Foreseen Risks*

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Abstract

Financial crises tend to follow rapid credit expansions. Causality, however, is far from obvious. We show how this pattern arises naturally when financial intermediaries optimally exploit economic rents that drive their franchise value. As this franchise value fluctuates over the business cycle, so too do the incentives to engage in risky lending. The model leads to novel insights on the effects of unconventional monetary policies in developed economies. We argue that bank lending might have responded less than expected to these interventions because they enhanced franchise value, inadvertently encouraging banks to pursue safer investments in low-risk government securities.

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1 Introduction

Motivated by the financial crisis of 2007–2008 and subsequent Great Recession several empirical studies find that these collapses in economic activity tend to occur in the aftermath of large credit expansions.[1] This evidence leads some to argue that large credit expansions are a key *cause* of severe downturns. Specifically, studies argue that competitive pressures to lend, combined with perverse incentives or behavioral biases, are the underlying reason that both credit expansions, and subsequent downturns occur.[2]

In this paper, we propose an alternative explanation. We build a model in which the propensity of banks to engage in "riskier lending" over the cycle is a result of cyclical variations in economic conditions and their impact on the bank's own franchise value. Thus, there is no concept of a *credit cycle* that "causes" the business cycle. Instead, in our model, bank credit co-moves with – and even precedes – macro aggregates such as investment and output, even when these variables are, by design, fully independent of bank lending behavior.

Instead of suffering from irrational exuberance, our bank managers correctly forecast future economic growth and *optimally* respond to changes in the economic environment. Moreover, they make investment and financing decisions with the aim of maximizing shareholder value.[3] The key assumption in our

[1] See Borio and Lowe (2002); Reinhart and Rogoff (2009); Jordà, Schularick, and Taylor (2011); Schularick and Taylor (2012); Mian and Sufi (2009); Mian, Sufi, and Verner (2017); Krishnamurthy and Muir (2017).

[2] Work by Minsky (1977) and Kindleberger (1978) already emphasizes the potential for overoptimism to destabilize the economy. Behavioral explanations include neglected risks (Gennaioli, Shleifer, and Vishny, 2012) and extrapolative beliefs (Barberis, Shleifer, and Vishny, 1998; Greenwood and Hanson, 2013).

[3] While our model requires that risks be foreseen by some, we do not require that all investors, bank executives, or bank employees understood the risks. The model is thus not inconsistent with evidence of Cheng, Raina, and Xiong (2014), Chernenko, Hanson, and Sunderam (2016) and Richter and Zimmermann (2019) indicating that some individuals within the banking sector were overoptimistic. The question is not necessarily why bank executives acted in a way that failed to avoid risk, but rather why informed equity-holders

model is that banks benefit from economic rents, arising from a wedge between the return on assets and the cost of debt. Here we model this wedge as subsidized deposit insurance.[4,5] We show that the value of these rents fluctuates over time as local and aggregate economic conditions change and generally causes banks to take more risks when franchise values are low.

Our model of the banking sector builds on Merton (1978). Specifically, we treat banks as entities with access to an exogenous supply of deposits, paying a fixed deposit rate priced to reflect the presence of a government guarantee. To this simple structure, we then add an investment decision: banks must decide in each period on the composition of their loan portfolio. They invest their assets in a mixture of risky loans to the private sector and safer floating-rate government notes. The government guarantee on deposits provides banks with a source of economic rents. The discounted value of this stream of rents is effectively the bank's *franchise value* and its fluctuations over the business cycle drive lending behavior. During expansions, the franchise value is generally large and banks protect it by avoiding excessive risks that may lead to early bankruptcy. Over time however, as aggregate risks eventually build, franchise values begin to fall while risk premia rise and the bank's equity holders may find it preferable to exploit the additional reward from investing in risky assets.

To quantify the links between bank lending and macroeconomic activity we include a corporate sector that makes investment decisions. We assume banks lend only to households, ensuring corporate behavior remains fully independent of the loan decisions of the bank. We then confront our model's quantitative implications with recent empirical evidence on the relationship between bank

did not act to curtail risk-taking, and perhaps encouraged risky practices.

[4]Alternative, and equally compelling, sources of rents could be imperfect competition in the banking sector or a limited regulatory oversight relative to other institutions that provide similar services (which may capture the shadow banking sector in the period before the crisis).

[5]Buser, Chen, and Kane (1981) document that deposit insurance premia are subsidized in the US.

lending and financial crises. In particular, we show how our model replicates the empirical patterns in Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2016) showing that financial crises often follow periods of very fast credit growth, as well as the related findings in Mian, Sufi, and Verner (2017) documenting the strong predictability of future GDP growth by the growth in household debt for 30 countries.

Beyond these core findings, our model provides important implications for the evaluation of recent unconventional monetary policy interventions. After the 2008 financial crisis, executive branches and central banks in advanced economies responded by providing the banking sector with additional guarantees on funding. The dominant policy rhetoric was that poor bank balance sheets lied behind the sharp reduction in credit. Although policymakers intended for banks to increase their lending to the private sector, in many cases this did not happen. Instead, banks invested heavily in government bonds or excess reserves with the central bank. We show that this behavior need not be puzzling if we plausibly interpret those stabilization policies as lowering the cost of financing for banks. In this case our model suggests that by effectively increasing the franchise value of banks these policies only worked to reinforce their incentives to hold more safe assets.

Our work is related to several bodies of literature on banking, corporate finance and macroeconomics. Starting from the empirical evidence that the banking industry is both highly regulated and subject to limited entry, an early literature suggests that competition reduces banks' franchise value and induces banks to assume more risk. Marcus (1984), Keeley (1990), and Hellmann, Murdock, and Stiglitz (2000) use comparative statics to argue for a link between franchise value and a preference for risky investments, motivated by increases in competition in the banking industry.[6] Like us, they build on the

[6]Boyd and De Nicoló (2005), however, presents an argument that less competition can lead banks to take on greater risk.

idea of risk shifting in Jensen and Meckling (1976), originally formulated as a conflict between overall claimholders and equityholders in the context of corporations. The key difference in our work is that we argue franchise values must fluctuate endogenously with local and aggregate economic conditions. This in turn, induce to important changes in bank lending behavior over the business cycle.

Our work also relates to more recent studies analyzing the the specific impact of regulatory policies on bank balance sheets, lending, and on franchise values. Some of these studies are mainly qualitative in nature (Acharya and Yorulmazer, 2007, 2008; Farhi and Tirole, 2012; Sarin and Summers, 2016). Others are similar to ours in that explicitly model the bank's maximization problem (Van den Heuvel, 2008; Kisin and Manela, 2016; Egan, Hortaçsu, and Matvos, 2017; Gourio, Kashyap, and Sim, 2018; Begenau and Landvoigt, 2018; Elenev, Landvoigt, and Van Nieuwerburgh, 2018) or work with quantitative accounting identities (Atkeson, d'Avernas, Eisfeldt, and Weill, 2018). While these papers focus on ex-ante optimal policy to deal with financial crises, our model offers a novel perspective on the unintended consequences of policy that might either promote or destroy oligopolistic rents in the financial sector.

Finally, and more broadly, this paper is also connected to the recent literature examining the causal links between credit market conditions and economic fluctuations. In particular, our paper relates to Santos and Veronesi (2016) and Gomes, Grotteria, and Wachter (2018) who show how endogenous co-movements between leverage and several macroeconomic aggregates are the natural outcome of standard models without requiring financial frictions or behavioral biases. This literature focuses on risk premia as driving asset prices and lending to rational agents based on risk-sharing motives or on investment opportunities. These papers cannot, however, explain the observed negative relation between household credit growth and future adverse economic

outcomes.[7]

The rest of the paper is organized as follows. Section 2 discusses relevant properties of the data in the lead-up to the 2018 financial crisis. These properties help motivate our approach. Section 3 presents a theoretical framework to study the optimal composition of bank lending in the presence of deposit insurance and time variation in economic rents. The model's results are quantitatively assessed in Section 4, while Section 5 studies our key policy implications. Section 6 then discusses novel empirical evidence in support of the role deposit insurance in financial crises. Section 7 concludes.

2 Beliefs and Bank Leverage and Payout Policies Leading up to the Financial Crisis

In this section, we provide a brief description of several key facts related to banks' behavior in the lead up to the 2007–2008 financial crisis. These facts complement the findings of Jordà et al. (2016) and Mian et al. (2017), which form the basis for our quantitative analysis. While this behavior undoubtedly reflects a multitude of perhaps complementary forces, these facts highlight the importance of the mechanism we describe in this paper.

Fact 1: Pessimism concerning future house prices rose sharply from 2004 to 2007. As Figure 1 shows, the percentage of respondents to the Michigan Survey of Consumers answering that "now is a bad time to buy a house" reached a peak in 2007 (Piazzesi and Schneider, 2009; Mian and Sufi, 2019). Thus, while it is possible that some investors may have failed to fully appreciate the risks they faced (Gennaioli and Shleifer, 2018) there was clearly a general

[7]The distinction between growth in corporate lending and growth in household lending appears to be important in the data: growth in corporate lending does not predict adverse outcomes, and is even associated with positive economic conditions, at least in the short term. This suggests that growth in corporate lending is driven by investment opportunities, perhaps in a way that is associated with changes in risk.

expectation that economic conditions would deteriorate in the build up to the crisis.

Fact 2: Bank dividend payouts were high before and even during the crisis. More strikingly, as Figure 2 shows, each of the 12 largest bank holding companies repurchased stock extensively just before the crisis (Hirtle, 2016).[8]

Fact 3: Bank leverage increased steadily from 2004. As Figure 3 shows, leverage was moderate in the early 2000s but increased significantly especially after 2006.

Fact 4: The market-to-book ratio for the banking industry, dropped precipitously before the crisis, as Figure 4 shows.

Fact 5: The share of safe assets (Treasuries, agency securities, and cash) in banks' balance sheet decreased before the crisis. Commercial banks' holdings of these assets decreased steadily until the 3rd quarter of 2008, then spiked back after the subprime mortgage crisis spiraled into a full-blown financial collapse.

Taken together, these facts suggest a picture of increased risk-taking by banks in the face of rising pessimism about aggregate economic prospects in the years just before the 2007–2008 financial crisis. In the next few sections we will show how these facts can be reconciled in a model of optimal bank behavior in the face of increasingly likelihood of a crisis.[9]

[8]Evidence suggests that commercial banks actively manage their equity. Figure 6 shows the relation between log asset and log leverage (assets over equity) growth for commercial banks. Along the 45-degree line assets and leverage adjust one-for one so equity remains unchanged. The data however lines up more closely to the vertical line suggesting banks adjust both equity and asset growth to keep leverage more or less constant. This is in contrast to the behavior of broker-dealers (Adrian and Shin, 2010).

[9]Our aim is to provide a benchmark quantitative model that unites a wide range of facts. We do not attempt to provide a full account of all credit-cycle related phenomena. Our model thus accounts for the relation between the sharp increase in credit spreads and implied volatilities observed in 2007 (Kelly, Lustig, and Van Nieuwerburgh, 2016; Krishnamurthy and Muir, 2017), and a sharp increase in pessimism, dividend payouts, leverage, and lending. It does not, for example, account for the period of high lending and very low credit spreads that prevailed roughly between 2004 and 2007. We discuss further empirical implications in Section 4.2.

3 Model

Our model economy consists of three elementary units: a banking sector, a representative investor/consumer and a productive sector. They all share a common exposure to an extreme economic adverse event, or "crisis," that occurs with a time-varying probability, p_t. To avoid clouding on our key underlying mechanism, we do not fully integrate these sectors in a general equilibrium setting.

The representative investor owns both banks and the production sector; all of these entities' decisions are made in a manner consistent with this agent's pricing of risk. Banks lend to households which may differ from the representative investor, and may also lend to the firms in the productive sector. However, the productive sector faces no financial frictions and may equivalently be financed with equity alone.

3.1 The Stochastic Discount Factor

We assume that all financial claims are owned and priced by an infinitely-lived representative investor with an Epstein and Zin (1989) utility function. The representative agent's utility is identified by a time preference rate $\beta \in (0, 1)$, a relative risk aversion parameter γ, and an elasticity of intertemporal substitution ψ.

3.2 Consumption and Uncertainty

We assume the following stochastic process for the representative investor's consumption:

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

where ϵ_{ct} is a standard normal random variable that is iid over time. Importantly, this process allows for the possibility of a rare collapse in economic activity

when consumption drops by a large fraction, ξ, as in (Rietz, 1988; Barro, 2006). If a crisis materializes, an event that occurs with probability p_t, we set $x_{t+1} = 1$. Otherwise $x_{t+1} = 0$. The realization of x_{t+1}, conditional on p_t, is independent of $\epsilon_{c,t+1}$.

