lowest possible level (see the blue line in the bottom right corner of Figure A.9). Intuitively, since external financing is costly and banks want to avoid default, banks are more cautious about lending risky loans when their net worth is low and the disaster probability in the last period was high. As a result, we get a hump-shaped impulse response function for the loan growth rate in the OE model, which more closely resembles the data (Panel (c) of Figure 2).

It is worth noting that the OE model generates a milder decline in lending upon impact of the shock to disaster probability. This is because lending at the (stochastic) steady state is lower in the OE economy than in the RE economy, which means that the capital requirement constraint becomes binding more quickly as banks reduce their loan portfolios. Hence, on average, aggregate lending falls by less in percentage deviation terms in the OE model.

Impact on Bank Expectations   Figure 4 shows the evolution of beliefs during and after a credit crisis. For each model, we plot the net fraction of banks that expect a worsening of loan performance and forecast errors, respectively, following two consecutive years of shocks to disaster probability in 2008 and 2009. To facilitate comparison, we construct these variables as closely as possible to the data definition. In Panel (a), the net fraction of banks that expect 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. In Panel (b), forecast errors are the difference between the expected and the actual change in loan performance, so positive forecast errors indicate that banks are over-optimistic (or the expected loan default rate is lower than the actual default rate) while negative forecast errors indicate that banks are over-pessimistic. We compute forecast errors for each bank over time, and average them across banks for each year.

Following the positive shocks to disaster probability in 2008-9, more banks expect loan performance to worsen than to improve in both models, i.e. the net fraction in Panel (a) becomes positive. However, in the post-crisis period, bank expectations follow the data more closely in the OE model. While it starts declining in 2010 in the RE model as the disaster probability begins to revert to the long-run mean, it rises further in the OE model and matches the data almost exactly in 2010-11. In the data, it is not until 2014 – seven years after 2008 – for bank expectations to be "neutral", i.e. to have the same number of banks to expect worsening and improvement. The OE model matches this fact, whereas in the RE model, more banks start to expect improvement than worsening

from 2012.

Turning to forecast errors, the main difference between the two models occurs in the post-crisis period (see Panel (b) of Figure 4). In the RE model, banks' forecast errors remain above zero between 2007 and 2011. By contrast, in the data, banks turn pessimistic (with forecast errors below zero) from 2009 and remain as such until 2018. In the RE model, banks' expectations of loan defaults fall more quickly than the actual default rates, as the disaster probability starts to revert back after 2009. In the OE model, expectations are more "sticky", i.e. banks continue to over-predict the loan default rate after 2009. The OE model closely matches the data on forecast errors from 2008 to 2018.

Bottom Line We model the 2008-09 financial crisis as two consecutive positive shocks to the disaster probability. In terms of matching the post-crisis dynamics, the OE outperforms the RE model on two fronts. First, it generates a much slower recovery in the level of lending and hence a hump-shaped response in the loan growth rate. Secondly, the belief process backed out from the OE model follows the data much more closely than the RE model: banks remain persistently pessimistic long after 2009.

5.3 Beliefs as AR(2) Processes

In the model, agents perceive the processes of p_t and ω_{it} to be AR(2) processes (equations 17 and 18), while the true processes follow AR(1). This modeling choice is motivated by the empirical evidence in Table 1, as we calibrate the belief parameters to match the dynamics of forecast errors in the data.

As a result, agents over-extrapolate, and this generates significantly more persistence in the model compared to the rational expectations counterpart due to a combination of two forces. First, lending is not only decreasing in the current disaster probability, but also last period's probability, so even when the disaster probability starts to revert back to the long-run mean, bank lending continues to decline. Second, with over-extrapolative beliefs, the realized loan return increases more slowly as disaster probability decreases. Since both lending and realized loan return recover more slowly, banks' current profit and hence net worth also recover more slowly. This in turn exacerbates the slow recovery in lending, which is a function of net worth.

Now we ask the question: What if we model agents' over-extrapolative beliefs as an AR(1) process, where the perceived degree of persistence is higher than the actual persistence? To this end, we perform the following counterfactual exercise. While the

true processes of p_t and ω_{it} continue to be (3) and (8), we let agents' beliefs follow:

$$\omega_{i,t+1} = \tilde{\rho}_\omega \omega_{it} + \varepsilon_{\omega i,t+1},$$
$$\log p_{t+1} = (1 - \tilde{\rho}_p) \log \tilde{p} + \tilde{\rho}_p \log p_t + \varepsilon_{p,t+1}.$$

With over-extrapolation, $\tilde{\rho}_\omega > \rho_\omega$ and $\tilde{\rho}_p > \rho_p$. To maintain comparability with the AR(2) specification in the baseline model, we set $\tilde{\rho}_\omega = \hat{\rho}_{1\omega} \omega_{it} + \hat{\rho}_{2\omega} \omega_{it}$ and $\tilde{\rho}_p = \hat{\rho}_{1p} + \hat{\rho}_{2p}$ in the counterfactual. In Figure A.2, we compare the impulse response functions to an increase in disaster probability under RE and two OE models: one with AR(2) (baseline) and one with AR(1) (counterfactual).

To understand the difference between the two OE specifications, let $P_t \equiv \log p_t$ and rewrite the belief process (18) as follows:

$$\begin{aligned} P_{t+1} &= (1 - \hat{\rho}_{1p} - \hat{\rho}_{2p})\tilde{P} + \hat{\rho}_{1p}P_t + \hat{\rho}_{2p}P_{t-1} + \varepsilon_{p,t+1} \\ &= (1 - \hat{\rho}_{1p} - \hat{\rho}_{2p})\tilde{P} + (\hat{\rho}_{1p} + \hat{\rho}_{2p})P_t - \hat{\rho}_{2p}\Delta P_t + \varepsilon_{p,t+1} \\ &= (1 - \tilde{\rho}_p)\tilde{P} + \tilde{\rho}_p P_t \underbrace{- \hat{\rho}_{2p}\Delta P_t}_{\text{momentum}} + \varepsilon_{p,t+1} \end{aligned}$$

The first term is the same as the AR(1) process above. The second term represents where the economy has been – in other words, whether the economy is in a recovery phase (with $\Delta P_t < 0$) or heading into a recession (with $\Delta P_t > 0$) – and it is the key difference between an AR(2) belief process and a corresponding AR(1) with $\tilde{\rho}_p = \hat{\rho}_{1p} + \hat{\rho}_{2p}$.

Figure 1 illustrates the role of momentum in agents' expectations of future disaster probability when $\hat{\rho}_{2p} > 0$, which is the case in our calibration disciplined by the forecast error dynamics. The key observation is that if beliefs follow an AR(1), only the current state of the economy (P_t) matters for expectation formation, regardless of whether beliefs are rational or over-extrapolative. However, the current state of the economy does not tell us where the economy has been, which is captured by ΔP_t. As a result, an AR(1) specification of agents beliefs does not capture the asymmetry illustrated in Figure 1: As the economy recovers from a crisis ($\Delta P_t < 0$), agents with AR(2) beliefs are more likely to be *more pessimistic* about the state of the economy next year than agents with over-extrapolative AR(1) beliefs; by contrast, if the economy is at the end of a boom or the beginning of a crisis ($\Delta P_t > 0$), agents are more likely to be *more optimistic* under AR(2).

The impulse response functions in Figure A.2 confirm the intuition above. When the economy is disturbed by an unexpected increase in disaster probability, the decline in lending is milder at the beginning but the recovery is slower in the OE-AR(2) model than the OE-AR(1) model (see Figure A.2). At the beginning of a crisis, since $\Delta P_t > 0$, agents

Figure 1: Role of Momentum in Expectations of Disaster Probability

$\Delta P_t > 0$ $\Delta P_t < 0$

$\tilde{\rho}P_t - \hat{\rho}_{2p}\Delta P_t$

$\tilde{\rho}P_t$ $\tilde{\rho}P_t$

$\tilde{\rho}P_t - \hat{\rho}_{2p}\Delta P_t$
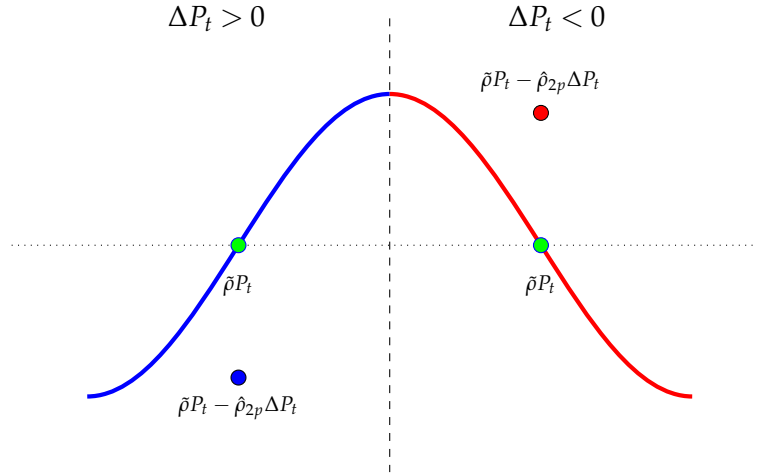
● Over-extrapolation of P_{t+1} under AR(1)

● Over-expectation of P_{t+1} under AR(2), with $\Delta P_t > 0$ and $\hat{\rho}_{2p} > 0$

● Over-expectation of P_{t+1} under AR(2), with $\Delta P_t < 0$ and $\hat{\rho}_{2p} > 0$

with AR(2) expectations under predict the probability of disaster in the forthcoming year. On the other hand, when disaster probability starts declining, agents with AR(2) expectations over-predict the probability of disaster in the forthcoming year. Quantitatively, the degree of persistence in the OE-AR(1) model is not sufficient to match the slow lending recovery in the data post-2009. Specifically, the OE-AR(1) model does not generate a "hump-shape" in the loan growth rate, or match the banks' expectations of loan performance after 2009.

Although the focus of the paper is on the post-crisis period, we also examine the model predictions during a boom, which is modeled as a temporary decrease in disaster probability. In the face of an unexpected decrease in disaster probability (see Figure A.3), the increase in lending is milder immediately after the shock in the OE-AR(2) model than in the OE-AR(1) since $\Delta P_t < 0$. However, the lending boom continues well after the shock is over in the OE-AR(2) model as agents are over-optimistic when at the end of a boom when disaster probability starts to increase ($\Delta P_t > 0$).[8]

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[8]The asymmetry is that a negative disaster probability generates a larger boom, whereas a positive disaster probability generates a milder recession in the OE-AR(2) model compared to the OE-AR(1) model. This is because the capital requirement constraint becomes binding more quickly in the OE-AR(2) model, which has a lower stochastic steady state for lending.

5.4 Bank Heterogeneity

Figure 5 presents the impulse response functions from the OE model by bank size: small banks are those whose asset-to-deposit ratios (l_{it}) are below the sample median before the crisis (i.e. before the increase in disaster probability), while large banks are those with total assets above the median. All banks are subject to the same sequential shocks as in Figure 3.[9] The main takeaway from Figure 5 is that disaster probability shocks have a deeper and longer-lasting impact on larger banks' lending decisions.

In order to understand the different responses, we first examine loan returns for small and large banks, respectively. It turns out that the decline in realized return is quantitatively similar for the two groups, and slightly greater for smaller banks (see the bottom right panel of Figure 5). However, small banks are much closer to the capital requirement constraint than large banks. As shown in the top panel of Figure A.9.C, the lending decision for banks with low l_{t-1} quickly becomes flat at the level at which the capital requirement constraint binds, as disaster probability increases.

For banks with high l_{t-1}, there is some asymmetry. Focusing on the policy function between $P_t = 0.02$ and $P_t = 0.0549$ in the top panel of Figure A.9.C, we see that the slope for the pink solid line on is steeper on the left (i.e. when P_{t-1} is low) than on the right (when P_{t-1} is high). In other words, for large banks, optimal lending falls steeply during the crisis when P_t unexpected increases from the stochastic steady state level, and rises slowly after the crisis. Intuitively, the rate at which banks change their lending policies depends on the asset adjustment cost and their risk-taking incentives. If they believe that a disaster is coming, their primary concern is to reduce risk-taking in order to avoid shutting down. If they believe that the probability of disaster is diminishing, the benefit of adjusting assets gradually over time outweighs the benefit of rebuilding their loan portfolios quickly.

5.5 A Disaster Realization

Figure 6 illustrates the response of the economy to a typical disaster that lasts for two years ($x_t = 1$ for $t = 0, 1$), with the realizations of p_t and ω_{it} equal to the mean of their distributions. In both economies, ex-post returns on loan portfolios (r_t^L) fall significantly – and slightly more in the OE model – during the disaster years, and recover when each economy exits the disaster state. Aggregate lending, bank value and current net worth fall in both economies. More specifically, in the OE economy, lending falls by less but

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[9]In our simulations, all banks have the same belief process (17)-(18), and have the same values for $\{\hat{\rho}_{1p}, \hat{\rho}_{2p}, \hat{\rho}_{1\omega}, \hat{\rho}_{2\omega}, \chi\}$. Assigning a greater degree of over-extrapolation to large banks as observed in the data would amplify the difference between small and large banks in Figure 5.

takes much longer to recover; bank value and current net worth fall by a greater extent and also take longer to recover than in the RE economy.

Since the disaster realization is not a state variable, the current net worth of banks n_{it} plays an important role in the propagation of a realized disaster. Recall that the current net worth includes banks' beginning-of-period equity and the current net profit. When the returns on loan portfolios fall, banks' current profits take a hit and hence their net worth decreases. Since external financing is costly, banks decrease their loan portfolios in response to a reduction in net worth. As a result, both the current and future values of a bank decrease. Due to the asset adjustment cost, lending gradually reverts back to the steady state when the disaster is over.