The natural log of the crisis probability p_t follows a first-order autoregressive process with persistence ρ_p and mean $\log \bar{p}$:

$$\log p_{t+1} = (1 - \rho_p) \log \bar{p} + \rho_p \log p_t + \sigma_p \epsilon_{p,t+1}, \tag{2}$$

where ϵ_{pt} is standard normal, iid over time, and independent of ϵ_{ct} and x_t.[10] Let $S(p_t)$ denote the ratio of aggregate wealth to aggregate consumption. It is well-known that the stochastic discount factor (SDF) satisfies

$$M_{t,t+1} = \beta^\theta e^{-\gamma(\mu_c + \sigma_c \epsilon_{c,t+1} + \xi x_{t+1})} \left(\frac{S(p_{t+1}) + 1}{S(p_t)} \right)^{-1+\theta}, \tag{3}$$

where the wealth-consumption ratio $S(p_t)$ solves the equation

$$\mathrm{E}_t \left[\beta^\theta \left(\frac{C_{t+1}}{C_t} \right)^{1-\gamma} \Big(S(p_{t+1}) + 1 \Big)^\theta \right] = S(p_t)^\theta. \tag{4}$$

Following Barro (2006), we consider a government bill that is subject to default in times of crisis. We let q denote the loss in case of default. The price of the government bill is thus given by

$$P_{Gt} \;=\; \mathrm{E}_t[M_{t,t+1}(1 - q x_{t+1})]. \tag{5}$$

The ex-post realized return on government debt is given by

$$r^G_{t+1} = \frac{1 - q x_{t+1}}{P_{Gt}} - 1. \tag{6}$$

[10] In our simulations, we discretize the process (2) so that $p_t < 1$.

3.3 Banks

Key to our analysis is the definition of a bank:

Definition 1. *A bank is a licensed investment management company whose risky investments or loans are financed by equity and guaranteed deposits.*

In our model, a bank is able to extract rents from subsidized deposits and takes advantage of stochastic investment/lending opportunities by responding optimally to unexpected changes in the economic environment.[11]

Every period, bank managers maximize the value of the equity holders by making optimal investment and payout decisions. More specifically, managers decide how much capital to allocate to a portfolio of risky loans and to holdings of government securities as well as on the amount of equity to fund these investments. A bank's risky loan portfolio consists of a diversified pool of collateralized loans which is subject to bank specific and aggregate shocks.

3.3.1 The Bank's Balance Sheet

Bank i enters time t with book equity BE_{it} and deposits D_{it}. Following Merton (1978), we assume $D_{i,t+1} = D_{it}e^{g}$, namely that deposits grow at a constant rate.[12,13]

When a bank is not in default (discussed below), it decides on the overall size of its current loan portfolio (its assets) denoted by A_{it} and on how much to repay its equity-holders, Div_{it}. A bank must also pay operational, or non-interest expenses, Φ_{it} in every period, so that its resource constraint at time t

[11] Deposit guarantees are funded with taxes on the aggregate economy and their impact is not internalized by the bank managers.

[12] It is easy to allow the demand for deposits to be stochastic but this feature is not essential to our results.

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

$$g = \log((1 - \mathrm{E}p_t)e^{\mu_c + \sigma_c^2/2} + \mathrm{E}p_t e^{\mu_c + \sigma_c^2/2 + \xi}). \tag{7}$$

is:

$$A_{it} = BE_{it} + D_{it} - Div_{it} - \Phi_{it}. \tag{8}$$

The evolution of book equity over time depends on the ex-post rates of return between t and $t+1$ on the bank's assets, $r^A_{i,t+1}$, and liabilities, r^D_{t+1}. Given these ex post returns, book equity in the next period equals

$$BE_{i,t+1} = (1 + r^A_{i,t+1})A_{it} - (1 + r^D_{t+1})D_{it}. \tag{9}$$

3.3.2 Loans and the Return on Assets

Asset returns depend on the banks' loan portfolio and overall economic conditions. If $\varphi_{it} \in [0, 1]$ is the share of bank i's total assets that is allocated to a pool of private sector loans, and $r^L_{i,t+1}$ is the ex-post rate of return on this portfolio, the return on the bank's assets equals:

$$r^A_{i,t+1} = \varphi_{it} r^L_{i,t+1} + (1 - \varphi_{it}) r^G_{t+1}. \tag{10}$$

Each bank's portfolio of private sector loans is made of a large number of individual loans within a local economy. We think of these as collateralized loans (e.g. mortgages) to households that are not the marginal investor and thus price no assets.[14] We let the time-t collateral value for each individual loan $j = 1, \ldots, n$ of bank i equal

$$W_{ijt} = e^{\sigma_c \epsilon_{ct} + \xi x_t + \omega_{it} + \sigma_j \epsilon_{jt}}. \tag{11}$$

Note that this value depends on the state of the aggregate economy (ϵ_{ct}, x_t), a borrower-specific shock, ϵ_{jt}, and a measure of the health of local market conditions, ω_{it}.

[14] Yeager (2004) shows the vast majority of the U.S. banks remain small and geographically concentrated and 61% have operated within a single county. Mortgages (and other household loans) account for the majority of most bank's assets.

As an example, the bank-specific variable ω_{it} could represent a local determinant of house prices. A persistent bank-specific determinant of loan performance ensures the cross-section of banks will remain non-trivial. We assume ω_{it} evolves according to the Markov process:

$$\omega_{i,t+1} = \rho_\omega \omega_{it} + \sigma_\omega \epsilon_{\omega_i,t+1}. \tag{12}$$

We assume both ϵ_{jt} and $\epsilon_{\omega_i t}$ to be iid over time, independent of each other and also of ϵ_{ct}, x_t, and ϵ_{pt}. Shocks to all these variables will change both the collateral value of an individual loan and the probability it will default.

We assume a common face value of each individual loan of κ so that borrower j is said to default at time t if $W_{ijt} < \kappa$. In this case the bank recovers a fraction $1 - \mathscr{L}$ of the collateral value. In Appendix A we use the central limit theorem to integrate out borrower risk and derive the distribution of the ex-post return on the bank's pool of private sector loans, $r^L_{i,t+1}$. As a result, the ex-ante distribution of $r^L_{i,t+1}$ depends only on p_t and ω_{it}.

Figure 7 shows how the spread between the rates of return on these two investments changes with macroeconomic conditions. Like other risky spreads this is increasing in the probability of a crisis, p_t. In addition, risk premia on the bank loan portfolio decline when local market conditions improve, as measured by collateral values, ω_{it}. An improvement in local market conditions decreases the chance/severity of default in the loan portfolio, given a crisis, and hence lowers the exposure to p_t.

3.3.3 The Deposit Rate

Following Merton (1978), we assume that the interest rate on deposits is constant over time and below the unconditional average of government bill rate, so that $r^D < E[r^G_{t+1}]$.

As is well known, this wedge can readily arise when deposits provide liquidity

services as in Sidrauski (1967) or Van den Heuvel (2008). Here we prefer instead to invoke the existence of deposit insurance guaranteeing that bank depositors receive at least partial compensation in the event of a bank default. More generally, however, this wedge also arises in any imperfectly competitive model where banks have the ability to earn excess rents on their operations (Drechsler, Savov, and Schnabl, 2017).

Regardless of the precise reason, the notion that deposit rates are both sticky and below the rates on money market accounts and government bills is well-grounded in data. Figure 8 shows the rate on the three-month Treasury bill and the average deposit rate earned on large-denomination interest checking accounts over the last 20 years. Although not constant, deposit rates are very slow moving and, on average, well below those on Treasuries.

3.3.4 Regulation and Termination

Bank regulation takes two forms. First, banks face regulatory requirements on their use of leverage: whenever the bank's chosen debt-to-asset ratio at time t, D_t/A_t, exceeds the regulatory threshold, χ, the bank must incur an additional cost f per unit of deposits.[15] Generally, even a small cost will be enough to ensure that banks comply with the regulatory constraint.

Second, as in Merton (1978), we assume that regulators monitoring the bank intervene and seize the bank's operating license whenever the value of its book equity at the beginning of the period, BE_{it}, drops below 0. Formally, this means that whenever $BE_{it} < 0$ a bank cannot raise equity ($Div_{it} < 0$) to avoid being shut down. If the bank is terminated, its assets are seized, the deposits are paid and its equity holders receive nothing. As a result, from the perspective of its equity holders, excessive risk taking by the bank may result in sub-optimal termination.

[15]Note that this cost is fixed except for the scale factor.

3.3.5 The problem of the bank

It follows from the description above that the market value of bank i's equity at time t is given by:

$$V_{it} = \begin{cases} \mathrm{E}_t \left[\sum_{s=t}^{T_i^*-1} M_{t,t+s} Div_{is} \right], & t < T_i^* \\ 0, & t \geq T_i^* \end{cases} \tag{13}$$

where

$$T_i^* = \inf\{t : BE_{it} < 0\} \tag{14}$$

denotes bank i's (stochastic) termination time, and $M_{t,t+s}$ denotes the SDF between times t and $t+s$.[16]

Conditional on survival at time t, the market value of bank i satisfies the recursion

$$\begin{aligned} &V_i(BE_{it}, A_{i,t-1}, D_{it}, p_t, \omega_{it}) = \\ &\max_{\varphi_{it}, Div_{it}} \; Div_{it} + \mathrm{E}_t \left[M_{t,t+1} V_i(BE_{i,t+1}, A_{it}, e^g D_{it}, p_{t+1}, \omega_{i,t+1}) \mathbb{1}_{BE_{i,t+1}>0} \right], \end{aligned} \tag{15}$$

subject to (9),

$$\begin{aligned} r_{i,t+1}^A &= \varphi_{it} r_{i,t+1}^L + (1-\varphi_{it}) r_{t+1}^G \\ \log p_{t+1} &= (1-\rho_p) \log \bar{p} + \rho_p \log p_t + \sigma_p \epsilon_{p,t+1} \\ \omega_{i,t+1} &= \rho_\omega \omega_{it} + \sigma_\omega \epsilon_{\omega_i,t+1}, \end{aligned} \tag{16}$$

and

$$A_{it} = BE_{it} + D_{it} - Div_{it} - \Phi(A_{it}, D_{it}, A_{i,t-1}),$$

[16] Specifically, $M_{t,t+s} = \prod_{\tau=t}^{t+s-1} M_{\tau,\tau+1}$, for the one-period SDF $M_{\tau,\tau+1}$ defined in (3).

where

$$\Phi(A_{it}, D_{it}, A_{i,t-1}) = \eta_B A_{i,t-1} \left(\frac{A_{it} - A_{i,t-1}}{A_{i,t-1}} \right)^2 + f D_{it} \mathbb{1}_{D_{it} > \chi A_{it}}.$$

The cost function Φ summarizes the non-interest expenses, inclusive of regulatory charges, incurred by the bank. Operating expenses are assumed to depend on the growth in bank assets over time.

We greatly simplify the computation of the bank's problem using two economic insights. First, the problem is jointly homogeneous of degree 1 in assets and deposits, because both the current stream of cash flows and the constraints are linear in $A_{i,t}$ and $D_{i,t-1}$. Second, we solve for the gap between (scaled) market and book equity:

$$\widetilde{v}(a_{i,t-1}, p_t, \omega_{it}) = \frac{V_i(BE_{it}, A_{i,t-1}, D_{it}, p_t, \omega_{it}) - BE_{it}}{D_{it}}, \tag{17}$$

where $a_{it} = \frac{A_{it}}{D_{it}}$ and $be_{it} = \frac{BE_{it}}{D_{it}}$. Appendix B shows that (17) is indeed a function of lagged scaled assets ($a_{i,t-1}$), crisis probability (p_t), and local conditions (ω_{it}).[17] We refer to (17), the (scaled) difference between market equity and book equity, as the bank's *franchise value*.

In our model, franchise value is driven by the ability of the bank to earn greater returns, in a risk-adjusted sense, on its asset portfolio, than it is required to pay to its debtholders. In what follows, we show that banks seek to protect this franchise value; this mitigates the moral hazard problem resulting from deposit insurance. When franchise value falls, however, incentives change.

Figure 9 depicts scaled franchise value as a function of the crisis probability, p_t, for alternative values of (scaled) lagged assets. Franchise value is strictly decreasing in the crisis probability and is increasing in lagged assets. The negative relation between the franchise value and the crisis probability arises

[17] Technically, (17) is well-defined only when $BE_{it} \geq 0$. See Appendix B for details.

endogenously. When p_t rises, safe asset values rise because of precautionary savings. Risky asset values might either rise or fall, depending on whether the negative effect of the crisis probability on expected cash flows and on the risk premium outweighs the precautionary savings effect. For the bank, there is an additional consideration: the bank can choose its portfolio and therefore its level of risk in response to changes in p_t. The net effect is that an increase in p_t leads to a decrease in franchise values.

3.4 Bank Risk-Taking

Figures 10 and 11 illustrate the two key choices of a bank. Figure 10 depicts the bank's decision with respect to the size of its overall loan portfolio, a_{it}. Given an exogenous supply of deposits, this is also the optimal leverage decision of the bank, with a higher a_{it} corresponding to lower leverage. As Figure 10 shows, current leverage choices will be generally increasing in past leverage. This is because asset growth is costly. The nature of the bank's operating costs generates a plausibly strong persistence in lending and leverage decisions.

Figure 10 also shows the rich dynamics generated by the model as the previous leverage choice interacts with the crisis probability. For banks beginning the period with low leverage, the optimal level of assets (relative to deposits) decreases as a function of the crisis probability; for low values of the crisis probability the slope is relatively flat, and then steepens as the probability rises. For banks beginning the period with moderate leverage, optimal assets increase, and then decrease. Finally, highly levered banks, optimal assets in the next period are virtually flat in p_t.

How does the relatively simple model of Section 3 generate these patterns? All else equal, assets are costly to the bank (this is modeled through the cost function ϕ, which multiplies the level of assets). However, the main business of the bank, taking deposits and investing in assets, is profitable, so the bank

would like to avoid being shut down. Thus the bank would like to maintain positive book equity, not only in the present, but also in the future (provided that the benefits are high, and the costs are sufficiently low). When the probability of a crisis, p_t, is low, this effect dominates for all banks but the ones with the highest leverage. If a bank happens to start the period with a high level of assets, it slowly reduces assets to gradually get to to the (stochastic) steady state.[18] This is shown by the dotted line in Figure 10. If a bank happens to start the period at moderate leverage, it *increases* assets (decreasing leverage). The higher is p_t, the more it seeks to increase assets. This effect, illustrated by the dashed line in Figure 10, is due to precautionary motives specific to the bank – mainly the desire to have high book equity in the future. Thus, when p_t is low, the bank's primary incentive is to stay in business, not just in the present period, but in the future, to protect its franchise value. It is noteworthy that this occurs despite the presence of the moral hazard problem due to deposit insurance.

As the probability of a crisis rises, however, the bank's incentives change in a dramatic way. The probability of shutdown increases, and avoiding it entirely becomes too costly. The bank shifts from being a "good bank", making safe investment and seeking to stay in business, to being a "bad bank," in effect taking advantage of the subsidy offered to depositors. This is illustrated by the kinks in the policy functions shown in Figure 10. The threshold for p_t at which this occurs depends on leverage from the previous period. For the bank with low leverage the shift does not occur until the probability of a crisis is as high as 5%. For the bank with with the middle value, it occurs at 2%. For the bank with the highest leverage, all value of p_t lead it to maintain assets at their lowest value.[19]

[18]For low values of p_t, a_t declines as a function of p_t. This is because of the usual trade off between the income and substitution effect. At higher p_t, investment opportunities are less favorable and the bank returns capital to its equity holders.

[19]Recall that this maximum leverage position is defined by need to pay a fine proportional

We can see the same mechanisms at work in the optimal portfolio allocation of the bank, as Figure 11 shows. When the probability of a crisis is low, well-capitalized banks avoid risky loans to households; these are made, however, by poorly capitalized banks (contrast the solid line with the dotted and dashed lines in Figure 10). At a threshold level of p_t, however, the loan portfolio shifts toward the risky household loans. This shift occurs at the same point at which the bank decides to hold less equity in Figure 10.

What explains the shift from "good bank" to "bad bank" at higher levels of the crisis probability? As discussed above, franchise value decreases in the crisis probability.[20] At higher levels of p_t, the bank is not as incentivized to protect this lower value, and so engages in risk shifting. That is, the claim of bank equity holders resembles a call option, which benefits from increased volatility in a way that the overall asset does not. By increasing leverage and investing in risky household loans, the bank "gambles for resurrection." A good outcome generates high returns for the equity holders. A bad outcome results in being shut down; however, if shutdown is likely regardless, equityholders cannot be further penalized. As for any call option, the sensitivity to volatility increases the more the underlying asset is out of the money. Thus the greater is p_t, the lower is franchise value, and the greater the incentive to gamble for resurrection. Exacerbating this effect is an endogenous decline in the market interest rate as p_t rises, due to the precautionary motive of the representative agent. It becomes costlier for the bank to protect its franchise value, even as the bank has less of an incentive to do so. This realistic mechanism leads to behavior sometimes referred to as "reaching for yield." Furthermore, consistent with empirical evidence, in our model a credit boom emerges when bank profitability is relatively high, so that accounting profitability prior to the crisis is associated with higher systematic tail risk (Meiselman, Nagel, and Purnanandam, 2018;

to deposits when leverage exceeds this value.

[20]The argument in this paragraph shows why this is in fact an equilibrium outcome.

Richter and Zimmermann, 2019).

Figure 12 summarizes our findings by showing the implications of optimal bank behavior to its overall probability of default. For well-capitalized banks the expected failure rate remains essentially at 0 as long as a crisis is somewhat unlikely. As p_t rises however, risk premia widens, expected returns on government debt fall and even well-capitalized banks can no longer be assured of survival. Increased risk taking exposes these banks to more and more systematic risk and raises overall default probabilities until they become indistinguishable from p_t itself.

3.5 Firms, Production and Output

As we will show, the model has realistic implications for the relation between leverage, risky lending, and growth in GDP. These implications arise naturally from a production sector. For simplicity, we assume a representative firm maximizing the present value of cash flows, taking the investors' stochastic discount factor (3) as given. We assume this sector faces no financial frictions, and is all-equity financed.

3.5.1 Technology

A firm uses capital K_t to produce output Y_t according to the Cobb-Douglas production function

$$Y_t = z_t^{1-\alpha} K_t^{\alpha}, \tag{18}$$

where α determines the returns to scale of production and z_t is the productivity level. We assume z_t follows the process

$$\log z_{t+1} = \log z_t + \mu_c + \epsilon_{c,t+1} + \phi\xi x_{t+1}. \tag{19}$$

During normal-times, productivity grows at rate μ and is subject to the same shocks as consumption ($\epsilon_{c,t+1}$). Importantly, this process implies that the productive sector is exposed to the same Bernoulli shocks as consumers and banks through the term $\phi\xi x_{t+1}$. ϕ is the sensitivity of TFP to an economic crisis.

3.5.2 Investment Opportunities

The law of motion for the firm's capital stock is

$$K_{t+1} = \Big[(1-\delta)K_t + I_t\Big]e^{\phi\xi x_{t+1}}, \tag{20}$$

where δ is depreciation and I_t is firm's investment at time t. Equation (20) captures the depreciation cost necessary to maintain existing capital. Following the formulation of Gabaix (2011) and Gourio (2012), it also captures the impact of a possible destruction of productive capital during a crisis. This can proxy for either literal capital destruction (in the case of war), or simply misallocation due to economic disruption.

Finally, to allow us to match the relative volatility of investment and output in the data the firm is assumed to face convex costs when adjusting its stock of capital (Hayashi, 1982). To be precise, we assume that each dollar of added productive capacity requires $1 + \lambda(I_t, K_t)$ dollars of expenditures, where

$$\lambda\left(I_t, K_t\right) = \eta_F \left(\frac{I_t}{K_t}\right)^2 K_t, \tag{21}$$

and the parameter $\eta_F > 0$ determines the severity of the adjustment cost.

Optimal production and investment decisions, can then be constructed by

computing the total value of the firm, V^f, which obeys the recursion

$$V^F(K_t, z_t, p_t) = \max_{I_t, K_{t+1}} \left[z_t^{1-\alpha} K_t^{\alpha} - I_t - \lambda(I_t, K_t) + \mathrm{E}_t[M_{t,t+1} V^F(K_{,t+1}, z_{,t+1}, p_{t+1})] \right],$$

subject to (20) and (21).

4 Crisis, Bank Lending and the Predictability of Macro Aggregates

The joint exposure of consumers, firms and banks to common aggregate shocks generates interesting co-movements between the various macroeconomic aggregates and bank lending over the business cycle. In this section we investigate the implications of a quantitative version of our model for these movements with a special focus on the role of bank risk-taking decisions.

4.1 Parameter Values

We begin by picking a set of values for our model's parameters. We calibrate the model at an annual frequency. Tables 1-3 summarize our choices for the parameters used to solve the problems of investors, banks and firms, respectively.

The representative investor prices all risky claims in our economy. Thus, we choose the preference parameters (β, γ, ψ) and consumption parameters to match key asset pricing moments and well-established macro patterns. We take the values for the parameters γ and ψ from the recent literature on asset pricing with rare events (e.g. Gourio (2012) and Gomes, Grotteria, and Wachter (2018)), while the values chosen for the parameters μ_c, σ_c and β follow from a long tradition in extant macro literature (e.g. Cooley and Prescott (1995))

Due to their rare nature, precise calculations of the probabilities and distributions implied by (2) are difficult. We generally follow Barro and Ursua

(2008) and set the average probability of an economic collapse $\bar{p}$ to be 2% per annum and an associated drop in consumption of $\xi = 30\%$.[21] Next, we set the autoregressive coefficient to be 0.8 (annually) with an unconditional standard deviation of 0.42, values that are consistent with those used in Gourio (2013). Finally, we assume the government bills experience a loss of $q = 12\%$ during a crisis.

To solve the problem of the bank, we set the loss given default on private loans to 60% so that it matches the observed average recovery rate on secured senior debt (Ou, Chlu, and Metz, 2011). The face value of an individual private loan κ is set so that the average loan-to-value ratio equals 80%, the typical value for newly originated or refinanced residential mortgages (Korteweg and Sorensen, 2016). The parameters governing the evolution of local conditions, σ_ω and ρ_ω, are determined from volatility and persistence U.S. house prices, at the individual state level. The value for the idiosyncratic component of volatility, σ_j, is borrowed from Landvoigt, Piazzesi, and Schneider (2015) who estimated an annual volatility of individual house prices between 8% and 11%.

The regulatory capital requirement parameter χ is set to be 0.92, corresponding to an 8% equity to asset ratio, in accordance to Basel rules. Finally, the value of the operating cost parameter η_B is chosen to generate a plausible cross sectional dispersion in the asset-to-debt ratio in the model that approximates that for US bank holding companies.

Parameter values used to solve the problem of the firm are either in line with standard choices in the macroeconomics literature (α and δ) or chosen to match specific facts, like the relative drop in GDP during crises (ϕ) or the volatility of investment growth relative to the volatility of output growth in the data (η_F).

[21] Our estimate of p_t is slightly below Barro and Ursua (2008) estimates of an average probability of disaster of 2.9% on OECD countries and 3.7% for all countries.

4.2 Quantitative Results

We now quantify the links between bank lending and macroeconomic activity. We focus on a well-known set of empirical results that have been interpreted to indicate a causal relation between credit and poor subsequent economic performance (e.g. Gennaioli and Shleifer (2018)). We show that our model can quantitatively account for these findings, though the interpretation is quite different. We simulate 10,000 years of artificial data from the economy described above (see Appendix C for further detail). We consider a crisis to have occurred in simulated data if realized GDP growth is in the bottom 4% of its unconditional distribution, matching the empirical frequency of crisis in the Schularick and Taylor (2012) data. This definition captures not only all the observations in which $x_t = 1$ but also a number of periods during which the probability of a crisis, p_t, rose sharply, leading firms in the model to reduce investment and thus output to fall. It addresses the concern that the econometrician, in identifying crises, does not observe the variable x_t; indeed there may be no clear line between $x_t = 1$ events and events in which there is a large positive shock to p_t in terms of observables. Our results are not sensitive to this definition.[22]

Each simulation contains a cross-section of 1,000 ex-ante identical banks. To quantitatively match the model's behavior to the data, we focus on variables that are stationary. Recall that, normalized by deposits, the dollar value of the loans of bank i at time t equals $\varphi_{it} a_{it}$. We therefore define aggregate lending as this quantity, summed over banks. That is, aggregate lending equals $L_t = \sum_i \varphi_{it} a_{i,t}$.

Table 6 replicates the results of Schularick and Taylor (2012) that an increase in lending raises the probability of a crisis. That is, crisis occurrence is regressed

[22]We use this definition of crisis only for comparison with existing empirical results. In later sections of the paper, we will continue to use the terminology "crisis" to refer to the exogenous event that $x_t = 1$.

on lagged values of bank loans in an international sample, spanning the years 1870 to 2008. Schularick and Taylor (2012) find that an increase in lending is a statistically significant predictor of a crisis. The standard interpretation is that increased bank lending causes a crisis. We find a similar effect in the model, which holds with similar magnitude. In our model, however, time-varying exogenous risk drives both, and the relation between lagged bank lending and crises is merely a correlation.

Figure 13 compares our model's findings with the evidence in Jordà, Schularick, and Taylor (2016) showing that financial crises often follow periods of very fast credit growth. It breaks down the frequency of a crisis for each quintile of lagged credit growth. The top figure replicates the evidence in the original paper showing that crises frequencies increase significantly after periods of fast credit-to-GDP growth. However, Panel B, taken from our artificial dataset, shows how we can substantively replicate these same facts, even when our model assumes that a crisis is *never* caused by changes in bank lending. High credit growth is correlated with more frequent realizations of crises.[23]

We also examine our model's implications for the related findings in Mian, Sufi, and Verner (2017), documenting the strong predictability of future GDP growth by the lagged growth in household debt for 30 countries. Figure 15 replicates and updates their work to show negative relation between growth in lagged household debt (scaled by GDP) and GDP growth over a three-year window. In our model, the growth rate in bank loans also negatively predicts the growth rate in GDP. Note that this empirical exercise has no explicit link to financial crises. In the model, however, it is the increased probability of a crisis that leads to lower growth.

Why is the model able to produce these findings? The key mechanism is the fluctuating value of the bank's franchise. During periods of high probability

[23]In the model, we look directly at growth in credit L_t, rather than growth in credit scaled by GDP. This is because, as we have defined defined it, credit growth is stationary. However, the ratio of loans to GDP may not be stationary.

of financial crises, banks' franchise value falls. Some banks, and in particular those with poor balance sheets, find it optimal to gamble for resurrection, taking on risky household loans. Thus growth in risky loans predicts crises. It also predicts lower GDP growth because non-financial firms, perceiving the same economic instability, reduce their investment, leading to lower output.

The model is also consistent with a number of other recent empirical findings linking credit growth, valuations, and financial crisis. Consistent with Muir (2017), the model predicts that a financial crisis, represented in the model by a large increase in p_t, implies higher risk premia. Specifically, large declines in bank stocks (as opposed to a panic aspect of a crisis), imply higher risk premia, as Baron, Verner, and Xiong (2019) show in recent work. This large decline in bank stocks, through the channel of a higher probability of disaster, depresses investment, and therefore GDP growth. Mean reversion in p_t then implies that credit offered by banks shrinks following expansions of credit. Baron et al. (2019) show that both of these results also hold in the data.[24]

To conclude then, our quantitative model is broadly consistent with the observed empirical patterns in bank credit that generally precedes economic collapses. In the model, however, these patterns merely reflect optimal decisions taken in response to *exogenous* fluctuations in the probability of a financial and economic collapse and thus, by construction, have no effect on the odds that this event will occur.