As explained above, the capital requirement constraint becomes binding more quickly in the OE economy, which has a lower stochastic steady state level of lending. Thus, lending decreases by less in terms of percentage deviation from the steady state in the OE model. Moreover, the optimal lending policy is less responsive to changes in bank net worth in the OE economy, especially if the disaster probability was high in the last period (see Appendix A.9).[10] As a result, in the OE model, lending falls by less upon impact of a disaster, but also takes much longer to return to the stochastic steady state, and the loan growth rate exhibits a hump-shape recovery.

6 Policy Evaluation

In this section, we conduct two policy experiments in turn: first, we increase the minimum equity to asset ratio from 8% ($\lambda = 12.5$) to 10% ($\lambda = 10$); secondly, we examine the impact of quantitative easing by considering the effects of an increase in the discount factor β.

6.1 Tighter Capital Adequacy Requirements

In this experiment, we solve the two models again, but this time we set $\lambda = 10$, which corresponds to a minimum equity-to-asset ratio of 10%. Then we compute the impulse response functions to an increase in disaster probability under the baseline scenario (with a minimum equity-to-asset ratio of 8%) with those in the policy experiment. In doing so, we ask the following question: If banks face tighter capital adequacy requirements in normal times, how does this affect the variables of interest in a crisis?

We first examine the stochastic steady state. Higher capital adequacy requirements increase the overall loan portfolio a_{it} in both models' steady states, with a higher a_{it} cor-

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[10]This is also the case if we set the same asset adjustment cost η^B in the two models.

responding to a lower leverage. Banks respond to tighter capital requirements by accumulating more equity, and quantitatively, such incentives are stronger in the OE model. In the (stochastic) steady state, book equity (scaled by deposits) be_{it} increases by 23% in the OE model, and by 10% in the RE model; similarly, current net worth (scaled by deposits) n_{it} increases by 24% in the OE model, and by 9% in the RE model.

If agents are rational (Panel A), tighter capital requirements can, to some extent, mitigate the adverse impact of a disaster risk: lending and current net worth fall by less than the baseline, though the mitigating effect on bank values is more limited. However, in the OE model (Panel B), a higher minimum equity-to-asset ratio has little impact on the dynamic impact of a disaster risk: the impulse responses for lending and bank value are similar to those in the baseline, though net worth falls by less compared to the baseline.

Overall, the model suggests that tighter capital requirements raise aggregate lending and bank values in normal times, but if the disaster risk increases unexpectedly, its stabilization role is limited in the presence of belief distortions.

6.2   Quantitative Easing

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 model to examine the effectiveness of this policy tool during and after a crisis in the presence of belief distortions. Formally, for the first 2,979 periods in our simulation, we use the $\tilde{r}^D$ specified in Table 4. Then from $t = 2,980$ (i.e. when the disaster risk increases unexpectedly and thereafter), we lower $\tilde{r}^D$ by 10 basis points in each model.

In our model, this policy affects the shock propagation through the accumulation of banks' net worth n_{it}, which is a function of $\tilde{r}^D$. If banks face a lower cost of debt through government interventions, their profits fall by less during the crisis; hence their net worth also falls by less and recovers faster when shocks are over. As shown in Figure 8, this is true in both RE and OE models. Bank values also fall by less, and as a result, bank default rates are lower in the presence of policy interventions.

By subsidizing bank equity holders, these policies have some positive effects on bank lending: in the RE model, lending falls by 15 percent less and recovers more quickly with QE (Panel A). However, the effect is much milder in the OE model (Panel B). As shown in Appendix A.9, lending policies are less responsive to changes in bank net worth in the OE economy, especially when last period's disaster probability P_{t-1} was high. In other words, the success of unconventional monetary policies in stimulating bank credit to the private sector after a financial crisis may be limited in the presence of belief distortions.

7 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 significant persistence in forecast errors, suggesting that banks process information inefficiently. Moreover, we find that over-pessimistic banks are more likely to cut their lending in the future. The behavioral bias is stronger for large banks, whose loan portfolios are also more sensitive to beliefs. 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, our policy counterfactuals suggest that biased beliefs dampen the effectiveness of stimulative policies.

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Table 1: Dynamics of Bank Forecast Errors

Panel A of this table summarizes results of time-series regressions of bank expectation errors:

$$R_{it}^{FE} = \alpha + \sum_{k=1}^{K} \beta_k R_{it-k}^{FE} + \sum_{k=1}^{K} g_k X_{it-k} + \tau_t + u_{it}$$

We measure bank expectation errors, R_{it}^{FE}, as the difference between the expected and the actual change in loan performance over the next year at time t. We include loan performance in the control set, X_{it-k}. Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). In Panel A, the number of lags is 1-, 2-, and 3-years. For reference, in Columns 4-6 we report results for repeating the analysis for actual loan performance. 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					
	Forecast Errors			Loan Performance		
	k=1 year	k=2 year	k=3 year	k=1 year	k=2 year	k=3 year
	(1)	(2)	(3)	(4)	(5)	(6)
β_k	0.233***	0.153***	0.024	0.064	-0.070**	-0.086***
[t]	[5.57]	[4.33]	[0.68]	[0.70]	[-2.16]	[-3.36]
Time FE		Yes			Yes	
R^2		0.59			0.42	

Table 2: Bank Expectations and Lending Dynamics

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

$$\Delta Loans_{it} = \alpha + \sum_{k=1}^{K} \beta_k R^{FE}_{it-k} + \sum_{k=1}^{K} g_k X_{it-k} + \tau_t + u_{it-1}$$

We measure the change in bank loans, $\Delta Loans_{it}$, as the logarithmic change of total bank loans relative to pre-crisis, and bank expectation errors, R^{FE}_{it}, as the difference between the expected and the actual change in loan performance over the next year at time t. We include loan performance in the control set, X_{it-k}. Information on bank expectations is from the Senior Loan Officer Opinion Survey (SLOOS). In Panel A, the number of lags is 1-, 2-, and 3-years. 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					
	Forecast Errors			Loan Performance		
	k=1 year	k=2 year	k=3 year	k=1 year	k=2 year	k=3 year
	(1)	(2)	(3)	(4)	(5)	(6)
β_k	-0.071	0.239***	0.048			
[t]	[-0.52]	[2.96]	[0.55]			
g_k				-0.161	-0.199***	-0.170**
[t]				[-0.89]	[-2.49]	[-3.03]
Time FE			Yes			
N			1,702			
R^2			0.14			

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Table 3: Heterogeneity and Analysis by Loan Type

This table repeats the analysis of Table 2 by sub-sample based on bank size (Panel A) and by sub-groups of loan types (Panels B-C). In Panel A, we split the sample into two groups of banks, small and large based on the bottom and top quartiles of bank total loans respectively. We report the estimates for repeating the analysis of lending dynamics of Table 2 separately for each of the two size sub-samples, in turn. In Panels B-C, we repeat the analysis of Table 2 separately for each loan type regressed on its respective forecast error as well as on the (average) forecast error for other loan types, 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.

	Panel A: Bank Expectations and Lending Dynamics by Bank Size					
	Small Banks			Large Banks		
	k=1 year	k=2 year	k=3 year	k=1 year	k=2 year	k=3 year
	(1)	(2)	(3)	(4)	(5)	(6)
β_k	0.021	0.258*	-0.079	0.246	0.313**	0.121
[t]	[0.15]	[1.81]	[-0.86]	[1.46]	[2.36]	[0.82]
	Panel B: Bank Expectations and Lending Dynamics by Loan Type					
	C&I Loans			RRE Loans		
	k=1 year	k=2 year	k=3 year	k=1 year	k=2 year	k=3 year
	(1)	(2)	(3)	(4)	(5)	(6)
β_k^{own}	0.023	0.025*	0.032	-0.021	0.092**	-0.045
[t]	[1.48]	[1.88]	[1.52]	[-0.30]	[2.37]	[-0.39]
β_k^{other}	0.021	0.015	0.021	0.050	0.036	0.037
[t]	[0.89]	[0.64]	[1.17]	[0.35]	[0.50]	[0.39]
	Panel C: Bank Expectations and Lending Dynamics by Loan Type					
	CRE Loans			Consumer Loans		
	k=1 year	k=2 year	k=3 year	k=1 year	k=2 year	k=3 year
	(1)	(2)	(3)	(4)	(5)	(6)
β_k^{own}	0.091	0.111*	0.121	-0.212	0.005	0.125
[t]	[1.47]	[2.59]	[1.40]	[-1.25]	[0.03]	[-0.65]
β_k^{other}	-0.121	0.065	-0.010	0.042	0.215	0.142
[t]	[1.27]	[0.83]	[-0.14]	[0.29]	[1.40]	[1.15]

Table 4: Parameterization

A. Exogenous calibration

Parameter	Description	Value
β	Rate of time preference	0.987
ψ	Elasticity of intertemporal substitution	2
γ	Relative risk aversion	3
$\bar{p}$	Average probability of crisis	0.02
σ_p	Volatility of crisis probability	0.42
ρ_p	Persistence in crisis probability	0.80
σ_ω	Volatility of bank-specific shock	0.02
ρ_ω	Persistence in bank-specific shock	0.90
ξ	Impact of crisis on endowment	$\log(1-0.3)$
μ_c	Mean growth in consumption (normal times)	0.01
σ_c	Volatility of aggregate shock (normal times)	0.015
$\mathscr{L}$	Loss given default on loans	0.40
κ	Loan-to-value ratio	0.66
λ	Capital requirement	12.5
η^E	Equity issuance cost	0.05

B. Moment-matching exercise

Parameter	Description	OE	RE
σ_j	Volatility of loan-specific shock	0.09	0.1
η^L	Asset adjustment cost	0.51	0.5
c^L	Non-interest income	0.005	0.006
$\tilde{r}^D$	Interest & operating expenses	0.0066	0.0073
$\hat{\rho}_{1p}$	Overextrapolation of crisis probability	0.329	–
$\hat{\rho}_{2p}$	Overextrapolation of crisis probability	0.613	–
$\hat{\rho}_{1\omega}$	Overextrapolation of bank-specific shock	0.329	–
$\hat{\rho}_{2\omega}$	Overextrapolation of bank-specific shock	0.613	–
χ	Weight of p_t in subjective probability of disaster	0.349	–

Note: The model is calibrated at annual frequency. "$-$" indicates that the parameter is absent in the model.

Table 5: Moments

A. Targeted moments

Description	Data	OE	RE
Leverage (mean)	8.50	8.72	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
Dynamics of bank forecast errors			
1-year	0.233	0.243	—
2-year	0.153	0.169	—

Note: The model is calibrated at annual frequency.

Description	Data	OE	RE
Annual loan growth (Δl_t)			
Std dev	0.019	0.018	0.014
Corr(Δl_t, ΔGDP$_t$)	0.134	0.219	0.327
Corr(Δl_t, ΔGDP$_{t-1}$)	0.239	0.135	-0.015
Corr(Δl_t, ΔGDP$_{t-2}$)	0.218	0.056	-0.136
Corr(Δl_t, Δl_{t-1})	0.207	0.597	0.123
Corr(Δl_t, Δl_{t-2})	0.118	0.160	-0.036
Annual change in expected loan performance (ΔE$_t$[LoanDefault$_{t+1}$])			
Corr$\left(\Delta$E$_t$[LoanDefault$_{t+1}$], ΔGDP$_t\right)$	-0.354	-0.225	-0.192
Corr(ΔE$_t$[LoanDefault$_{t+1}$], ΔGDP$_{t-1}$)	-0.023	-0.077	0.192
Corr(ΔE$_t$[LoanDefault$_{t+1}$], ΔGDP$_{t-2}$)	0.295	0.230	0.134
Corr$\left(\Delta$E$_t$[LoanDefault$_{t+1}$], ΔE$_{t-1}$[LoanDefault$_t$]$\right)$	0.465	0.197	-0.152
Corr$\left(\Delta$E$_t$[LoanDefault$_{t+1}$], ΔE$_{t-2}$[LoanDefault$_{t-1}$]$\right)$	0.153	0.082	-0.094
Annual change in realized loan performance (ΔLoanDefault$_{t+1}$)			
Corr$\left(\Delta$LoanDefault$_{t+1}$, ΔGDP$_t\right)$	-0.110	-0.013	-0.011
Corr(ΔLoanDefault$_{t+1}$, ΔGDP$_{t-1}$)	-0.064	-0.015	-0.015
Corr(ΔLoanDefault$_{t+1}$, ΔGDP$_{t-2}$)	0.023	0.017	0.016
Corr$\left(\Delta$LoanDefault$_{t+1}$, ΔLoanDefault$_t\right)$	-0.195	-0.499	-0.499
Corr$\left(\Delta$LoanDefault$_{t+1}$, ΔLoanDefault$_{t-1}\right)$	-0.083	-0.010	-0.009
Annual loan rate growth			
Corr(ΔE$_t$[r^L_{t+1}], ΔGDP$_t$)	0.075	0.375	0.306
Corr(ΔE$_t$[r^L_{t+1}], ΔGDP$_{t-1}$)	0.071	0.110	-0.301
Corr(ΔE$_t$[r^L_{t+1}], ΔGDP$_{t-2}$)	0.022	0.009	-0.270
Corr(ΔE$_t$[r^L_{t+1}], ΔE$_{t-1}$[r^L_t])	0.017	0.177	-0.141
Corr(ΔE$_t$[r^L_{t+1}], ΔE$_{t-2}$[r^L_{t-1}])	-0.013	-0.072	-0.109
Post crisis dynamics: years taken for the recovery of the following variables			
Net fraction of banks experience worsening	3	5	5
Net fraction of banks expect worsening	8	8	5
Loan growth	7	7	3

Note: The model is calibrated at annual frequency.