[24]The model cannot explain every feature of intermediary valuations around crises: the model does predict that the decline in bank equity should occur while bank lending increases, while in the data, increases in bank lending predict equity declines (Baron and Xiong, 2017). It may be that bank equity holders did not fully incorporate the risks of lending; thus while the risks were foreseen by some, they were not foreseen by all. The model does explain, however, that once a crisis is realized, it is those banks that lent the most that are most effected, broadly consistent with Fahlenbrach, Prilmeier, and Stulz (2017).

5 Policy Evaluation

In response to the recent financial crisis, fiscal and monetary authorities unleashed an array of polices aimed at influencing the behavior of the banking sector. These included the Capital Purchase Program (CPP) and the first round of quantitative easing measures (QE1) in the United States, and the long-term refinancing operations (LTRO) in Europe.

Much of the recent theoretical literature on unconventional interventions prefers to highlight the role of large-scale asset purchases of long-term government bonds and private securities in the context of segmented markets. It concludes that these policies could generate a large increase in bank credit to the private sector.(Gertler and Karadi, 2015; Curdia and Woodford, 2010; Del Negro, Eggertsson, Ferrero, and Kiyotaki, 2017; Williamson, 2012).

While these models seem compelling, empirically, the ultimate impact of the extraordinary amount of government support on bank lending is much less clear. In the US, institutions that were included in the Capital Purchase Program did not increase their loans (Duchin and Sosyura, 2014; Bassett, Demiralp, and Lloyd, 2017). Similarly, Carpinelli and Crosignani (2018) conclude that LTROs in Europe were equally ineffective in boosting bank lending.

By contrast, our model suggests understanding these interventions through their impact on bank franchise value. In effect, several of these policies worked to provide banks with funding at very favorable terms, in effect subsidizing the banking sector (CPP and LTROs were explicitly designed to do just that). By highlighting an alternative mechanism that is consistent with the available evidence, our paper offers a novel perspective on the impact of these policies on banks.

Formally, we examine the impact of government interventions by considering the effects of a reduction in banks cost of funding below its current market

value, $\widetilde{r}^D < r^D$.[25] Unsurprisingly, in our model, as Figure 16 shows, this intervention directly leads to an increase in the franchise value of banks, since they can now secure better terms to fund themselves. Figure 17 then shows that a consequence of this intervention is that banks will now also actually rely on (relatively) more equity. This is because with increased franchise values, default will now trigger larger losses for equity holders. As a result this policy intervention will produce a decline in expected bank failure rates.

However, this increased conservatism by equity holders also manifests itself in the optimal portfolio composition of banks. We can see in Figure 18 that the optimal asset composition now generally tilts more towards government bonds and away from risky private loans. Only poorly-capitalized banks eschew this behavior to remain fully invested in private sector loans.

Thus policies that effectively subsidize bank equity holders by allowing them tap debt markets at below-market rates lead many banks to reduce overall risk taking. Moreover, Figures 17 and 18 show that this effect is particularly strong when the likelihood of a crisis is high.

We believe these findings add a fresh perspective to the ongoing debate about the effects of unconventional monetary policies on bank lending. In particular they suggest an explanation for the perceived limited success of unconventional monetary policies in stimulating bank credit to the private sector during the economic recovery after the recent financial crisis. As Bocola (2016) shows, European banks mainly used LTROs to cheaply substitute liabilities, while in the US Di Maggio, Kermani, and Palmer (2016) describe a "flypaper effect" in which banks chose to hold excess reserves with the central bank rather than expand credit to the private sector.

Our results are also consistent with the evidence of Rodnyansky and Darmouni (2017), who find that U.S. banks with mortgage-backed securities on

[25] Although our model offers a simple description of bank liabilities a lower cost of deposit should be interpreted more broadly as a reduction in the bank's cost of debt.

their books increased lending relative to their peers after QE1. In our model this is unsurprising since those are the banks who optimally chose $\varphi = 1$. These banks will remain the most eager to replace safe assets with risky ones.

6 The Role of Deposit Insurance: Empirical Evidence

Rent-seeking behavior from banks is a crucial ingredient in delivering many of our results. Although, in practice, this behavior can also arise from a lack of competition in the sector, our model focuses on rents derived from explicit government guarantees on bank deposits. As we have shown above, access to subsidized financing can meaningfully alter a bank's incentives to hold risky securities in its loan portfolio over time.

In this section we provide independent supporting evidence on the link between the availability of deposit insurance and economic crises. We combine several databases to create a country-level unbalanced panel dataset that contains observations on aggregate household and non-financial firm debt to GDP, macro quantities and the availability of deposit insurance in both advanced and emerging economies. Effectively, this extends the sample used by Mian, Sufi, and Verner (2017) to include more countries, a longer time period and data on the use of deposit insurance.[26]

Our basic procedure is adapted from Mian et al. (2017). Let $\Delta_3 y_{t+h}$ be the three year change in log real GDP per capita in local currency between year $t+h-3$ and $t+h$. Similarly, define $\Delta_3 d^{HH}_{i,t-1}$ and $\Delta_3 d^{F}_{i,t-1}$ as the three year rates of growth in the household and firm debt to GDP ratios. Our baseline regression, reported in Panel A in Table 5, reports the estimates for

[26]Our data adds together the Bank of International Settlements (BIS) "Long series on total credit to the non-financial sectors", the World Bank's World Development Indicators (WDI) database and the Global Financial Database.

the following equation:

$$\Delta_3 y_{i,t+h} = \alpha_i + \beta_H \Delta_3 d^{HH}_{i,t-1} + \beta_F \Delta_3 d^{F}_{i,t-1} + u_{it}, \tag{22}$$

when $h = -1, \ldots, 5$. Consistent with prior evidence (Mian et al., 2017) we find that a 1 percentage point increase in household debt to GDP ratio is correlated with a 0.4 percentage point drop in GDP per capita after 3 years.

We next combine our data with the country-level database on deposit insurance schemes, constructed by Demirgüç-Kunt, Karacaovali, and Laeven (2005). For countries where no explicit scheme was reported before 2005, we hand collected the dates of enactment, if any.[27] Overall, we find that in about 25% of our country-year observations there is no deposit insurance scheme in place.

We then interact a zero-one dummy variable for the presence of explicit deposit insurance in the past three years to (22) and estimate the following equation:

$$\Delta_3 y_{i,t+h} = \alpha_i + (\beta_{HH} + \beta^{DI}_{HH} \mathbb{1}_{DI}) \Delta_3 d^{HH}_{i,t-1} + (\beta_F + \beta^{DI}_{F} \mathbb{1}_{DI}) \Delta_3 d^{F}_{i,t-1} + u_{it}, \tag{23}$$

for $h = -1, \ldots, 5$.

Panel B in Table 5 shows that the coefficients on the interaction between growth in household credit and the presence of deposit insurance are generally statistically significant, suggesting the variation captured by our regressors is mostly concentrated in periods and countries where deposit insurance is in place. Notably, the relation between credit and GDP is essentially flat and not significant in countries without explicit government insurance.[28] By contrast,

[27] While US introduced deposit insurance as early as 1934, it became common in most countries only in the late 80s.

[28] It is also noteworthy that there is no significant relation between firm credit and subsequent economic growth. The relation is confined to growth in the riskiest form of credit, that is, household credit. This is consistent with our model.

we find that when deposit insurance schemes are present, a 1 percentage point increase in household debt is correlated with a 0.51 percentage drop in GDP after 3 years.

While a detailed empirical assessment of the role of deposit insurance in financial crises is outside the scope of this paper, Table 5 strongly suggests that the relation between credit growth and financial crises is mediated through deposit insurance.

7 Conclusions

A large literature, motivated by empirical linkages between leverage and crises, argues that excessive household leverage is a cause of subsequent crises, and specifically the financial crisis of 2008. However, leverage is itself an outcome of endogenous decision-making. While it may be plausible that households, perhaps based on lack of experience, overoptimism, or simply rule-of-thumb behavior, took more risk than, ex post, proved optimal, it is harder to believe that banks, en masse, decided to lend to such households purely based on overoptimism, as economic conditions worsened.

This paper offers a quantitative resolution of this conundrum based on a dynamic model of risk-shifting by banks. In our model, banks endogenously provide more leverage to households in times of worsening economic conditions. The subsequent economic decline is in no way caused by household's over-leveraging. Rather, leverage and the subsequent crises are caused by the same economic phenomenon: in this model, a time-varying likelihood of an economic crisis.

Our study suggests that recent policy toward banks might have effects counter to what is intended. Banks' decisions over time are driven by fluctuations in their franchise value. Methods to strengthen banks, while conferring long-run benefits, might actually result in less lending because they increase

the franchise value. On the flip side, any policy with the side effect that weakens banks might actually result in more undesirable lending, and further bank instability, as banks gamble for resurrection. In both cases, ignoring the incentive effects of policy on banks, which operate through fluctuating franchise values, could itself exacerbate underlying risks.

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Appendix A Bank Lending

Following Vasicek (2002), and Nagel and Purnanandam (2017), we assume an exogenous process for bank loans. Define a payoff on an individual loan based on the random variable

$$W_{ijt} = e^{\sigma_c \epsilon_{ct} + \xi x_t + \omega_{it} + \sigma_j \epsilon_{jt}}, \tag{A.1}$$

where j indexes the borrower and i indexes the bank. Define a constant default threshold κ. If we assume (A.1) is a two-period process that has the value 1 at time $t-1$, then κ has the interpretation of the loan-to-value ratio. The lender receives repayment

$$\text{Rep}_j(\epsilon_{c,t}, x_t, \omega_t, \epsilon_{j,t}) = \kappa \mathbb{1}_{W_{j,t} \geq \kappa} + (1 - \mathscr{L}) W_{j,t} \mathbb{1}_{W_{j,t} < \kappa},$$

for a constant $\mathscr{L}$, interpreted as the loss given default. In what follows, we suppress the bank-specific i subscript.

Define

$$\begin{aligned} \text{Rep}(\epsilon_{c,t}, x_t, \omega_t) = \kappa \text{Prob}(W_{j,t} \geq \kappa | \epsilon_{c,t}, \omega_t, x_t) \\ + (1 - \mathscr{L}) E\left[W_{j,t} \mathbb{1}_{W_{j,t}} < \kappa | \epsilon_{c,t}, \omega_t, x_t \right]. \end{aligned} \tag{A.2}$$

It follows from the law of large numbers that

$$\lim_{n \to \infty} \frac{1}{n} \sum_{j=1}^{n} \text{Rep}_j(\epsilon_{c,t}, x_t, \omega_t, \epsilon_{j,t}) = \text{Rep}(\epsilon_{c,t}, x_t, \omega_t). \tag{A.3}$$

We assume, for simplicity, that the bank holds an equal-weighted portfolio of an arbitrarily large number of loans. Equation A.3 justifies the use of (A.2) as the repayment on the loan portfolio.

We now discuss the computation of (A.2). Define

$$\begin{aligned} f(\bar{\epsilon}, \bar{\omega}, 0) &= \log(\kappa) - \sigma_c \bar{\epsilon} - \bar{\omega} \\ f(\bar{\epsilon}, \bar{\omega}, 1) &= \log(\kappa) - \sigma_c \bar{\epsilon} - \xi - \bar{\omega}. \end{aligned}$$

Note that the function f is the inverse of the normal cumulative density function (cdf), applied at the default probability. The probability of default conditional on no crisis at time t equals

$$\begin{aligned} p(\bar{\epsilon}, \bar{\omega}, 0) &= \text{Prob}\left(\log W_{jt} < \log \kappa \,|\, \epsilon_{ct} = \bar{\epsilon}, \omega_t = \bar{\omega}, x_t = 0\right) \\ &= \mathcal{N}\left(\frac{1}{\sigma_j}\left(\log(\kappa) - \sigma_c \bar{\epsilon} - \bar{\omega}\right)\right) \\ &= \mathcal{N}\left(f(\bar{\epsilon}, \bar{\omega}, 0)\right), \end{aligned}$$

where $\mathcal{N}(\cdot)$ denotes the normal cdf. Similarly, the probability of default conditional on a crisis at time t equals

$$\begin{aligned} p(\bar{\epsilon}, \bar{\omega}, 1) &= \text{Prob}\left(\log W_{jt} < \log \kappa \,|\, \epsilon_{ct} = \bar{\epsilon}, \omega_t = \bar{\omega}, x_t = 1\right) \\ &= \mathcal{N}\left(\frac{1}{\sigma_j}\left(\log(\kappa) - \sigma_c \bar{\epsilon} - \xi - \bar{\omega}\right)\right) \\ &= \mathcal{N}\left(f(\bar{\epsilon}, \bar{\omega}, 1)\right). \end{aligned}$$

Note that $p(\bar{\epsilon}, \bar{\omega}, 1) > p(\bar{\epsilon}, \bar{\omega}, 0)$. Default is more likely if a crisis occurs. It is also the case that $f(\bar{\epsilon}, \bar{\omega}, 1) > f(\bar{\epsilon}, \bar{\omega}, 0)$; there is a higher effective threshold for avoiding default if a crisis occurs.

To compute repayment (A.2), note that

$$E\left[W_{j,t}\mathbb{1}_{W_{j,t}<\kappa}|\epsilon_{c,t},\omega_t,x_t\right]=$$
$$\begin{cases} e^{\sigma_c\epsilon_{c,t}+\omega_t+\frac{\sigma_j^2}{2}}\int_{-\infty}^{f(\epsilon_{c,t},\omega_t,0)}(2\pi)^{-1/2}\,e^{-\frac{(z-\sigma_j)^2}{2}}dz & x_t=0 \\ e^{\sigma_c\epsilon_{c,t}+\xi+\omega_t+\frac{\sigma_j^2}{2}}\int_{-\infty}^{f(\epsilon_{c,t},\omega_t,1)}(2\pi)^{-1/2}\,e^{-\frac{(z-\sigma_j)^2}{2}}dz & x_t=1, \end{cases}$$

where we use the result that, for any a,

$$\int_{-\infty}^{a}e^{z\sigma_j-\frac{z^2}{2}}dz=e^{\frac{\sigma_j^2}{2}}\int_{-\infty}^{a}e^{-\frac{(z-\sigma_j)^2}{2}}dz. \tag{A.4}$$

A loan portfolio is thus an asset whose time-t payoff is defined by the random variable (A.2). Consider a time-t investment in the time-$(t+1)$ loan portfolio. The price of the loan portfolio equals

$$P^L(p_t,\omega_t)=\mathrm{E}_t\left[M_{t,t+1}\mathrm{Rep}(\epsilon_{c,t+1},x_{t+1},\omega_{t+1})\right]. \tag{A.5}$$

It follows that the ex-post return on the portfolio of loans equals

$$r^L_{t+1}=\frac{\mathrm{Rep}(\epsilon_{c,t+1},x_{t+1},\omega_{t+1})}{P^L(p_t,\omega_t)}-1. \tag{A.6}$$

Note that p_t and ω_t are sufficient statistics for the distribution of the return on the loan portfolio.

Appendix B Franchise value

Define scaled franchise value:

$$\widetilde{v}(a_{i,t-1},p_t,\omega_{it})=\frac{V(BE_{it},A_{i,t-1},D_{it},p_t,\omega_{it})-BE_{it}}{D_{it}}, \tag{B.1}$$

where we conjecture that the left-hand side is a function of $a_{i,t-1}$, p_t and ω_{it}. The definition (B.1) holds as long as $BE_{it}\geq 0$. In this Appendix, we derive a

recursion for (B.1), thereby verifying the conjecture.

First, substituting (8) into (15) implies that, conditional on $BE_{it} \geq 0$,

$$V_i(BE_{it}, A_{i,t-1}, D_{it}, p_t, \omega_{it}) = \max_{\varphi_{it}, A_{it}} BE_{it} + D_{it} - A_{it} - \Phi(A_{it}, D_{it}, A_{i,t-1}) + \mathrm{E}_t \left[M_{t,t+1} V(BE_{i,t+1}, A_{it}, D_{it} e^g, p_{t+1}, \omega_{i,t+1}) \mathbb{1}_{BE_{i,t+1}>0} \right], \quad \text{(B.2)}$$

subject to (9) and (16). Otherwise $V_{it} = 0$.

Define scaled market value and conjecture that this is a function of be_{it}, a_{it}, p_t, and ω_{it}:

$$v_i(be_{it}, a_{i,t-1}, p_t, \omega_{it}) = V(BE_{it}, A_{i,t-1}, D_{it}, p_t, \omega_{it})/D_{it}. \quad \text{(B.3)}$$

We further define

$$\phi(a_{it}, a_{i,t-1}) \equiv \eta_B a_{i,t-1} e^{-g} \left(\frac{a_{it} - a_{i,t-1} e^{-g}}{a_{i,t-1} e^{-g}} \right)^2 + f \mathbb{1}_{a_{it}^{-1} < \chi}.$$

Note that $\phi(a_{it}, a_{i,t-1}) = \frac{\Phi(A_{it}, D_{it}, A_{i,t-1})}{D_{it}}$.

Recursively define $v_i(be_{it}, a_{i,t-1}, p_t, \omega_{it})$ as

$$v_i(be_{it}, a_{i,t-1}, p_t, \omega_{it}) = \max_{\phi_{it}, a_{it}} be_{it} + 1 - a_{it} - \phi(a_{i,t-1}, a_{it}) + \mathrm{E}_t \left[M_{t,t+1} e^g v(be_{i,t+1}, a_{it}, p_t, \omega_{t+1}) \mathbb{1}_{be_{i,t+1}>0} \right], \quad \text{(B.4)}$$

subject to

$$be_{i,t+1} = e^{-g} \left((1 + r^A_{i,t+1}) a_{it} - (1 + r^D_{t+1}) \right), \quad \text{(B.5)}$$

and (16), for $be_{it} \geq 0$; otherwise $v_{it} = 0$. Dividing both sides of (15) by D_{it} and applying the law of motion for deposits shows that the definitions (B.4) and (B.3) are consistent, verifying the conjecture.

Finally, define $\widetilde{v}(a_{i,t-1}, p_t, \omega_{it})$ as the solution to the recursion

$$\widetilde{v}(a_{i,t-1}, p_t, \omega_{it}) = \max_{\phi_{it}, a_{it}} 1 - a_{i,t-1} - \phi(a_{i,t-1}, a_{it}) + \\ \mathrm{E}_t \left[M_{t,t+1} e^g (be_{i,t+1} + \widetilde{v}(a_{i,t}, p_{t+1}, \omega_{i,t+1})) \mathbb{1}_{be_{i,t+1}>0} \right], \quad \text{(B.6)}$$

subject to (B.5) and (16). Then

$$v(be_{it}, a_{i,t-1}, p_t, \omega_t) = \begin{cases} \widetilde{v}(a_{i,t-1}, p_t, \omega_{it}) + be_{it} & be_{it} \geq 0 \\ 0 & \text{otherwise} \end{cases}$$

It follows that, provided that $be_{it} \geq 0$, we can define scaled franchise value as

$$\widetilde{v}(a_{i,t-1}, p_t, \omega_t) = v(be_{it}, a_{i,t-1}, p_t, \omega_t) - be_{it}.$$

Appendix C Solution Algorithm

We discretize the stochastic processes for the probability of crisis p, the collateral value ω, and the i.i.d. ϵ_c shocks following the method developed by Rouwenhorst (1995). For p we use a 10-node Markov chain, while for ω, and ϵ_c we use 5 nodes.

We then calculate asset prices. The equilibrium wealth-consumption ratio is found solving the fixed-point problem in (4). Under the assumptions described in the main text, the wealth-consumption ratio is function of p only. The investor's stochastic discount factor is computed from (3). Prices and returns for the Treasury bill and the loans to households are derived from the Euler equations presented in (5) and (A.5), respectively.

With this information at hand, we solve the problem of the bank. We solve for scaled franchise value on the discretized state space, by iterating on (B.4). The bank takes prices as given, and jointly decides on its capital and portfolio allocation to maximize the sum of current cash-flows and continuation value.

The solution to the firm's problem is given in Appendix C of Gomes, Grotteria, and Wachter (2018).

We obtain model-implied moments by simulating 10,000 banks for 10,000 periods. The burn-out sample consists of the first 1,000 periods. Simulations yield a series for the exogenous state variables $\omega_{j,t}$, p_t, the endogenous state variables, $a_{j,t}$ and firm capital, as well as a series of shocks that determine the ex-post return on the bank investments and the ex post output of the firm.[29] Using these series, we can calculate all quantities of interest based on the functions for the value of the bank and the value of the firm.

[29]We assume, for simplicity, that when a bank defaults, an identical bank is created with the same state variables. This implies we do not need to keep track of past defaults (the bank's optimal decisions depend only on the current value of the state variables). This assumption allows us to maintain a stationary distribution of banks.

Table 1. Parameter Values – Representative Investor

Description	Parameter	Value
Elasticity of intertemporal substitution	ψ	2
Relative risk aversion	γ	3
Rate of time preference	β	0.987
Average growth in log consumption (normal times)	μ_c	0.01
Volatility of log consumption growth (normal times)	σ_c	0.015
Average probability of crisis	$\overline{p}$	0.02
Impact of crisis on consumption size	ξ	$\log(1-0.30)$
Persistence in crisis probability	ρ_p	0.8
Volatility of crisis probability	σ_p	0.42
Government bill loss given crisis	q	0.12

Notes: The table shows the parameter values used to solve the representative investor's problem. The investor has Epstein and Zin (1989) utility with risk aversion γ, elasticity of intertemporal substitution ψ, and time discount factor β. Her consumption process is given by

$$C_{t+1} = C_t e^{\mu_c + \epsilon_{c,t+1} + \xi x_{t+1}},$$

where x_{t+1} is a crisis indicator that takes a value of 1 with probability p_t. We assume that the logarithm of p_t follows a Markov process with persistence ρ_p and volatility σ_p. Conditional on a crisis realization, government bills experience a loss of q per unit invested. The model is calibrated at annual frequency.

Table 2. Parameter Values – Bank

Description	Parameter	Value
Return on deposits	r_D	0.48%
Loss given default on loans to households	$\mathscr{L}$	0.40
Loan-to-value ratio	κ	0.80
Volatility of local market component of collateral	σ_ω	0.02
Persistence of local market component of collateral	ρ_ω	0.90
Volatility of household component of collateral	σ_j	0.10
Capital regulation requirement	χ	0.92
Adjustment cost on capital	η_B	3

Notes: The table shows the parameter values used to solve the problem of an individual bank. Each bank i has access to a portfolio of n infinitesimal one-period loans with the same loan-to-value ratio (κ) at issuance. Let $j = 1, \ldots, n$ index borrowers for bank i. Let

$$W_{ijt} = e^{\sigma_c \epsilon_{ct} + \xi x_t + \omega_{it} + \sigma_j \epsilon_{jt}}$$

denote the time-t collateral value for borrower j of bank i (assuming a time-$t-1$ value of 1). If a loan defaults, the bank recovers $1 - \mathscr{L}$ of its collateral value W_{ijt}. The dividends for bank i are:

$$Div_{it} = BE_{it} + D_{it} - A_{it} - \Phi(A_{it}, D_{it}, A_{i,t-1}).$$

where $\Phi(\cdot)$ are non-interest costs, inclusive of regulatory charges. They are given by:

$$\Phi(A_{it}, D_{it}, A_{i,t-1}) = \eta_B A_{i,t-1} \left(\frac{A_{it} - A_{i,t-1}}{A_{i,t-1}} \right)^2 + f D_{it} \mathbb{1}_{D_{it} > \chi A_{it}}.$$

The bank i deposits grow exogenously according to:

$$D_{i,t+1} = D_{i,t} e^g.$$

The model is calibrated at annual frequency.

Table 3. Parameter Values – Representative Firm

Description	Parameter	Value
Returns to scale	α	0.40
Depreciation rate	δ	0.08
Sensitivity to crises	ϕ	2
Adjustment cost on capital	η_F	5

Notes: The table shows the parameter values used to solve the firm's problem. The firm has a Cobb-Douglas production function of the form

$$Y_t = z_t^{1-\alpha} K_t^{\alpha},$$

where the logarithm of the firm productivity level, z_t, follows a random walk process given by:

$$\log z_{t+1} = \log z_t + \mu_c + \epsilon_{c,t+1} + \phi\xi x_{t+1}.$$

The law of motion for each firm's capital stock is: $K_{t+1} = \Big[(1-\delta)K_t + I_t\Big] e^{\phi\xi x_{t+1}}$. The model is calibrated at annual frequency.

Table 4. Predicting crises in data and model

	LPM – Data	LPM – Model	Logit – Data	Logit – Model
ΔL_{t-1}	-0.0182	0.1579	-0.0917	3.4280
ΔL_{t-2}	0.260	0.1580	6.641	3.4335
ΔL_{t-3}	0.0638	0.0200	1.675	0.5877
ΔL_{t-4}	-0.00423	0.0807	0.0881	1.9856
ΔL_{t-5}	0.0443	0.0347	0.998	0.9774
Sum of lag coefficients	0.345	0.4513	9.311	10.4122
R^2	0.0126	0.0048	0.0379	0.0047

Notes: The table reports the coefficients and R^2 for the crises prediction equation as estimated by Schularick and Taylor (2012). Let the crisis event be identified by a binary variable equal to 1 if a crisis occurs and 0 otherwise. The first two columns report estimates from the following linear probability model (LPM)

$$\text{crisis}_{it} = \beta_0 + \sum_{j=1}^{5} \beta_j \Delta L_{t-j} + \epsilon_{it}.$$

The third and fourth columns report estimates from the following logit model:

$$P(\text{crisis} = 1) = \frac{e^{\beta_0 + \sum_{j=1}^{5} \beta_j \Delta L_{t-j}}}{1 + e^{\beta_0 + \sum_{j=1}^{5} \beta_j \Delta L_{t-j}}},$$

where financial crises in the data are as identified by Schularick and Taylor (2012) and L stands for the total dollar value of bank loans in real terms. The data cover 14 developed countries between 1870 and 2008. In the model, a crisis is defined based on contemporaneous GDP growth so that the frequency equals that in the data (4%) and L_t is defined as the sum of the dollar value of bank loans for each bank, scaled by that bank's deposits.