Table 6: Dynamics of Bank Expectations and Lending in the Model

Panel A of this table summarizes results of time-series regressions of bank expectation errors:

$$R_{it}^{FE} = \alpha + \sum_{k=1}^{K} \beta_k R_{it-k}^{FE} + \sum_{k=1}^{K} g_k X_{it-k} + \tau_t + u_{it}$$

We measure bank expectation errors, R_{it}^{FE}, as the difference between the expected and the actual change in loan performance over the next year at time t. Panel B summarizes results of bank-level regressions of bank loans on bank expectations of loan perfornance:

$$\Delta Loans_{it} = \alpha + \sum_{k=1}^{K} \beta_k R_{it-k}^{FE} + \sum_{k=1}^{K} g_k X_{it-k} + \tau_t + u_{it-1}$$

We measure the change in bank loans, $\Delta Loans_{it}$, as the logarithmic change of total bank loans relative to pre-crisis, and We include loan performance in the control set, X_{it-k}. The number of lags is 1- and 2-years. t-statistics are based on standard errors clustered at the bank level, with ***, **, and * denoting significance at the 1%, 5%, and 10% level, respectively.

A. Dynamics of Bank Expectation Errors

	RE Model		OE Model	
	k=1 year	k=2 year	k=1 year	k=2 year
	(1)	(2)	(3)	(4)
β_k	0.920***	−0.599**	0.243**	0.169*
[t]	[3.64]	[−2.53]	[2.42]	[2.16]
Time FE	Yes		Yes	
R^2	0.78		0.80	

B. Bank Expectations and Lending Dynamics

	RE Model		OE Model	
	k=1 year	k=2 year	k=1 year	k=2 year
	(1)	(2)	(3)	(4)
β_k	0.417**	−0.082	0.218**	0.187*
[t]	[2.45]	[−0.43]	[2.79]	[2.10]
Time FE	Yes		Yes	
R^2	0.56		0.52	

Figure 2: Stylized Facts from Bank-Level Data

(a) Net fraction of banks that experience an **actual** worsening of loan performance
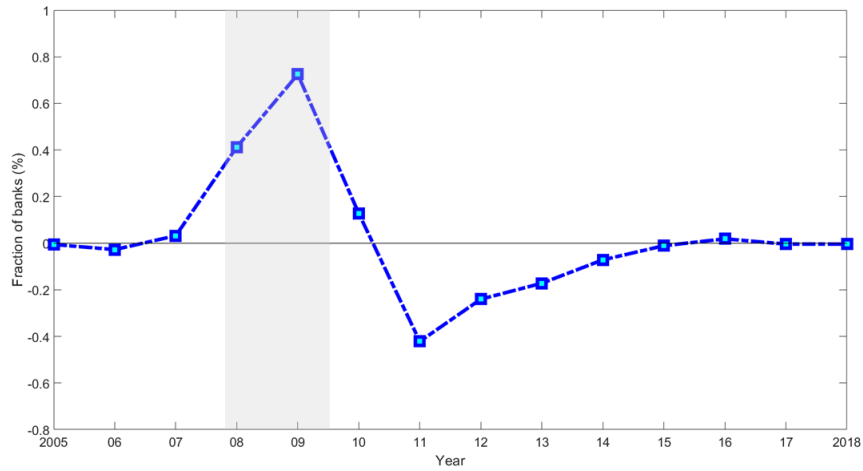
(b) Net fraction of banks that **expect** a worsening of loan performance
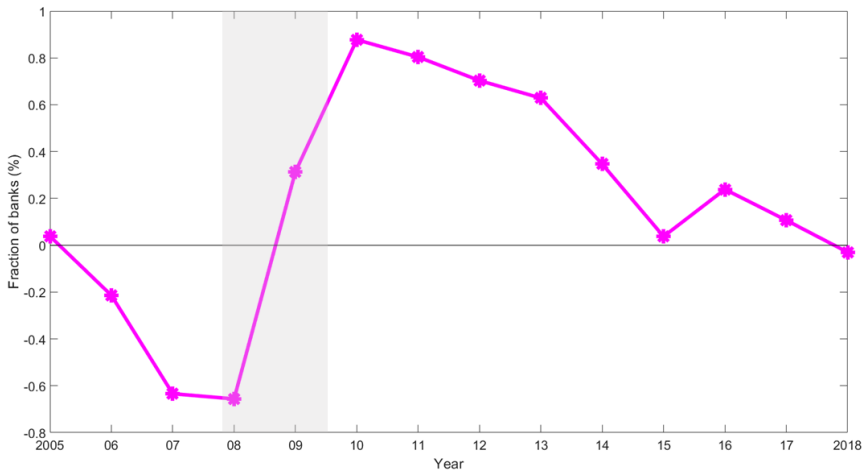
(c) Annual loan growth
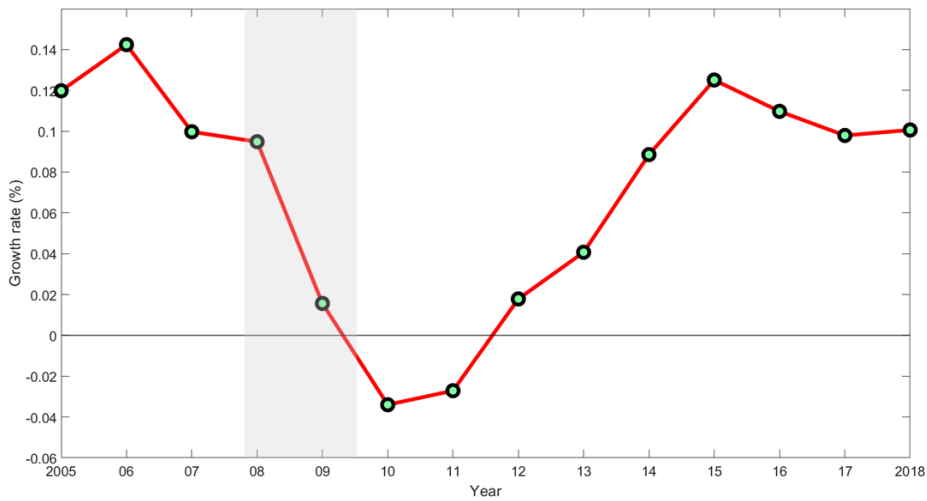

Note: Panel A plots the net fraction of banks that experience an actual worsening of loan performance: it is the number of banks that experience worsening (defined by an increase in expected the loan default rate) minus the number of banks that experience improving, divided by the total number of banks. Panel (b) demonstrates the net fraction of banks that expect a worsening of loan performance. Panel C shows the actual loan growth (aggregated across banks). The shaded area indicates the NBER recession dates.

Figure 3: Impulse Response Functions to A Temporary Increase in Disaster Probability
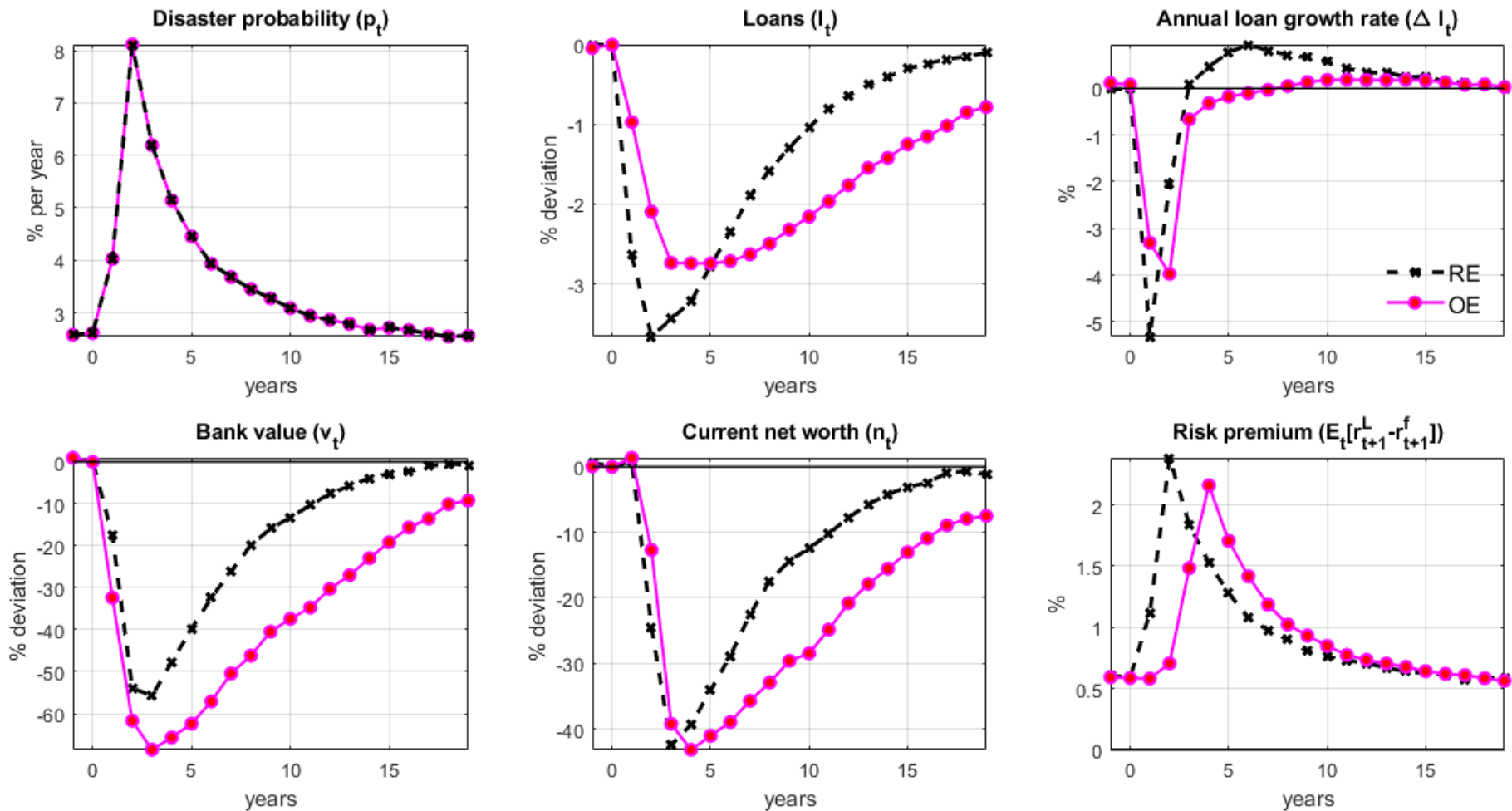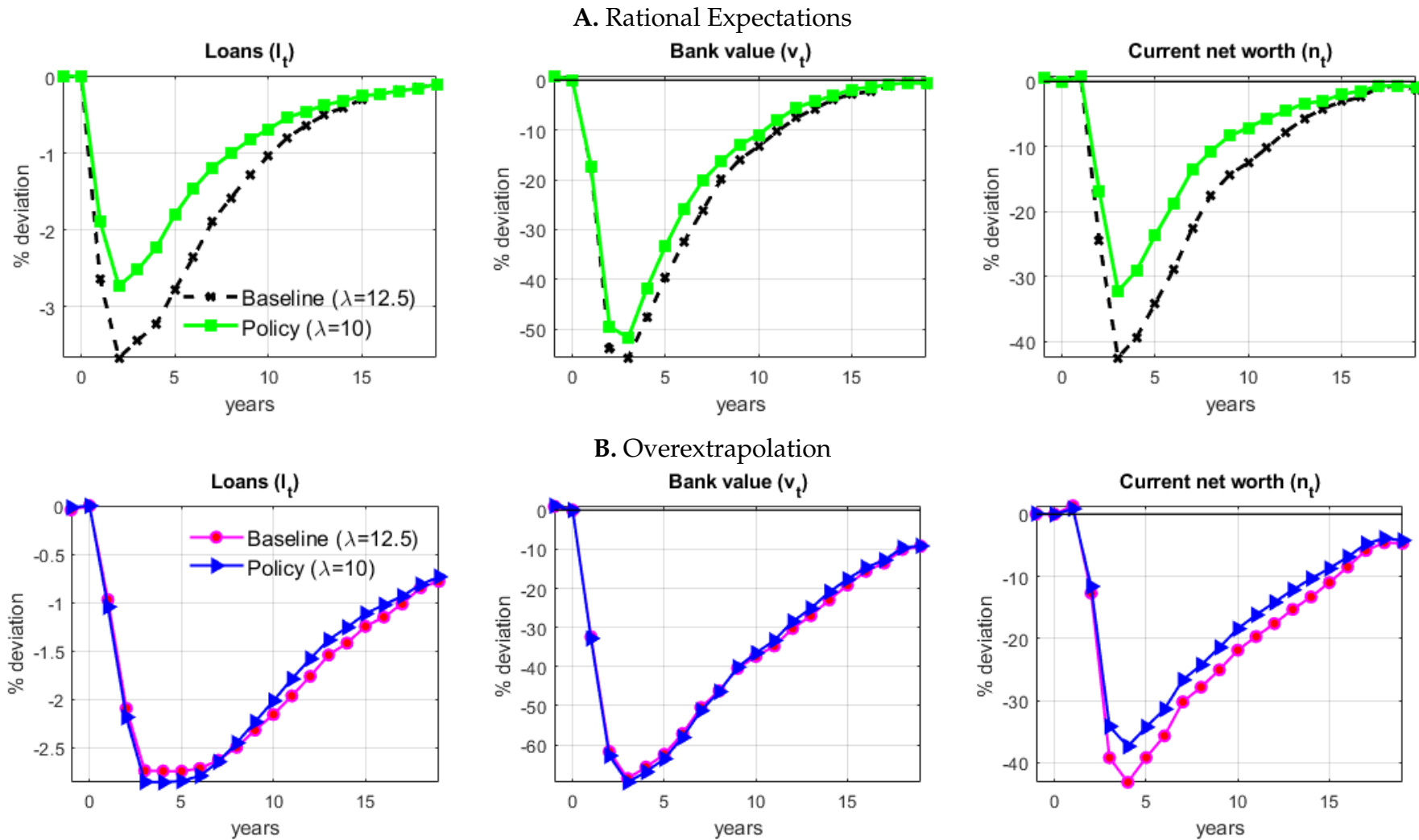

Note: The figure shows the response to a temporary increase in the annual disaster probability. We simulate the model for 3,000 years, and at $t = 2,980$ and $t = 2,981$ we perturb the model with two consecutive shocks to the probability of disaster. We repeat the procedure 1,000 times and calculate the average across simulations. All shocks and distributional dynamics are determined according to the true process (i.e. the rational expectations representation), even though the asset prices and bank polices may involve distorted expectations. OE: Overextrapolation. RE: Rational expectation.