Table 5. Dependent Variable: $\Delta_3 y_{t+h}$

	Panel A: Benchmark Estimates						
	(-1)	(0)	(1)	(2)	(3)	(4)	(5)
$\Delta_3 d^{HH}_{i,t-1}$	0.15**	0.06	-0.07	-0.25***	-0.41***	-0.45***	-0.42***
	(0.07)	(0.07)	(0.07)	(0.07)	(0.07)	(0.08)	(0.09)
$\Delta_3 d^{F}_{i,t-1}$	-0.04	-0.10**	-0.11***	-0.06**	-0.02	0.01	0.05*
	(0.04)	(0.05)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)
R^2	0.02	0.06	0.10	0.10	0.14	0.15	0.13
	Panel B: Control for Deposit Insurance						
	(-1)	(0)	(1)	(2)	(3)	(4)	(5)
$\Delta_3 d^{HH}_{i,t-1}$	0.30	0.29	0.23	0.11	-0.04	-0.09	-0.04
	(0.23)	(0.22)	(0.17)	(0.13)	(0.12)	(0.12)	(0.12)
$\Delta_3 d^{F}_{i,t-1}$	-0.03	-0.13	-0.15**	-0.12**	-0.07	-0.03	0.02
	(0.09)	(0.08)	(0.07)	(0.05)	(0.05)	(0.06)	(0.06)
$\Delta_3 d^{HH}_{i,t-1}\mathbb{1}_{DI}$	-0.18	-0.28	-0.37*	-0.45***	-0.47***	-0.47***	-0.49***
	(0.24)	(0.24)	(0.20)	(0.16)	(0.15)	(0.15)	(0.15)
$\Delta_3 d^{F}_{i,t-1}\mathbb{1}_{DI}$	-0.01	0.04	0.05	0.07	0.06	0.04	0.03
	(0.09)	(0.09)	(0.07)	(0.06)	(0.06)	(0.06)	(0.07)
R^2	0.03	0.06	0.11	0.13	0.17	0.18	0.16

Notes: Let y_{it} be the log real GDP per capita in local currency and d^{HH}_{it} and d^{F}_{it} be the household and firm debt to GDP ratios, respectively. $\mathbb{1}_{DI}$ is an indicator function equal to 1 if the country had explicit deposit insurance enacted in time $t-3$. For deposit insurance, dates before 2005 are from Demirgüç-Kunt et al. (2005). For countries without a deposit insurance by 2005, scheme dates have been hand collected. Panel A presents the estimated coefficients and R^2 of the following equation

$$\Delta_3 y_{i,t+h} = \alpha_i + \beta_H \Delta_3 d^{HH}_{i,t-1} + \beta_F \Delta_3 d^{F}_{i,t-1} + u_{it},$$

for $h = -1, \ldots, 5$. Each column gradually leads the left-hand-side variable by one year. Panel B presents the estimated coefficients and R^2 of the following equation

$$\Delta_3 y_{i,t+h} = \alpha_i + (\beta_{HH} + \beta^{DI}_{HH}\mathbb{1}_{DI})\Delta_3 d^{HH}_{i,t-1} + (\beta_F + \beta^{DI}_{F}\mathbb{1}_{DI})\Delta_3 d^{F}_{i,t-1} + u_{it},$$

for $h = -1, \ldots, 5$. Each column gradually leads the left-hand-side variable by one year. Reported R^2 values are from within-country variation. We control for country fixed effects. Standard errors in parentheses are dually clustered on country and year. *, ** and *** indicate significance at the 0.1, 0.05 and 0.01 level, respectively. The panel is unbalanced and data are from 1960 to 2015.

Table 6. Credit expansion predicts increased crash risk in the bank equity index: data and model

	1 yr	2 yr	3yr
		Data	
ΔBank credit	0.027	0.033	0.054
	[2.40]	[3.11]	[4.27]
		Model	
5th pct	0.055	0.044	0.053
50th pct	0.119	0.118	0.120
95th pct	0.199	0.199	0.205

Notes: This table reports the coefficients from the probit regression model specified in Equation ... for the bank equity index in subsequent 1, 2, and 3 years. The crash dummy takes value 1 if there is a drop of -30% in the next 1, or yrs and 0 otherwise. The crash indicator is regressed on ΔBank credit, i.e. the three-year change in bank credit, expressed in standard deviation units. The empirical coefficients are computed by Baron and Xiong (2016). In the model, we simulate 100 times 2000 years of artificial data with a burnout sample of 500 years and 500 banks. In each simulated sample we estimate the probit regression model. We report the median, 5th, and 95th percentile of the distribution of estimated coefficients.

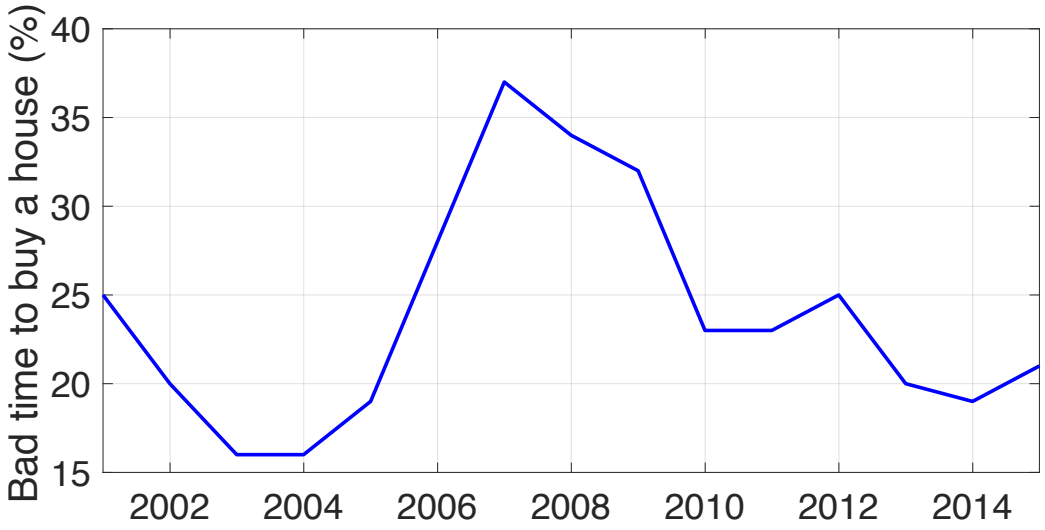


Fig. 1. Rising Pessimism. The figure shows the fraction of households answering the question "Generally speaking, do you think now is a good time or a bad time to buy a house?" with "now is a bad time." Data are from the Michigan Survey of Consumers.

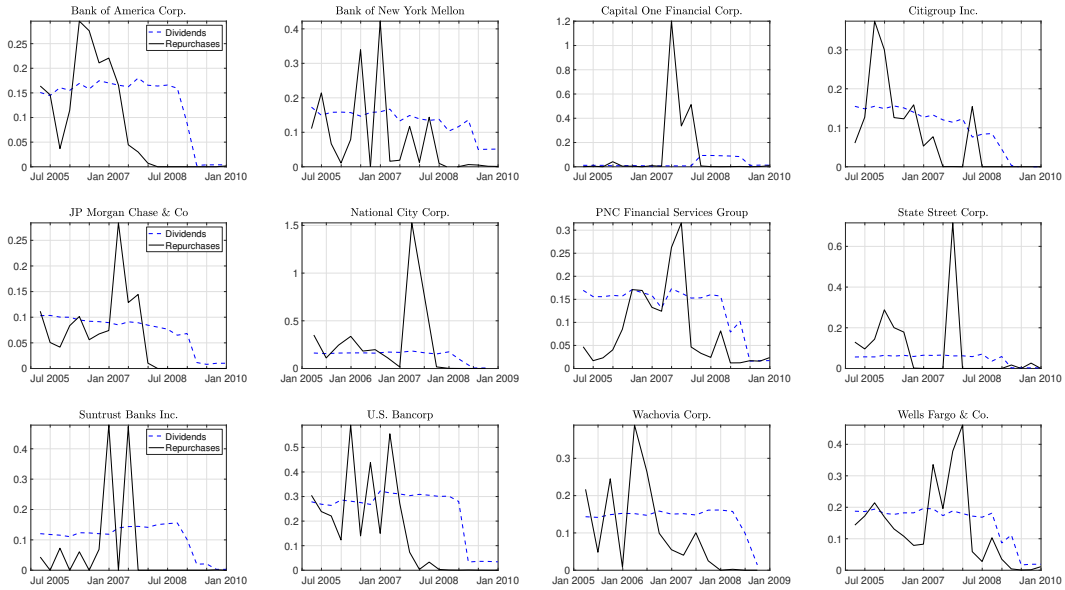


Fig. 2. Dividends and Repurchases by large bank holding companies. The figure shows the dividends and share repurchases made by large bank holding companies in the United States between 2005 and 2009. Values are in percentage of the total assets.

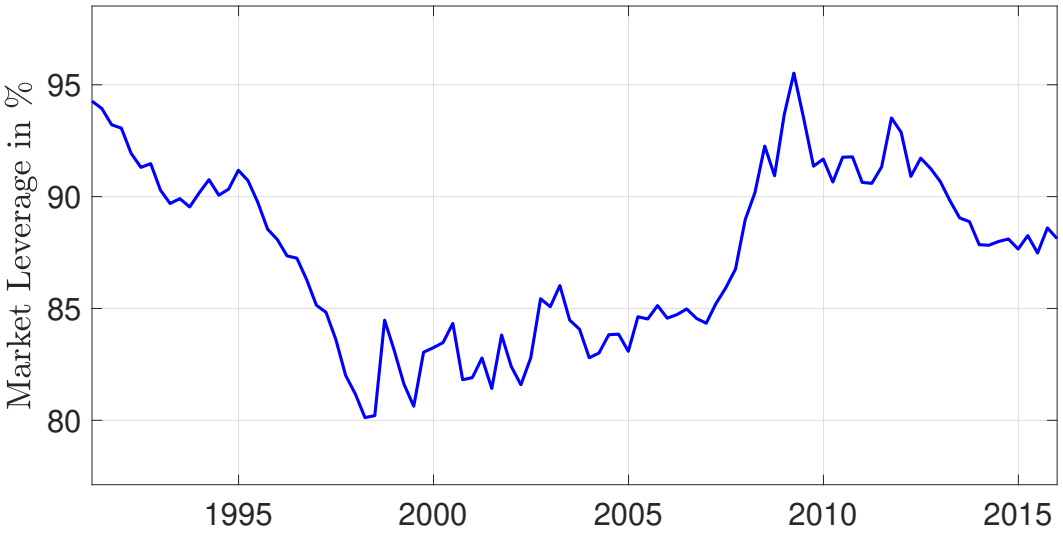


Fig. 3. Market Leverage for Bank Holding Companies. The figure shows the aggregate market leverage for bank holding companies. Leverage is computed as the sum of total liabilities across banks divided by the sum of market capitalization and total liabilities across banks.

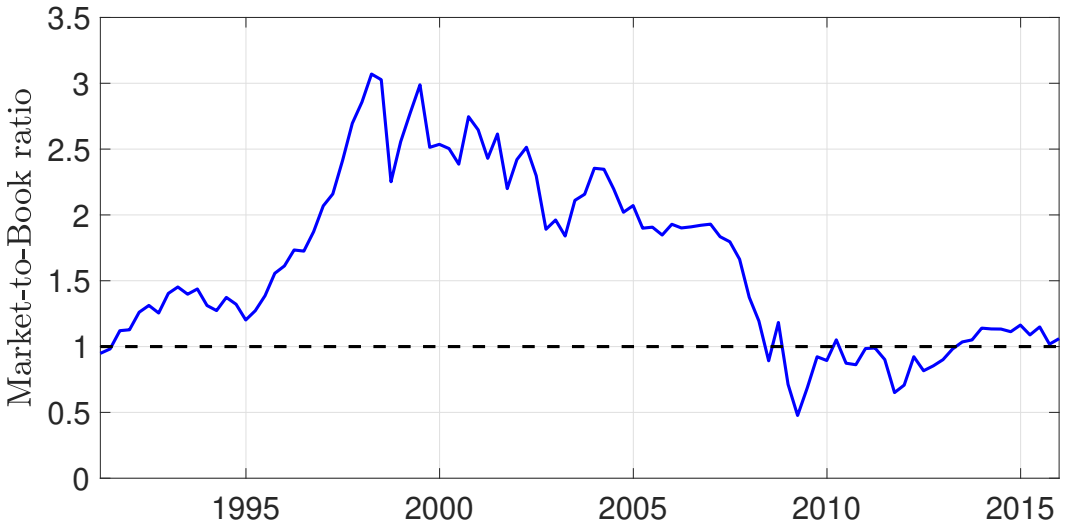


Fig. 4. Market to Book Value of Equity for Bank Holding Companies. The market to book ratio is the sum of market capitalization across bank holding companies divided by the sum of equity book value across bank holding companies.

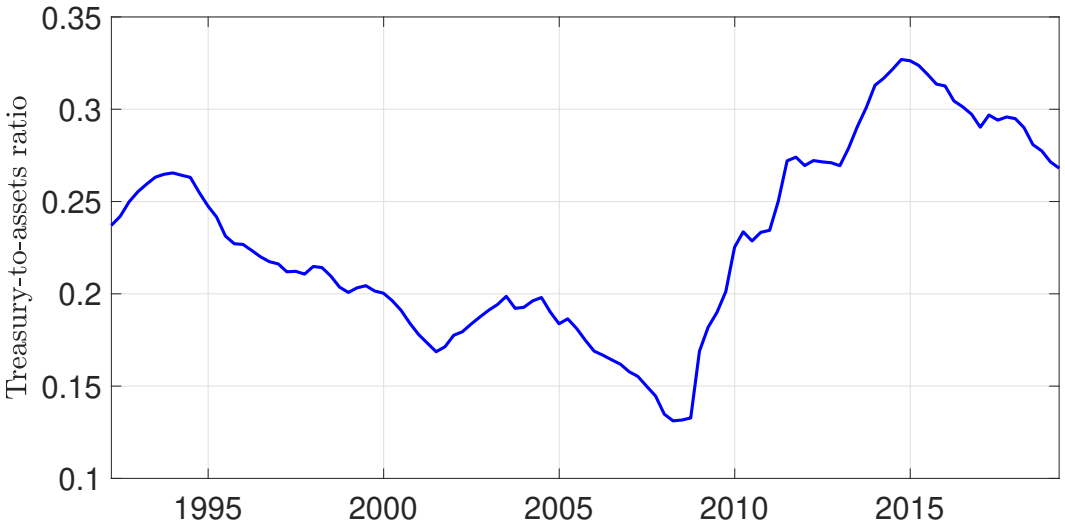


Fig. 5. Relative size of Treasury and cash in the bank portfolio. The ratio is computed as the sum of Treasury and agency securities and cash assets divided by the sum of total assets across commercial banks in the United States. Data are from the Federal Reserve H.8 Assets and Liabilities of Commercial Banks in the United States, and refer to the period ranging from 1992 to 2019.