Figure 4: Belief Process: Data vs. Model

(a) Net fraction of banks that expect a worsening of loan performance
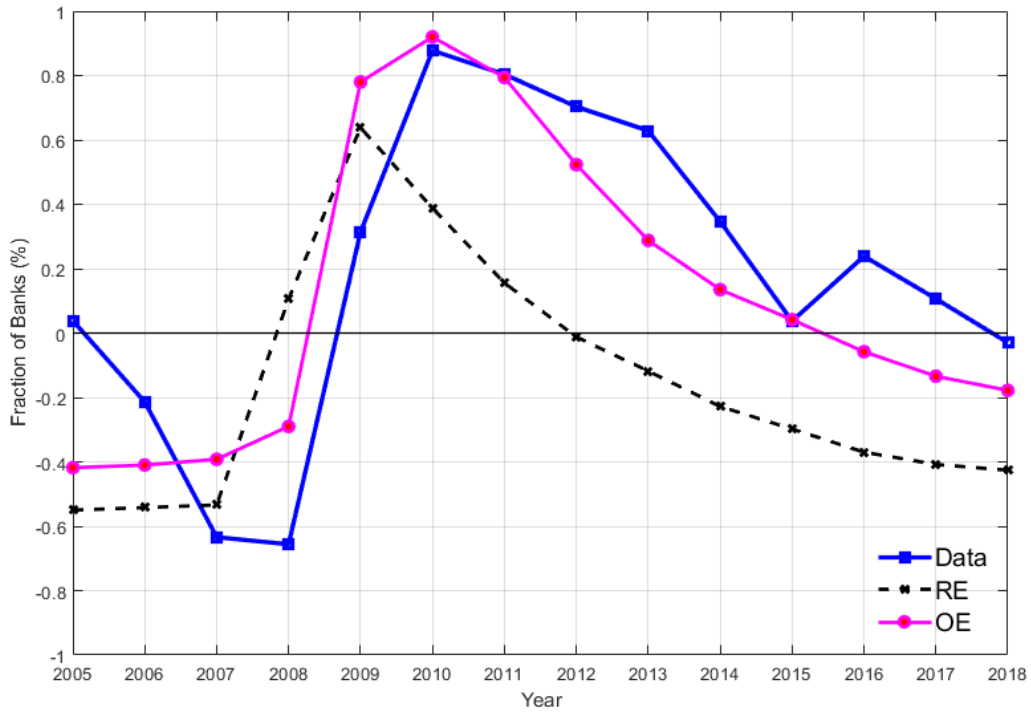
(b) Forecast Errors
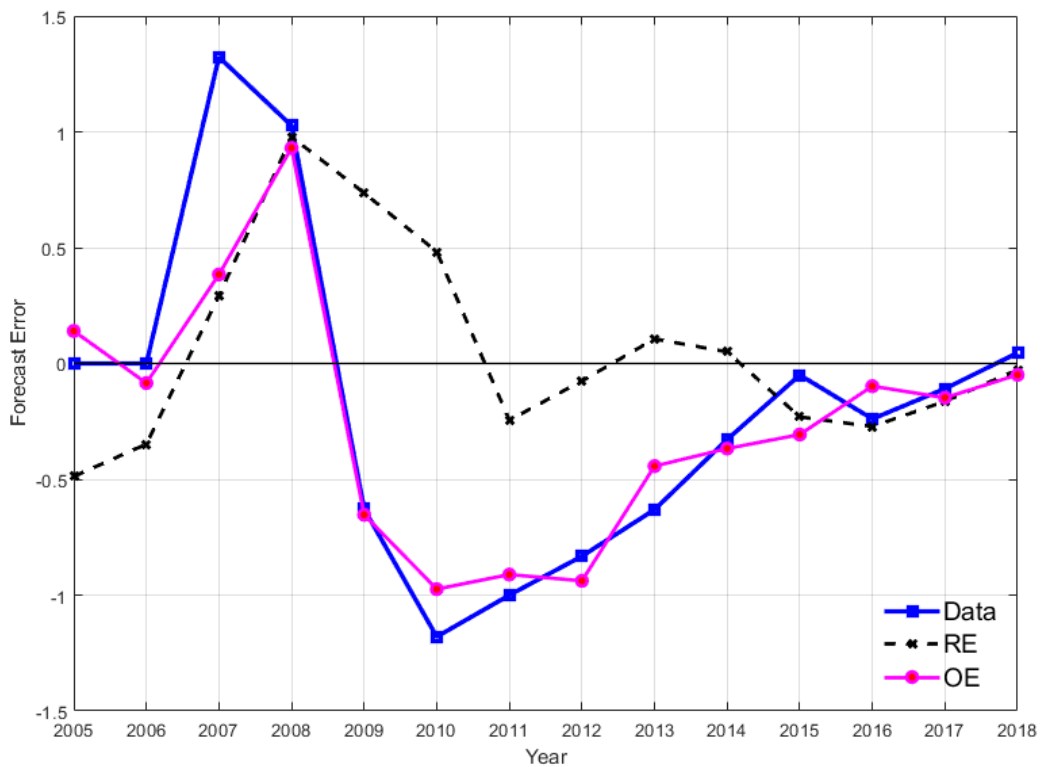
Note: Panel A plots the net fraction of banks that expect a worsening of loan performance in each year, i.e. it is the number of banks that expect worsening minus number of banks that expect improving, divided by the total number of banks. In Panel B, forecast errors are the difference between the expected and the actual change in loan performance, so positive forecast errors indicate that banks are over-optimistic (or the expected loan default rate is lower than the actual default rate) while negative forecast errors indicate that banks are over-pessimistic.

Figure 5: Impulse Response Functions By Bank Size (OE Model)

Loans (l_t)

Bank value (v_t)

Current net worth (n_t)

Ex-post loan return (r_t^L)

Large
Small
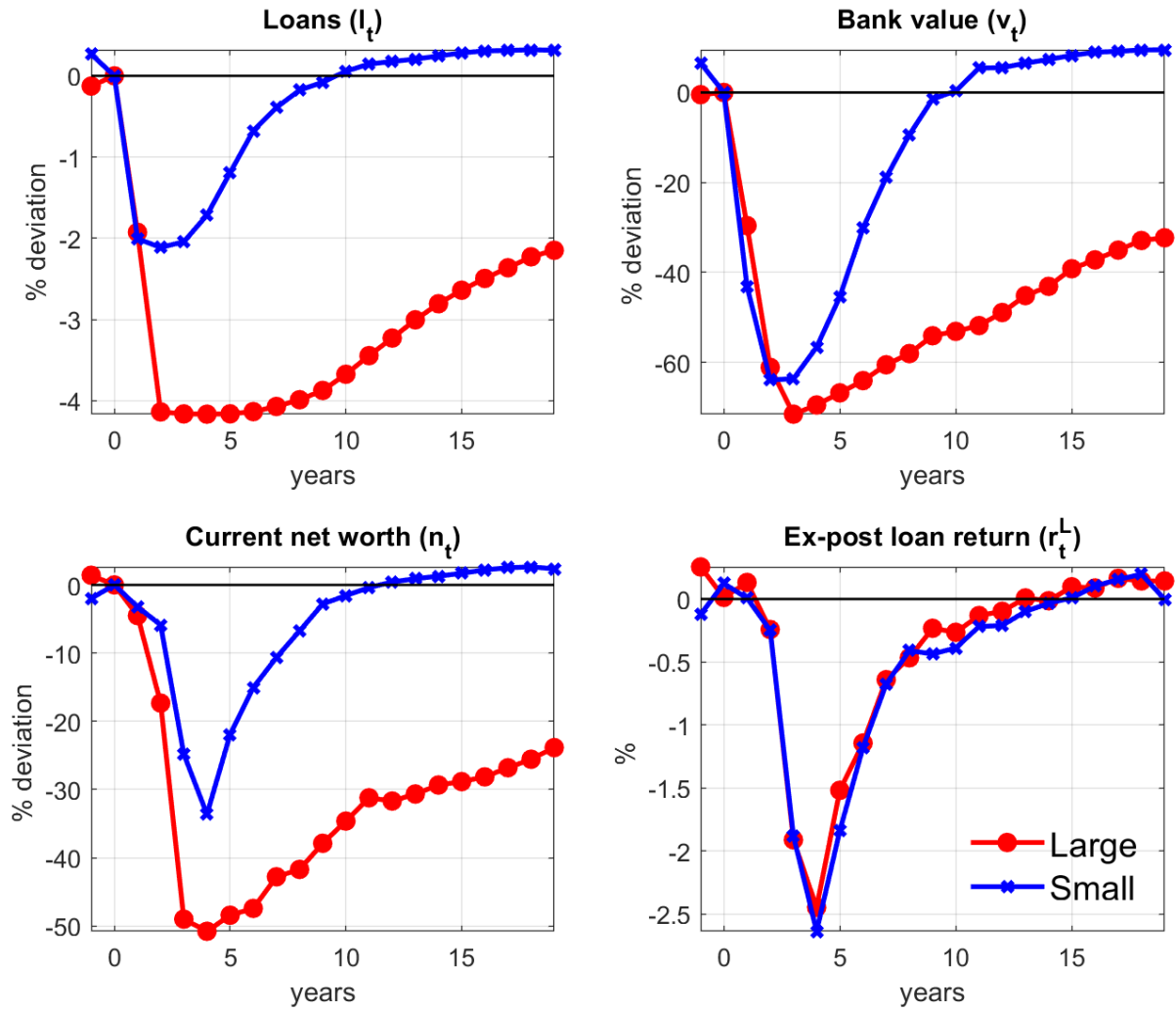
Note: The figure shows the responses to a temporary increase in the annual disaster probability in the overextrapolative model. We simulate the model for 3,000 years, and at $t = 2,980$ and $t = 2,981$ we perturb the model with two consecutive shocks to the probability of disaster. We repeat the procedure 1,000 times and calculate the average across simulations. Small banks are those whose total assets are below the median level before the increase in disaster probability, and large banks are those with total assets above the median. All shocks and distributional dynamics are determined according to the true process (i.e. the rational expectations representation), even though the asset prices and bank polices have over-extrapolative expectations.

Figure 6: Disaster in the Model
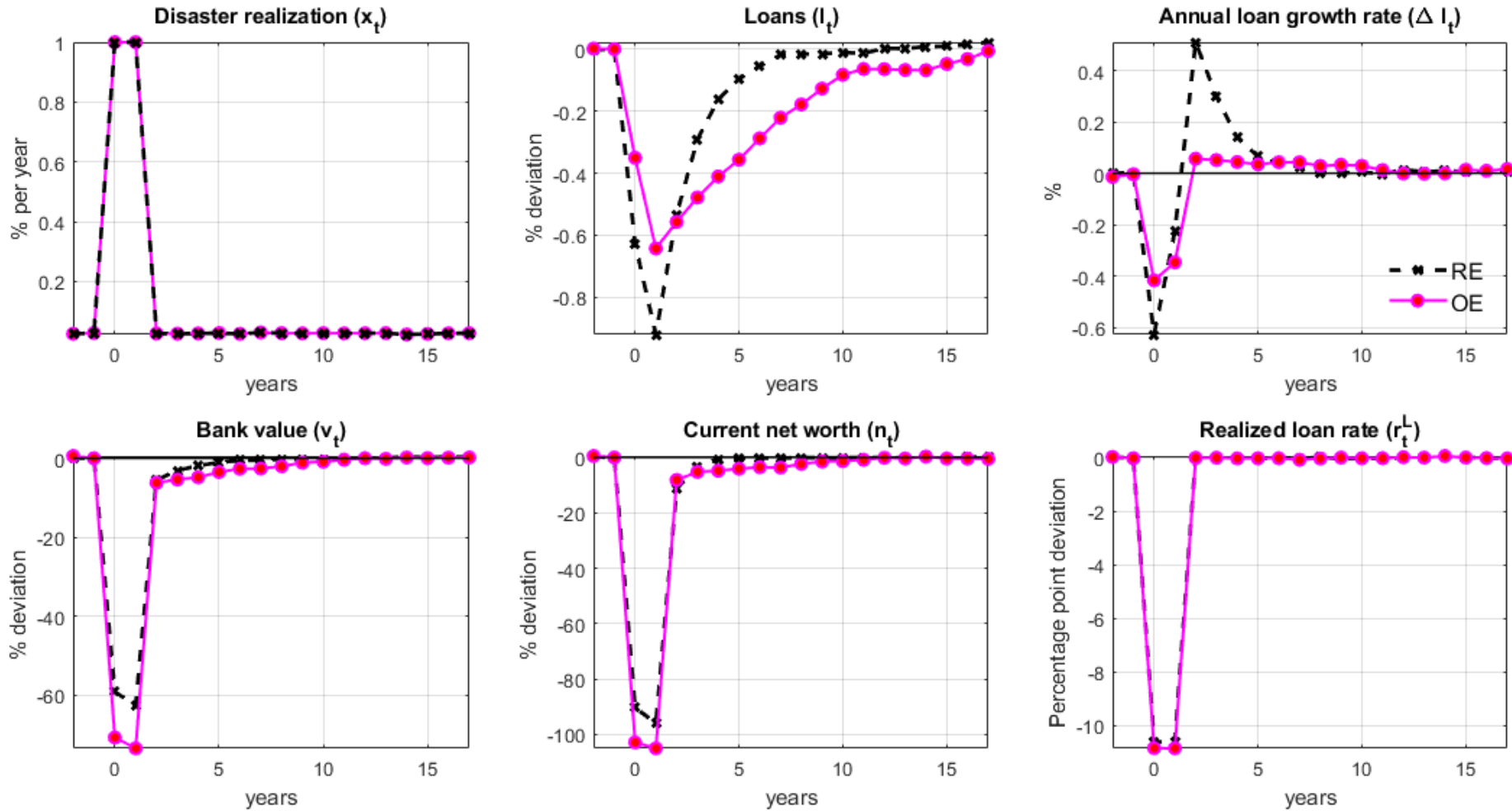
Note: The figure shows the response of the economy to a typical disaster, that lasts for 2 years. We simulate the model for 3,000 years, and at $t = 2,981 - 2,982$ we perturb the model with a disaster ($x_t = 1$). p_t and ω_{it} are randomly drawn according to their true processes. We repeat the procedure 1,000 times and calculate the average across simulations. OE: Overextrapolation. RE: Rational expectation.

Figure 7: Policy Counterfactual: Higher Capital Requirement

A. Rational Expectations

B. Overextrapolation

Note: The figure shows the response to a temporary increase in the annual disaster probability in terms of percentage deviation from the stochastic steady state. We simulate the model for 3,000 years, and at $t = 2,981$ and $t = 2,982$ we perturb the model with two consecutive shocks to the probability of disaster. We repeat the procedure 1,000 times and calculate the average across simulations. All shocks and distributional dynamics are determined according to the true process, even though the asset prices and bank polices may involve distorted expectations.

Figure 8: Policy Counterfactual: Quantitative Easing
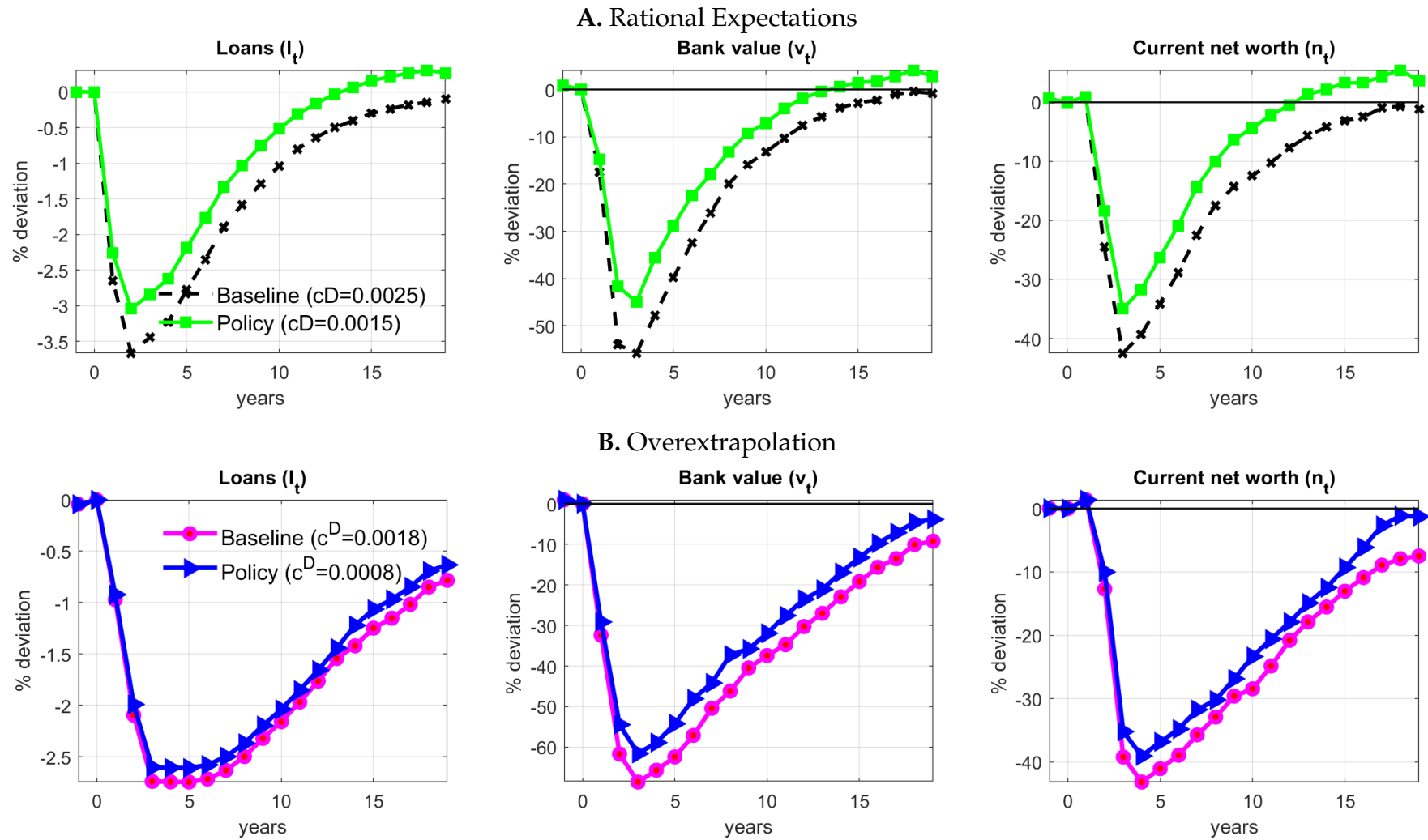
A. Rational Expectations

B. Overextrapolation

Note: The figure shows the response to a temporary increase in the annual disaster probability in terms of percentage deviation from the stochastic steady state. We simulate the model for 3,000 years, and at $t = 2,981$ and $t = 2,982$ we perturb the model with two consecutive shocks to the probability of disaster. We repeat the procedure 1,000 times and calculate the average across simulations. All shocks and distributional dynamics are determined according to the true process, even though the asset prices and bank polices may involve distorted expectations.

Expectations and Credit Slumps
Online Appendix

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March 2022

A Model Solution

A.1. 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 $\mathbf{s}_{it}$:

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

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 $div_{it} \equiv \frac{Div_{it}}{D_{it}} =$

$$\frac{1}{D_{it}} \Big(\underbrace{BE_{i,t-1} + (r_t^L + c)L_{i,t-1} - \tilde{r}^D D_{i,t-1}}_{\equiv N_{it}} - (L_{it} - D_{it}) - \Phi(L_{i,t-1}, L_{it}) \Big)$$

$$= n_{it} + 1 - l_{it} - \phi(l_{i,t-1}, l_{it}),$$

which uses the evolution of equity (13), the balance sheet constraint (14), and

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

where $\phi(l_{i,t-1}, l_{it}) \equiv$. Recursively define the bank's problem as

$$v_i^C(l_{i,t-1}, n_{it}, \mathbf{s}_{it}) = \max_{l_{it}} \Big\{ n_{it} + 1 - l_{it} - \phi(l_{i,t-1}, l_{it}) + \Lambda(div_{it})$$

$$+ E_t \Big[M_{t,t+1} e^g \max \big\{ v_i^C(l_{it}, n_{i,t+1}, \mathbf{s}_{i,t+1}), 0 \big\} \Big| \mathbf{s}_{it} \Big] \Big\}, \quad \text{(A.1)}$$

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

$$n_{i,t+1} = e^{-g}\left(l_{it} - 1 + \left(r^L_{t+1}(\mathbf{s}_{it}, \varepsilon_{c,t+1}, x_{t+1}, \omega_{i,t+1}) + c\right)l_{it} - \tilde{r}^D\right) \tag{A.2}$$

the capital requirement constraint:

$$\frac{l_{it}}{l_{it} - 1} \leq \lambda \tag{A.3}$$

and the equity issuance cost:

$$\Lambda(div_{it}) = \mathbb{1}_{div_{it} < 0} \eta^E div_{it}, \tag{A.4}$$

thus verifying the conjecture.

A.2. Computation

Discretization and Asset Prices We discretize the shock processes for the probability of crisis p_t, the collateral value ω_{it} using the method by Tauchen (1986). We solve the fixed-point problem (6) to find the equilibrium wealth-consumption ratio S_t. Then the stochastic discount factor follows from (5), and the price of the loan portfolio $P^L_t(\mathbf{s}_t)$ and $r^L_{t+1}(\varepsilon_{c,t+1}, x_{t+1}, \omega_{t+1}, \mathbf{s}_t)$ are derived from (11) and (9), respectively. Note that $\mathbf{s}_t$ include:

- (p_t, ω_t) for rational expectations;

- $(p_t, p_{t-1}, \omega_t, \omega_{t-1})$ for overextrapolation;

Value Function Iteration The bank takes 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.

1. Compute $n_{t+1}(l_t, r^L_{t+1})$ that satisfies (A.2), given $r^L_{t+1}(\varepsilon_{c,t+1}, x_{t+1}, \omega_{t+1}, \mathbf{s}_t)$.

2. Guess $v^C(l_{t-1}, n_t, \mathbf{s}_t)$, and denote it as v^C_0.

3. Evaluate $v^C(l_t, n_{t+1}, \mathbf{s}_{t+1})$ using piecewise interpolation of our guess v^C_0. Then solve the bank's problem (A.1) on the discretized state space. If the candidate l_t violates the capital requirement constraint (A.3), the default value $v^D = 0$ is assigned. Denote the maximum bank value as v^C_1.

4. Check for convergence:

   - If $|v^C_1(l_{t-1}, n_t, \mathbf{s}_t) - v^C_0(l_{t-1}, n_t, \mathbf{s}_t)| < \varepsilon$, the value function has converged;

- Otherwise update $v_0^C(l_{t-1}, n_t, \mathbf{s}_t)$ to $v_1^C(l_{t-1}, n_t, \mathbf{s}_t)$ and repeat step 3.

Simulation We obtain model-implied moments by simulating 1,000 banks for 3,000 periods, discarding the first 300 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 ω_{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 return on the bank investments and the ex post output of the firm. Importantly, when we simulate the model, all shocks and distributional dynamics are determined according to the true process (i.e. the rational expectations representation), even though the asset prices and bank polices may involve distorted expectations.

Recall that a bank defaults if its continuation value V^C falls below the threshold level V^D, which we normalize to zero. For simplicity, we assume that when a bank defaults, an identical bank is created with the same state variables. Hence we maintain a stationary distribution of banks.

Table A.1: Additional Heterogeneity

This table repeats the analysis of Table 1 by sub-sample based on bank size. In Panel A, we split the sample into two groups of banks, small and large, based on the bottom and top quartiles of bank total loans respectively. We report the estimates for repeating the analysis of forecast error dynamics of Table 2 separately for each of the two size sub-samples, 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.

	Panel A: Dynamics of Bank Forecast Errors by Bank Size					
	Small Banks			Large Banks		
	k=1 year	k=2 year	k=3 year	k=1 year	k=2 year	k=3 year
	(1)	(2)	(3)	(4)	(5)	(6)
β_k	0.254**	0.121*	0.107	0.308**	0.138**	-0.046
[t]	[2.15]	[1.73]	[1.28]	[4.64]	[2.14]	[-0.70]

Table A.2: Robustness to Controlling for Alternatives

This table repeats the analysis of Table 2 using a specification that adds controls for alternatives. In Panel A, we add controls for loan demand and loan performance in the crisis, in turn. In Panel B, we add controls for bank capital (tier 1 capital ratio) and liquidity (cash ratio), 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.

	Panel A: Bank Expectations and Lending Dynamics, Controlling for Alternatives					
	Loan Demand			Crisis Loan Performance		
	k=1 year	k=2 year	k=3 year	k=1 year	k=2 year	k=3 year
	(1)	(2)	(3)	(4)	(5)	(6)
β_k	-0.141	0.220***	0.053	-0.169	0.236**	0.039
[t]	[-0.97]	[2.64]	[0.58]	[-0.95]	[2.36]	[0.45]
$Control_k$	0.053	0.092	0.120**	-0.200	0.465*	-0.187
[t]	[0.60]	[1.39]	[2.42]	[-0.95]	[1.93]	[-0.62]