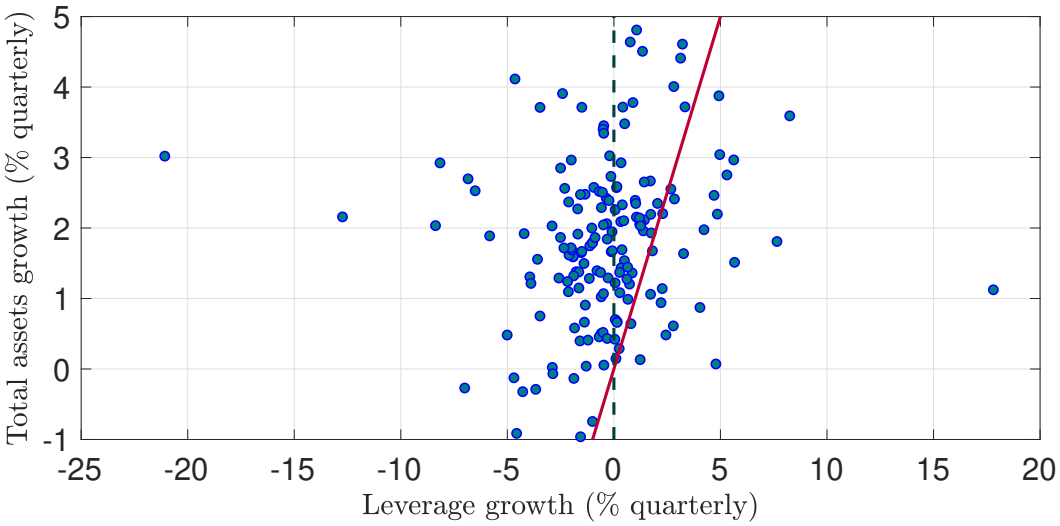


Fig. 6. Total Assets and Leverage growth of Commercial Banks. The figure represents assets growth plotted against leverage growth for commercial banks in the United States. Leverage is defined as assets divided by the difference of assets and liabilities. Data are from the Federal Reserve H.8 Assets and Liabilities of Commercial Banks in the United States, and refer to the period ranging from 1973 to 2014.

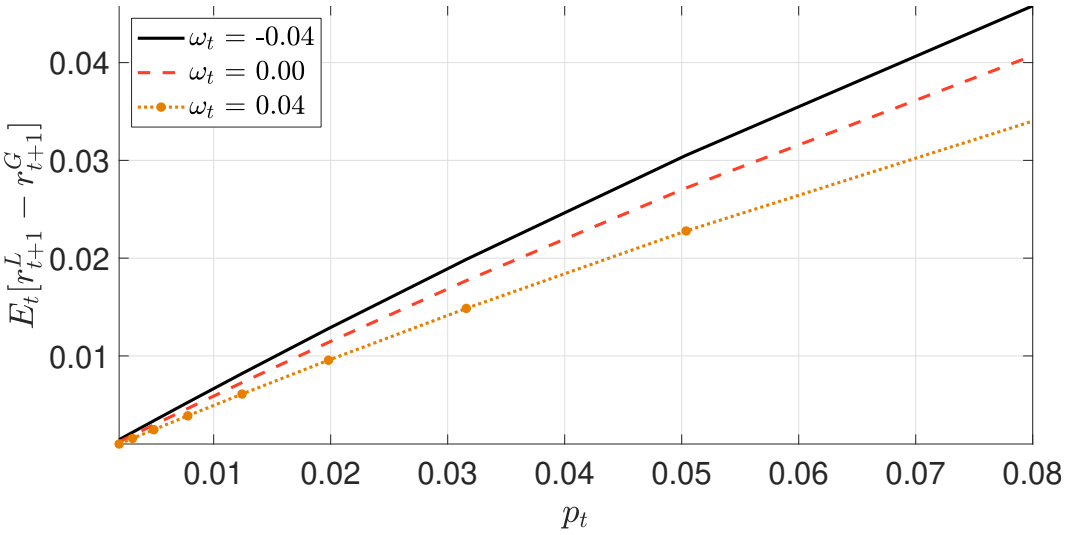


Fig. 7. Excess Return on Private Loans. The figure shows the ex-ante expected rate of return on bank loans, r^L_{t+1}, relative to the rate of return earned on a one-year government bill, r^G_{t+1} for each level of the probability of crisis, p_t, and alternative values of the current-period collateral, ω_t. The expected return and the probability are in annual terms.

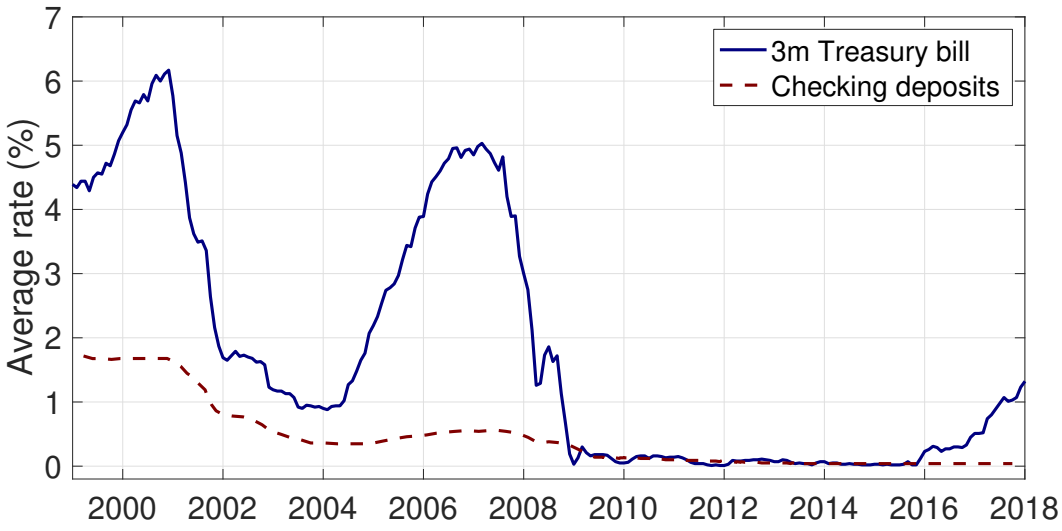


Fig. 8. Rates on deposits and Treasury bills The figure shows the deposit rate on checking accounts (US average) and the yield on the 3-month Treasury bill from March 1999 to May 2018. Treasury bill rates are from FRED. Data on checking deposits before 2009 are from Drechsler et al. (2017) while after 2009 are from FDIC.

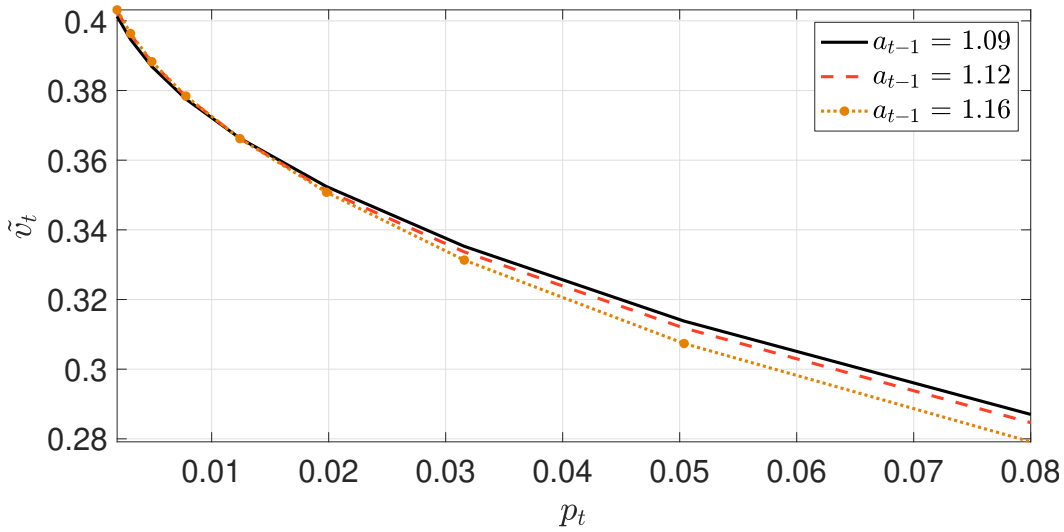


Fig. 9. Bank Franchise Value. The figure shows the bank's franchise value, scaled by deposits, $\widetilde{v}_t = \left(\frac{\widetilde{V}_t}{D_t}\right)$. Alternative levels of crises probability p_t are plotted on the x-axis. Different lines represent different lagged asset-to-debt ratio $a_{t-1} = \left(\frac{A_{t-1}}{D_{t-1}}\right)$. ω_t is fixed to 0.

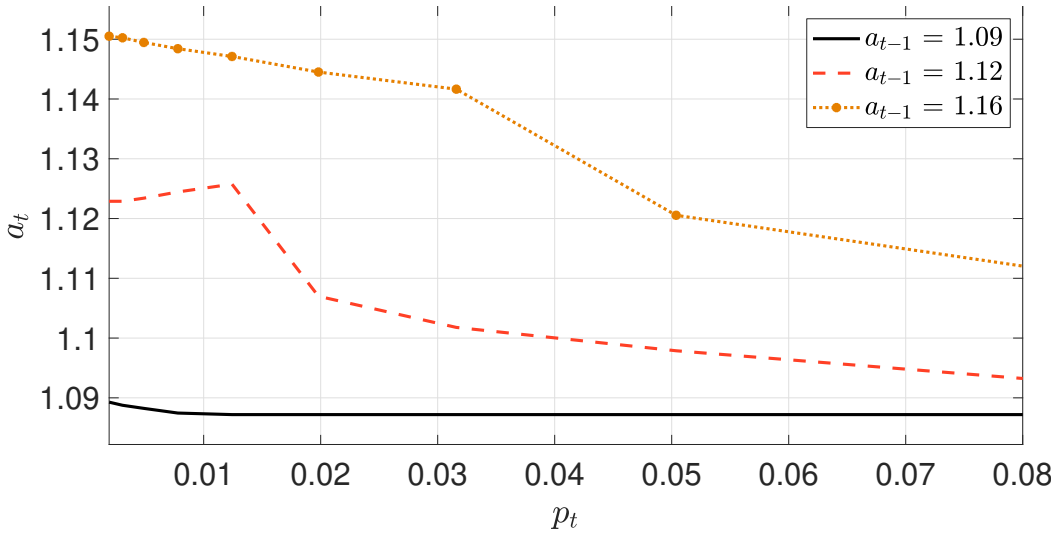


Fig. 10. Optimal Bank Lending. The figure shows the optimal amount of bank assets (lending), scaled by deposits. Alternative levels of crises probability p_t are plotted on the x-axis. Different lines represent different lagged asset-to-debt ratio $a_{t-1} = \left(\frac{A_{t-1}}{D_{t-1}}\right)$. ω_t is fixed to 0.

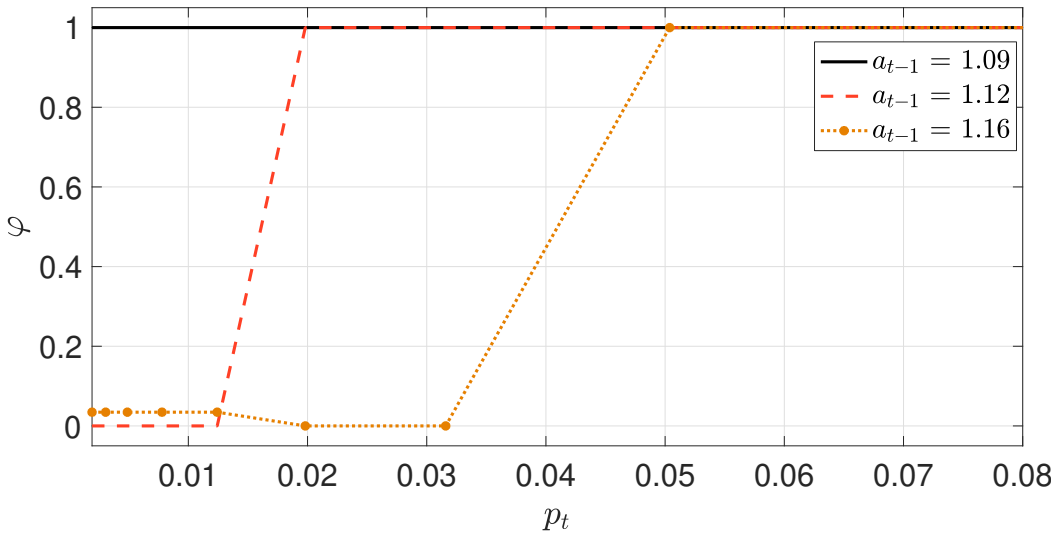


Fig. 11. Portfolio Allocation. The figure shows the policy for portfolio allocation of an individual bank (φ_t). Alternative levels of crises probability p_t are plotted on the x-axis. Different lines represent different lagged asset-to-debt ratio $a_{t-1} = \left(\frac{A_{t-1}}{D_{t-1}}\right)$. ω_t is fixed to 0. φ equal to 1 represents investment in the portfolio of household loans, while φ equal to 0 stands for investment in the government T-bill.