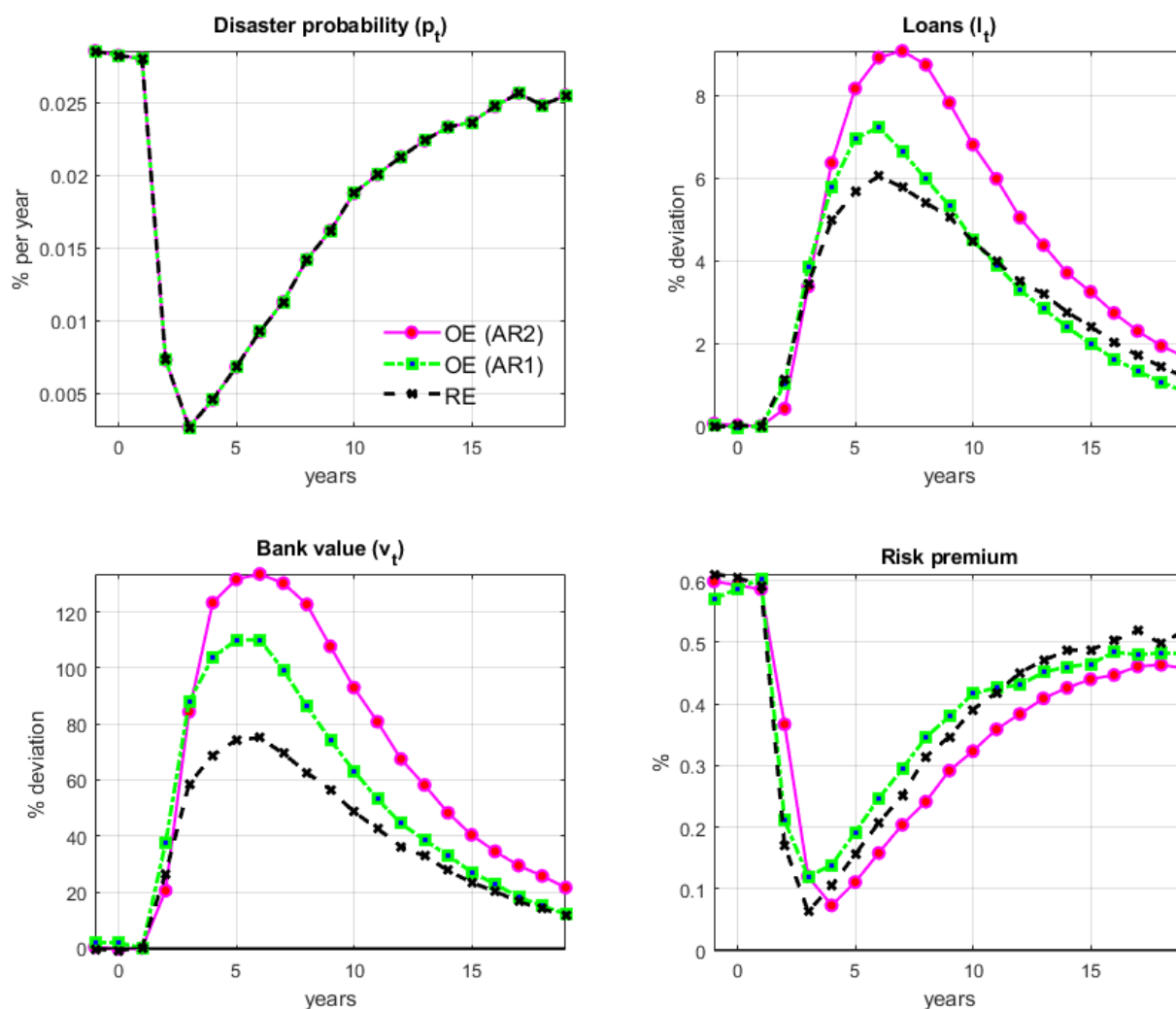|	Panel B: Bank Expectations and Lending Dynamics, Controlling for Alternatives					
	Bank Capital			Bank Liquidity		
	k=1 year	k=2 year	k=3 year	k=1 year	k=2 year	k=3 year
	(1)	(2)	(3)	(4)	(5)	(6)
β_k	-0.067	0.239***	0.048	-0.075	0.245***	0.043
[t]	[-0.48]	[2.96]	[0.55]	[-0.52]	[2.87]	[0.46]
$Control_k$	0.114	-0.182	-0.053	0.116**	-0.085**	-0.041
[t]	[0.77]	[-1.48]	[-0.49]	[2.07]	[-2.09]	[-0.57]

Figure A.1: Aggregate Data
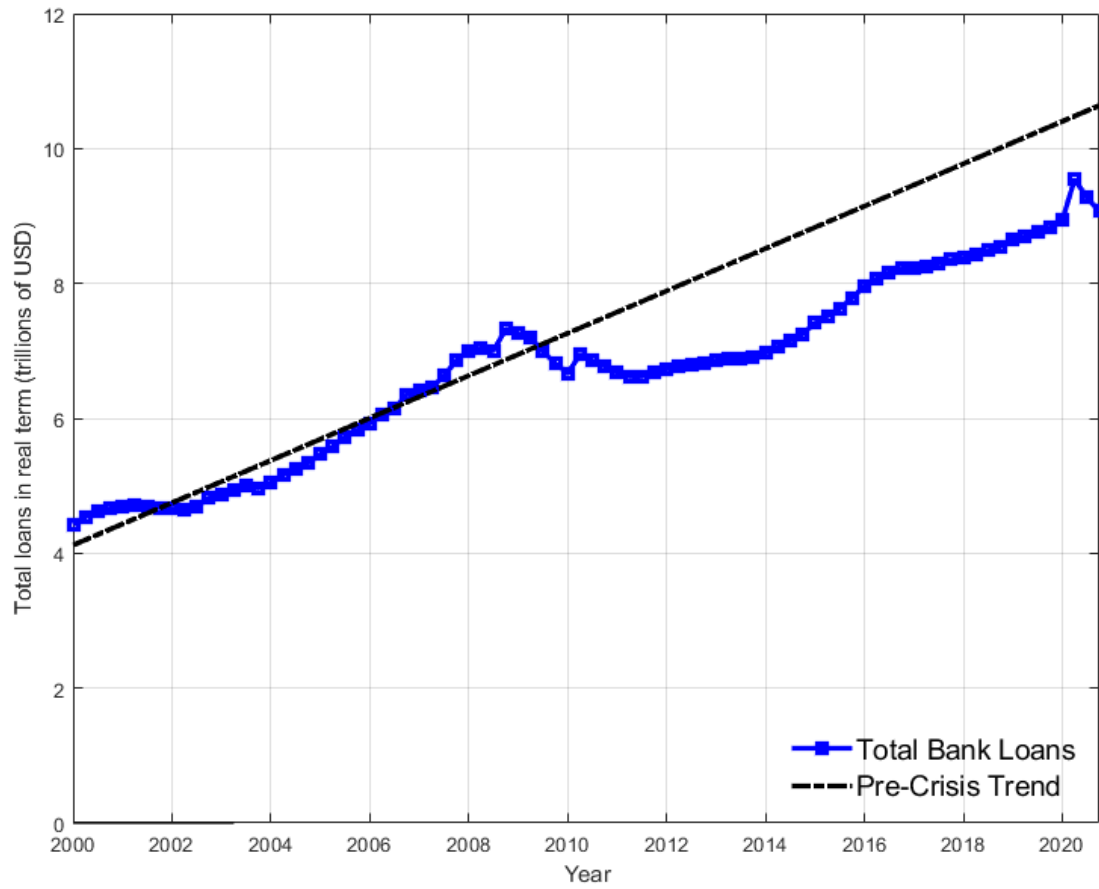
Note: This plots total bank loans (in trillions of dollars) by all commercial banks between 2000 and 2020, deflated by the GDP deflator, and the pre-crisis trend of the series. Source: H.8 Assets and Liabilities of Commercial Banks in the U.S.

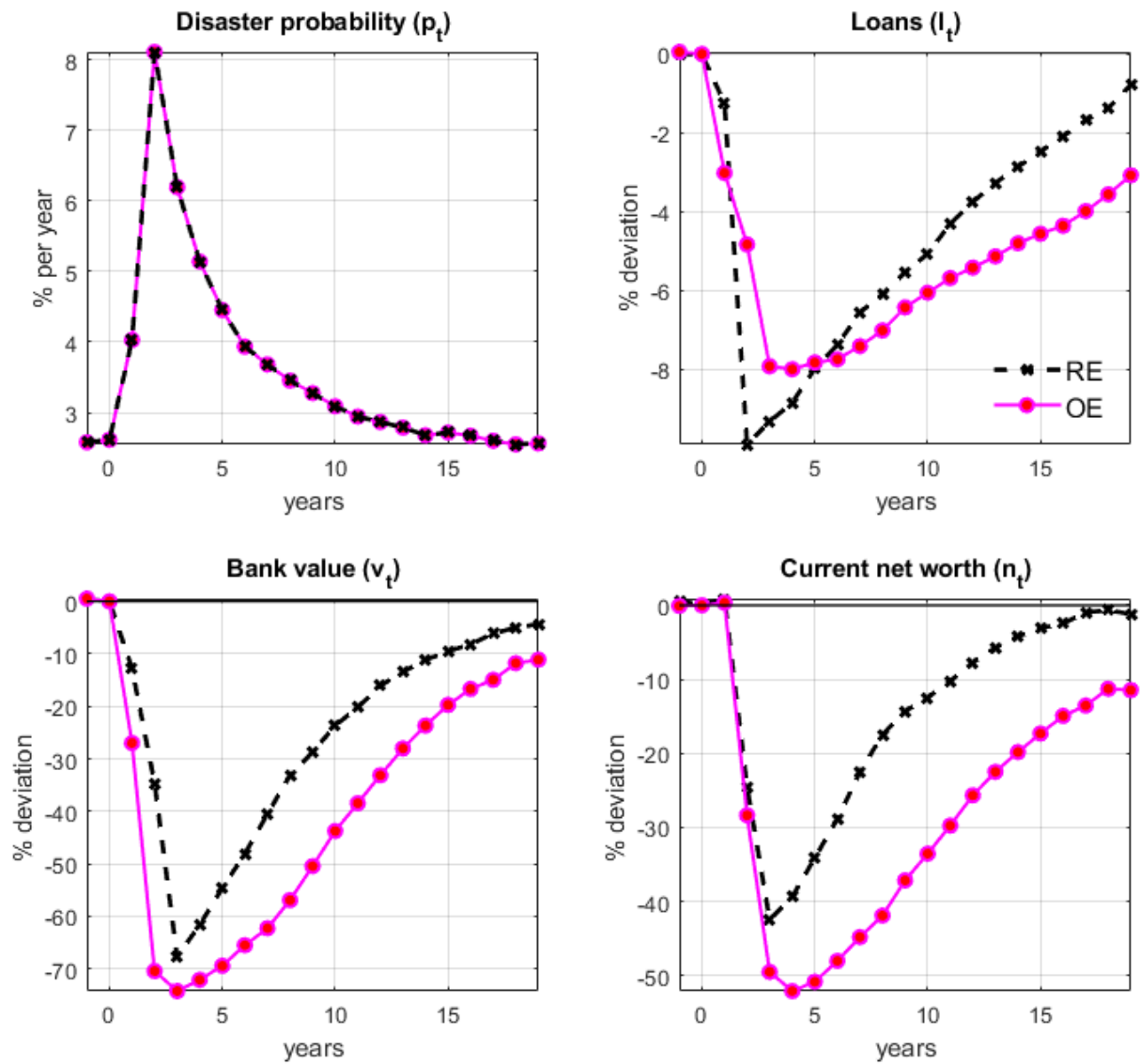**Figure A.2:** Impulse Response Functions to A Temporary Increase in Disaster Probability

Note: The figure shows the response to a temporary decrease in the annual disaster probability. We simulate the model for 3,000 years, and at $t = 2,980$ and $t = 2,981$ we perturb the model with two consecutive shocks to the probability of disaster. We repeat the procedure 1,000 times and calculate the average across simulations. All shocks and distributional dynamics are determined according to the true process (i.e. the rational expectations representation), even though the asset prices and bank polices may involve distorted expectations. OE with AR(2): Overextrapolation with AR(2) expectations. OE with AR(1): Overextrapolation with AR(1) expectations. RE: Rational expectation.

Figure A.3: Impulse Response Functions to A Temporary Decrease in Disaster Probability

Note: The figure shows the response to a temporary decrease in the annual disaster probability. We simulate the model for 3,000 years, and at $t = 2,980$ and $t = 2,981$ we perturb the model with two consecutive shocks to the probability of disaster. We repeat the procedure 1,000 times and calculate the average across simulations. All shocks and distributional dynamics are determined according to the true process (i.e. the rational expectations representation), even though the asset prices and bank polices may involve distorted expectations. OE with AR(2): Overextrapolation with AR(2) expectations. OE with AR(1): Overextrapolation with AR(1) expectations. RE: Rational expectation.

Figure A.4: Robustness: No Asset Adjustment Cost

Note: The figure shows the response to a temporary increase in the annual disaster probability. We simulate the model for 3,000 years, and at $t = 2,981$ we perturb the model assuming a change in the probability of disaster to a new value. We repeat the procedure 1,000 times and calculate the average across simulations. All shocks and distributional dynamics are determined according to the true process, even though the asset prices and bank polices may involve distorted expectations.

Figure A.5: Autocorrelation Functions

A. Disaster Risk Probability ($\log P_{it}$)
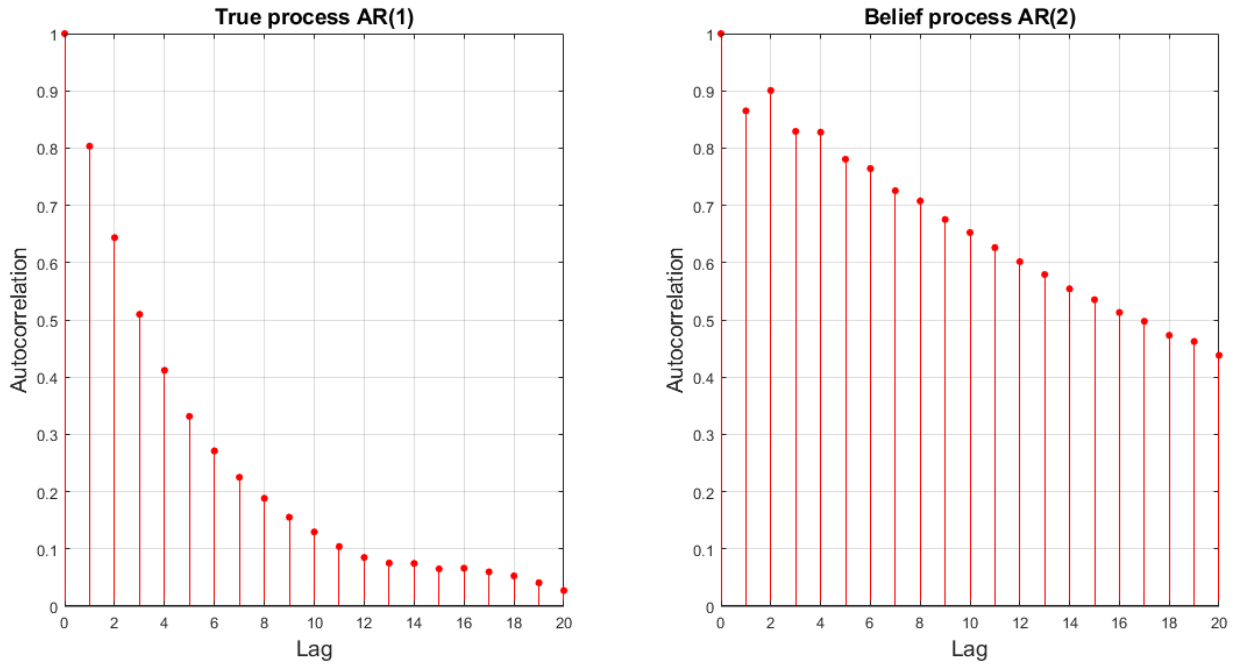
B. Bank-Specific Shock (ω_{it})
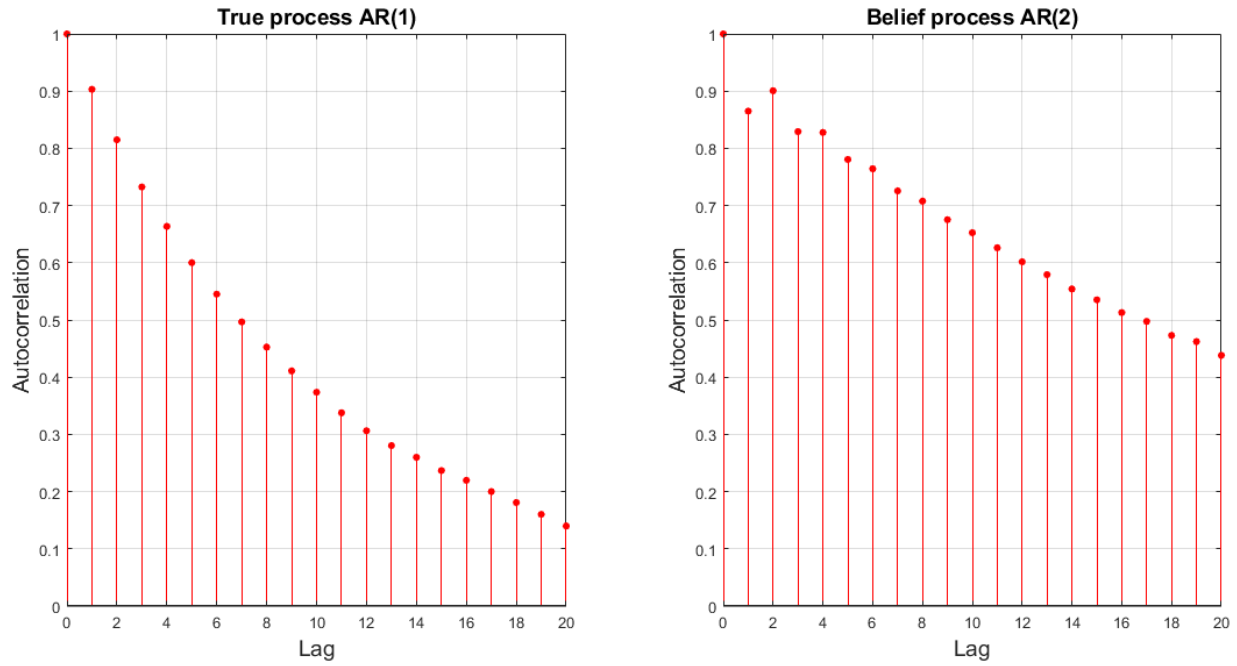
Note: This figure plots the autocorrelation functions for the persistent processes in the model, P_{it} and ω_{it}. The left panels give the ACF for the true processes, according to (3) and (8). The right panels give the ACF for the belief processes, according to (18) and (17) for the parameters given in Table 4.

Figure A.6: Asset Prices

A. Risk Premia

B. Realized Loan Return
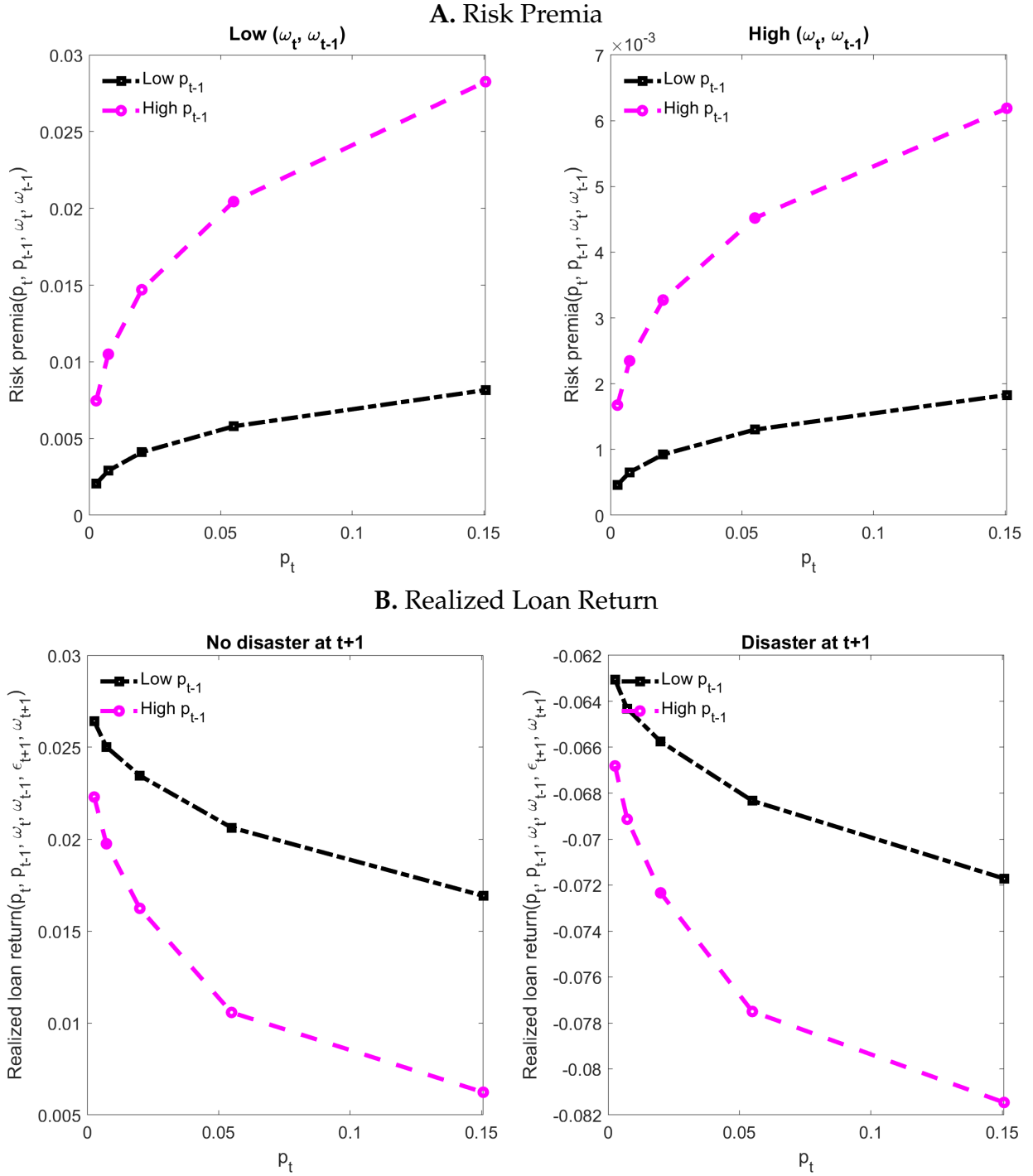
Note: This figure illustrates the asset prices in the OE model. Panel A shows – for each level of the probability of crisis p_t – the ex-ante expected rate of return on loans relative to the rate of return on a one-year safe asset, i.e. $E_t[r^L_{t+1} - r^f_{t+1}]$, where r^f_{t+1} satisfies $r^f_{t+1} = 1/P^f_t - 1$ and $P^f_t = E_t[M_{t,t+1}]$. The expected return and the probability are in annual terms. The risk premium is a function of $(p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1})$. Different lines represent alternative levels of p_{t-1}. Panel B shows – for each level of p_t – the realized return on loans in $t + 1$, depending on whether a disaster occurs in $t + 1$. The realized return is a function of $(p_t, p_{t-1}, \omega_{it}, \omega_{i,t-1}, \epsilon_{t+1}, \omega_{i,t+1})$. Different lines represent alternative levels of p_{t-1}, and the other states $(\omega_{it}, \omega_{i,t-1}, \epsilon_{t+1}, \omega_{i,t+1})$ are fixed.
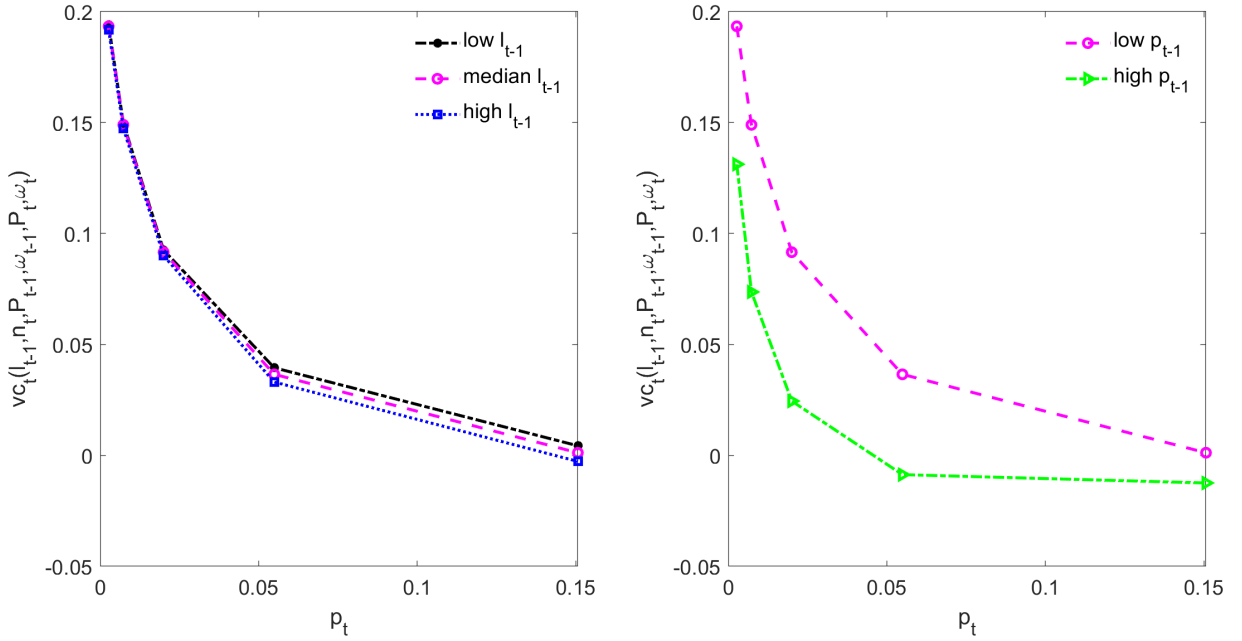
**Figure A.7:** Policy Functions in the OE Model

**A.** Lending
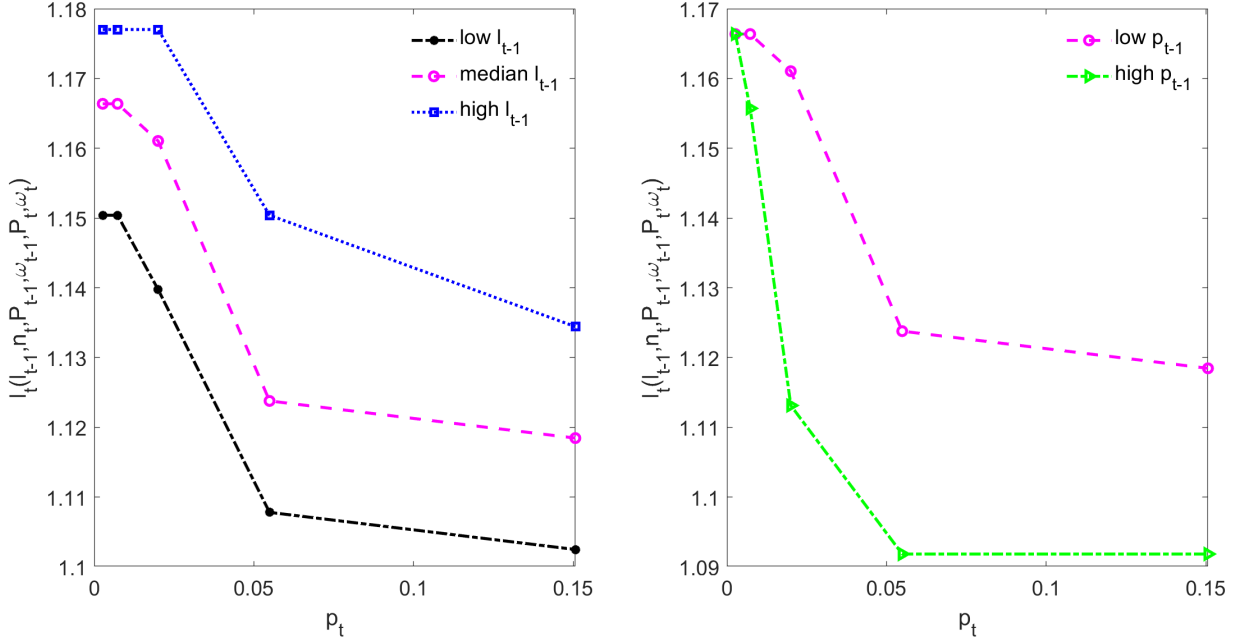
B. Bank value

Note: This figure illustrates the policy functions in the OE model. Panel A shows the optimal amount of bank lending scaled by deposits $l_{it} = L_{it}/D_{it}$ for each level of the probability of crisis p_t. Panel B shows the value of the bank scaled by deposits $v_{it}^C = VC_{it}/D_{it}$. In the left panels, different lines represent alternative levels of lagged asset-to-debt ratio $l_{i,t-1} = L_{i,t-1}/D_{it}$, holding the other states $(n_{it}, P_{t-1}, \omega_{it}, \omega_{i,t-1})$ fixed. In the right panels, different lines represent alternative levels of lagged disaster probability P_{t-1}, holding the other states $(l_{i,t-1}, n_{it}, \omega_{it}, \omega_{i,t-1})$ fixed.

Figure A.8: Comparison of Asset Prices in OE and RE Models

A. Asset prices as a function of disaster probability (for different levels of l_{t-1})
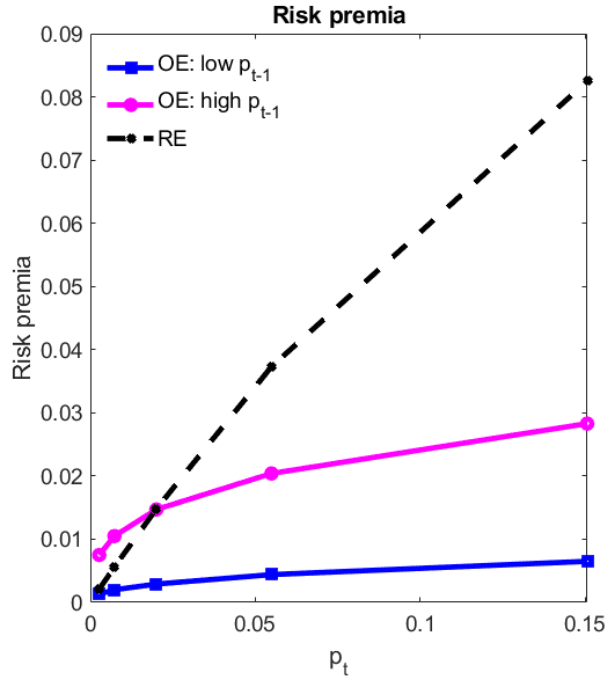
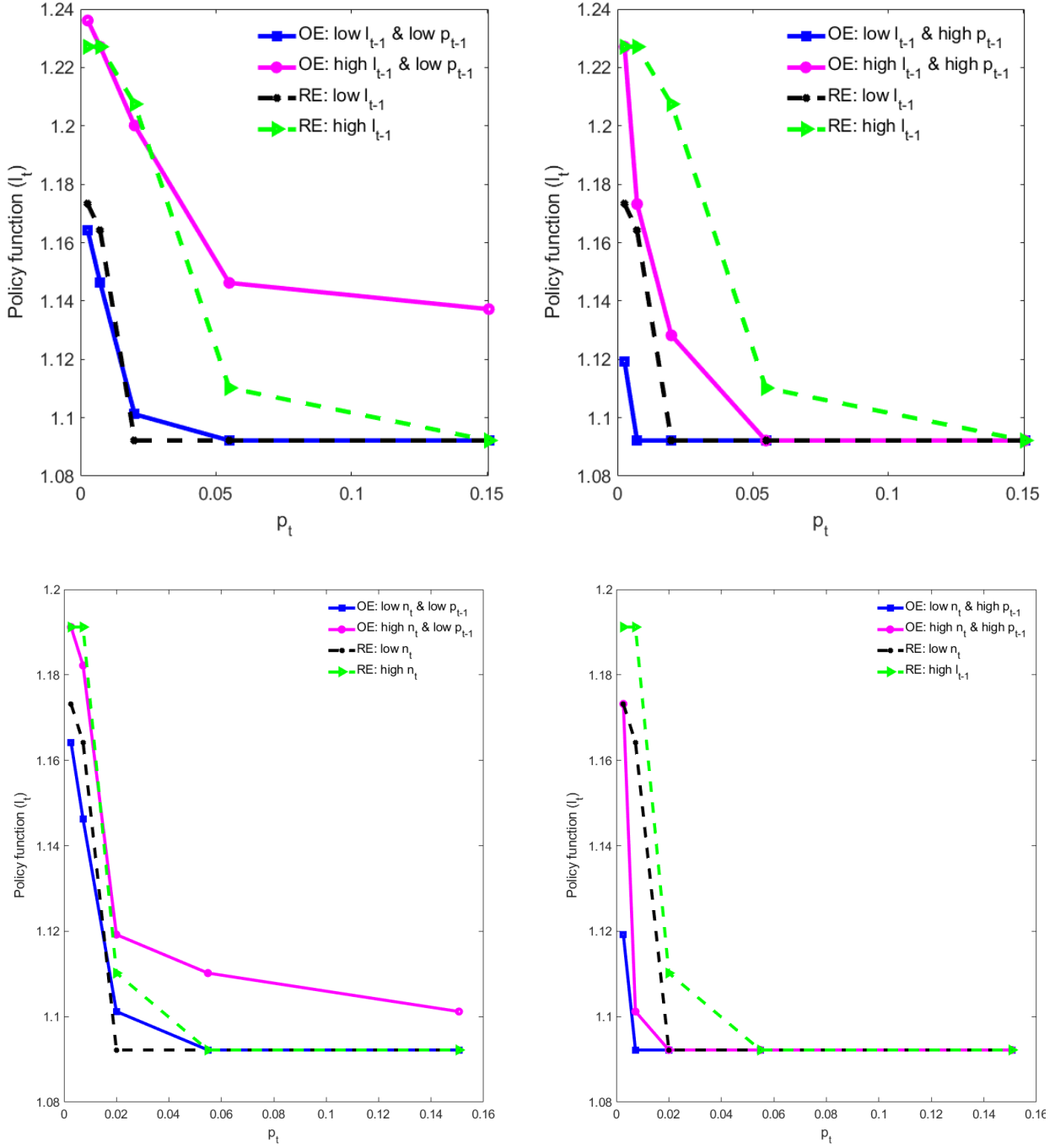**B.** Asset prices as a function of disaster probability (for different levels of n_t)
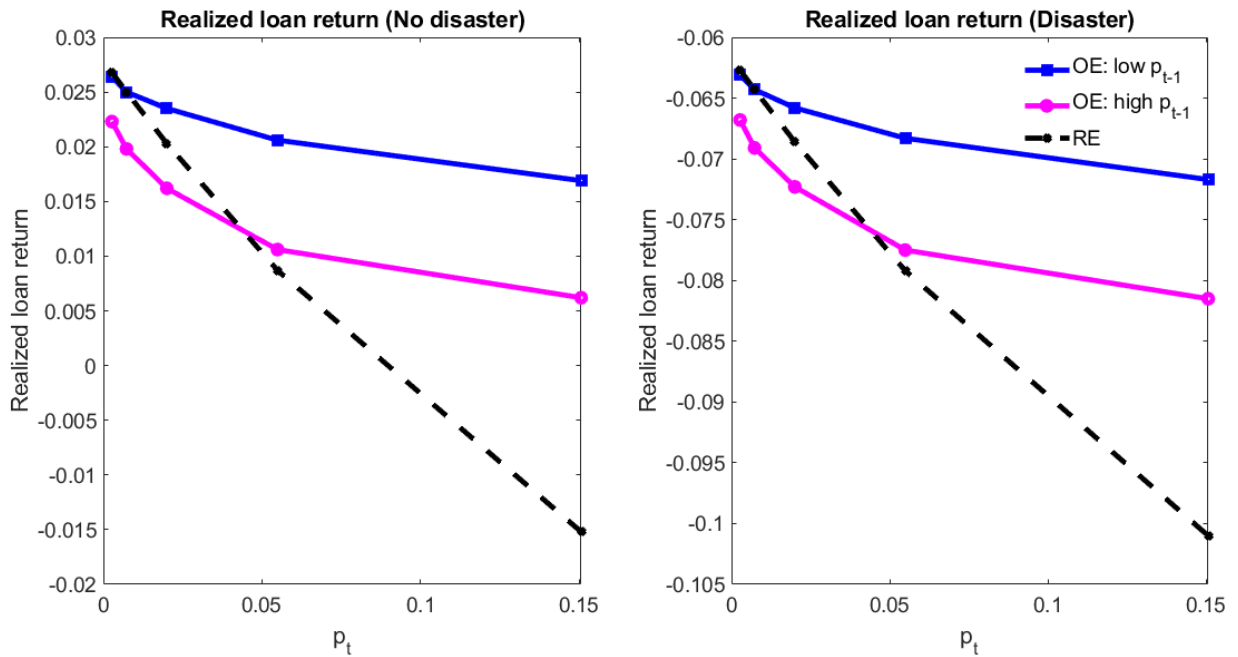
Note: This figure compares asset prices as a function of disaster probability P_t in the two models. OE: Overextrapolation. RE: Rational expectations. The risk premium is the ex-ante expected rate of return on loans relative to the rate of return on a one-year safe asset, i.e. $\mathrm{E}_t[r^L_{t+1} - r^f_{t+1}]$. The risk premium a function of $(P_t, P_{t-1}, \omega_{it}, \omega_{i,t-1})$ in the OE model, and a function of (P_t, ω_{it}) in the RE model. The realized return on loans depends on whether a disaster occurs. It is a function of $(P_t, P_{t-1}, \omega_{it}, \omega_{i,t-1}, \epsilon_{t+1}, \omega_{i,t+1})$ in the OE model, and a function of $(P_t, \omega_{it}, \epsilon_{t+1}, \omega_{i,t+1})$ in the RE model. We fix $\omega_{it}, \epsilon_{t+1}, \omega_{i,t+1}$ at the same level in both models, and we set $\omega_{i,t-1} = \omega_{it}$ in the OE model.

Figure A.9: Comparison of Policy Functions in OE and RE Models

C. Lending as a function of disaster probability

Note: This figure compares the optimal lending $l_{it} = L_{it}/D_{it}$ as a function of disaster probability P_t in the two models. OE: Overextrapolation. RE: Rational expectations. In the RE model, l_{it} is a function of $(l_{i,t-1}, n_{it}, P_t, \omega_{it})$; in the OE model, l_{it} is a function of $(l_{i,t-1}, n_{it}, P_t, \omega_{it}, P_{t-1}, \omega_{i,t-1})$. We fix $l_{i,t-1}, n_t, \omega_{it}$ at the same levels in both models, and in the OE model, we set $P_{t-1} = P_t$ and $\omega_{i,t-1} = \omega_{it}$.

B. Lending as a function of current net worth
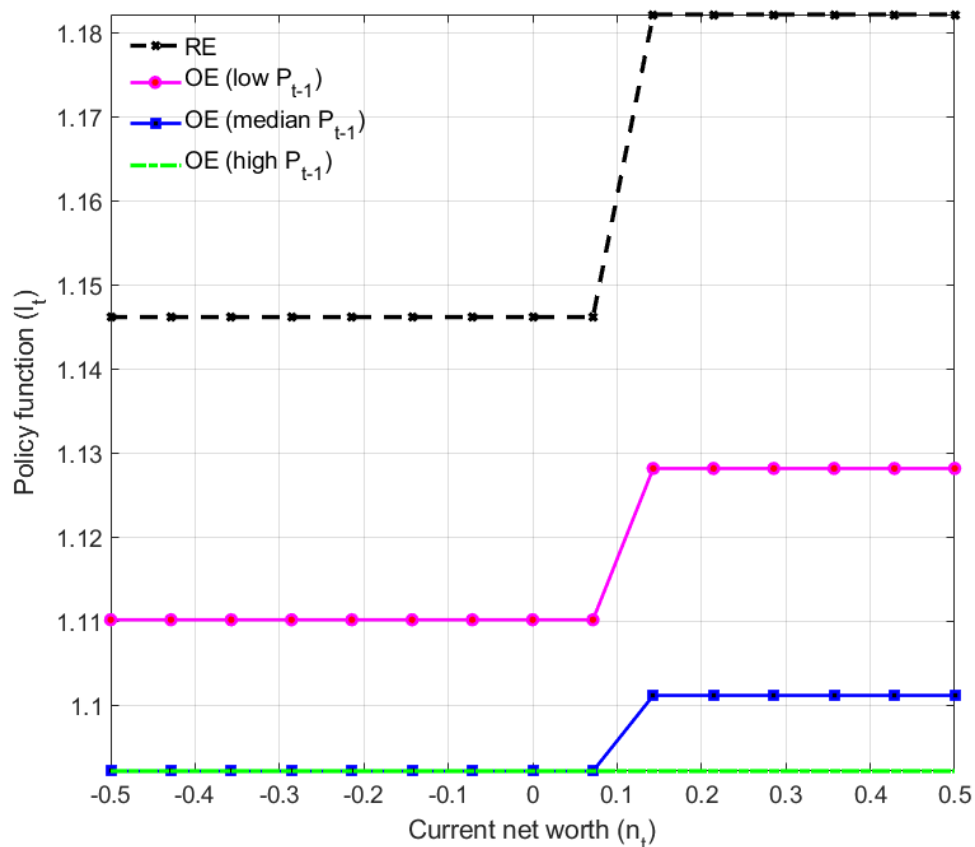
Note: This figure compares the optimal lending $l_{it} = L_{it}/D_{it}$ as a function of current net worth n_{it} in the two models. OE: Overextrapolation. RE: Rational expectations. In the RE model, l_{it} is a function of $(l_{i,t-1}, n_{it}, P_t, \omega_{it})$; in the OE model, l_{it} is a function of $(l_{i,t-1}, n_{it}, P_t, \omega_{it}, P_{t-1}, \omega_{i,t-1})$. We fix $l_{i,t-1}, P_t, \omega_{it}$ at the same levels in both models.