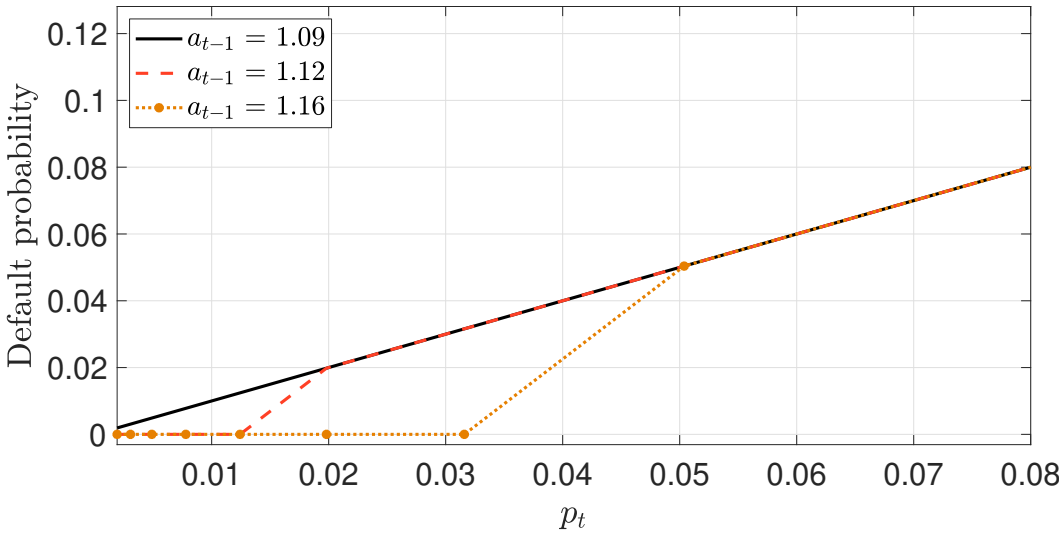


Fig. 12. Bank default probability. The figure shows the endogenous default probability of an individual bank after optimally deciding on the amount of capital and its portfolio allocation. Alternative levels of crises probability p_t are plotted on the x-axis. Different lines represent different lagged asset-to-debt ratio $a_{t-1} = \left(\frac{A_{t-1}}{D_{t-1}}\right)$. ω_t is fixed to 0.

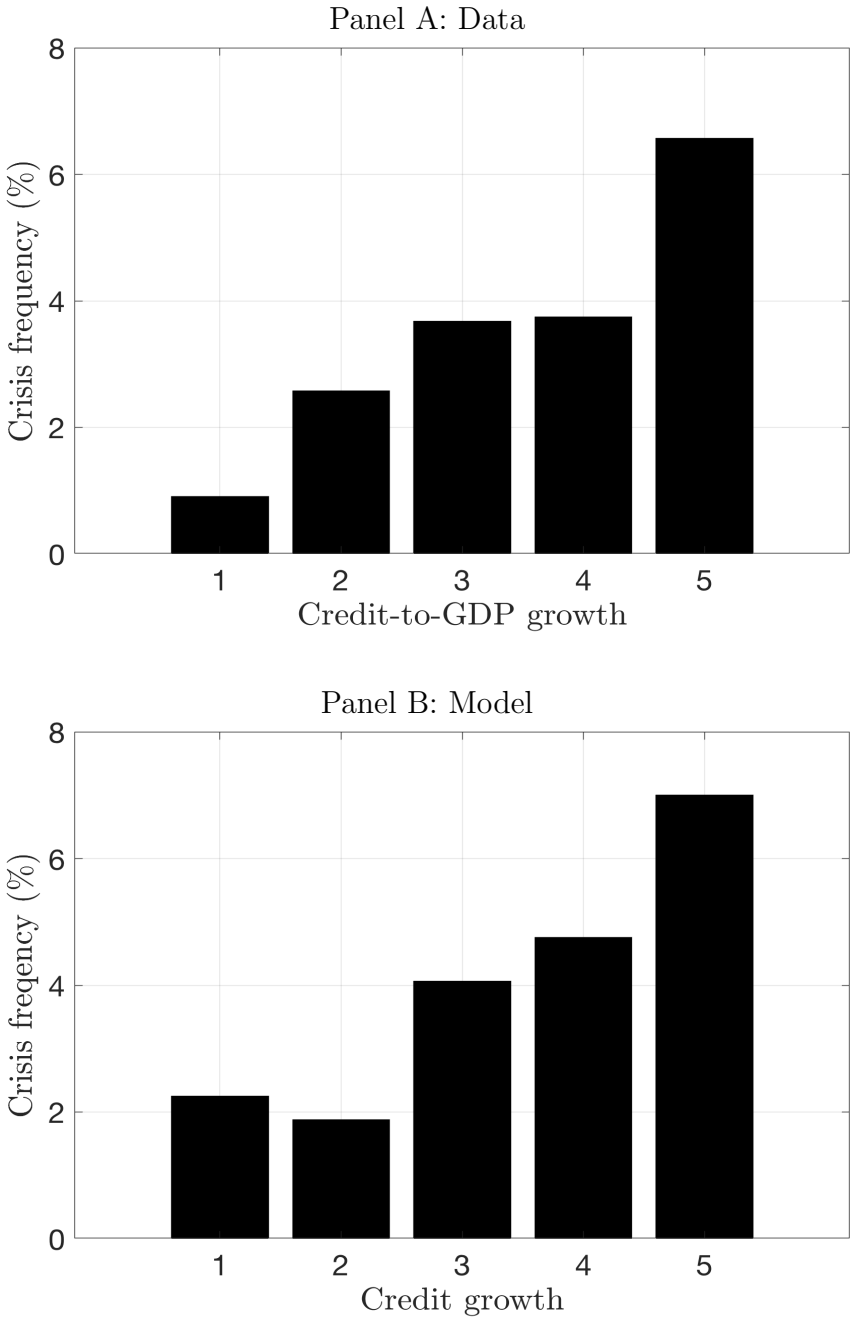


Fig. 13. Frequency of crises by credit growth. The top figure shows the empirical average frequency of a crisis in year t conditioning on a given quintile of credit-to-GDP growth rates from year $t-5$ to t. Data are from Jordà, Schularick, and Taylor (2016). For each country, we compute the growth rate in the ratio of total loans to GDP between year $t-5$ and t. Empirically, a crisis is a systemic financial crisis, as identified by Jordà et al. (2016). The bottom figure reproduces the relation in data simulated from the model using quintiles of credit growth rates from year $t-5$ to t. Results are from simulating the model with 10,000 banks for 10,000 periods. A crisis occurs when the 1-year GDP growth rate is in the bottom 4% of its distribution.

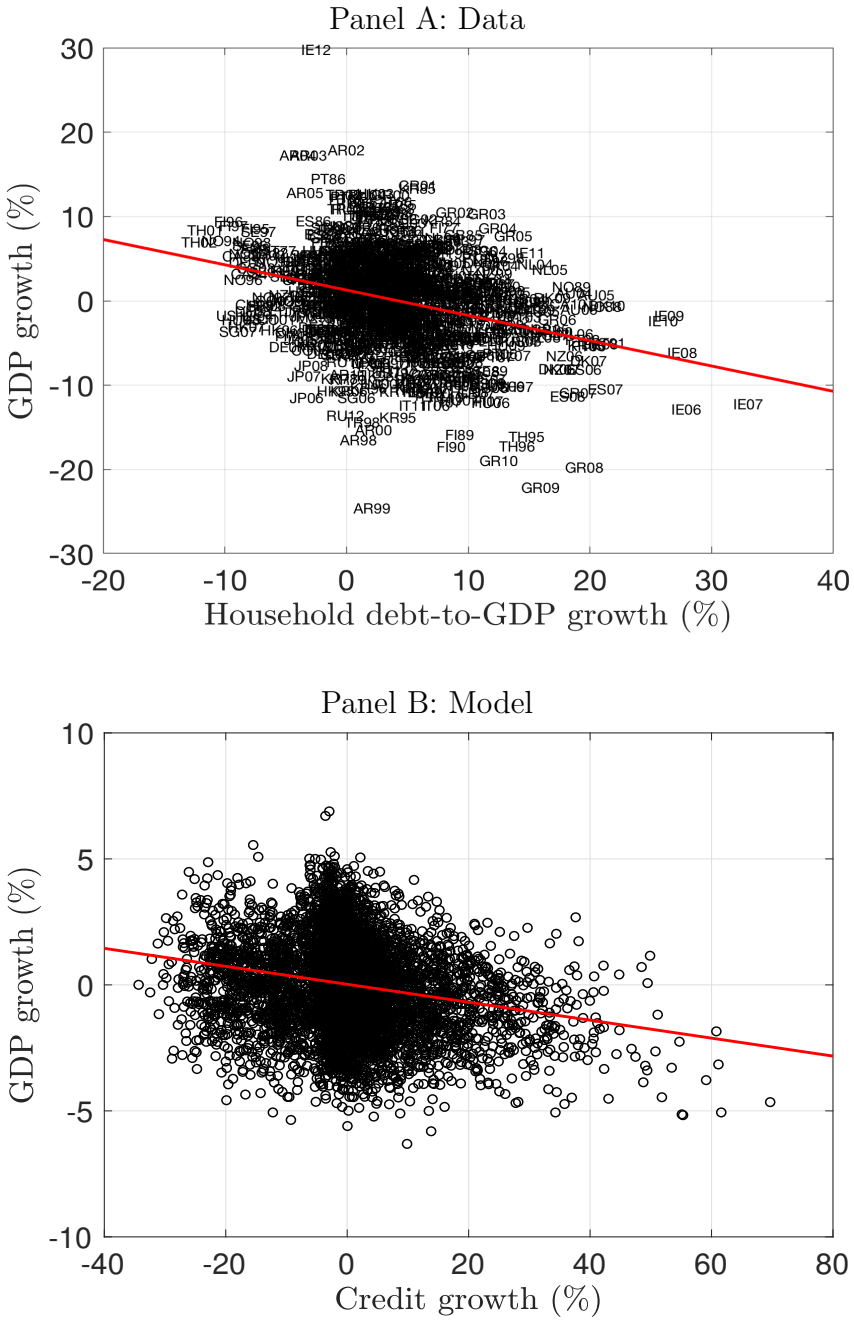


Fig. 14. GDP and Household Debt growth. The top figure shows the empirical relationship between the (demeaned) GDP growth rate from year t to $t+3$ and the growth rate of the household debt to GDP ratio from year $t-4$ to $t-1$. Data are from the Bank of International Settlements and cover 39 countries between 1961 and 2012. The bottom figure reproduces the same relationship in the model using however the growth rate of aggregate bank's loans (to household) from year $t-5$ to t. Results are from simulating the model with 10,000 banks for 10,000 periods. The solid line is the estimated regression line from

$$\Delta_3 y_{i,t+3} - \overline{\Delta_3 y_i} = \alpha_i + \beta_H \Delta_3 d^{HH}_{i,t-1} + u_{it},$$

where y is GDP and d^{HH} is the measure of credit to households.

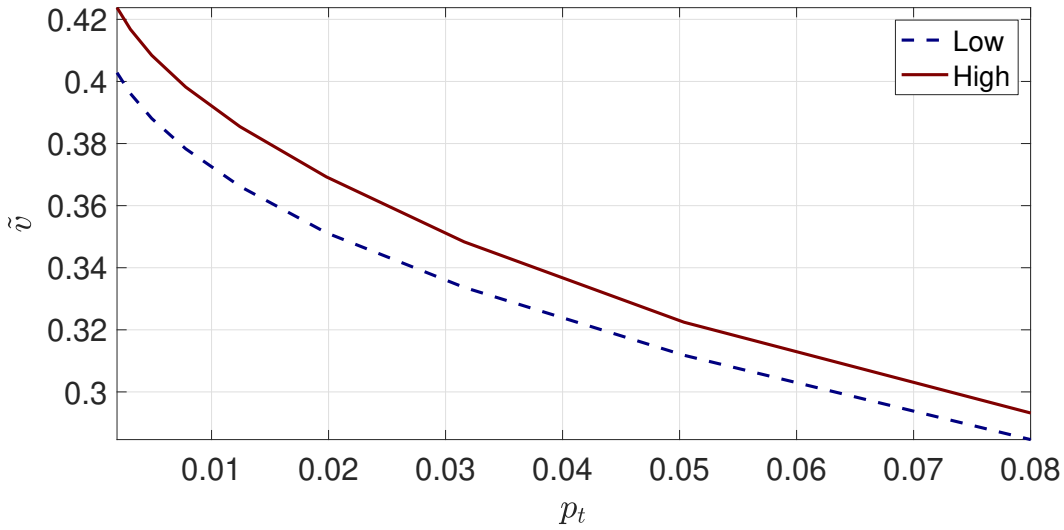


Fig. 15. Impact of subsidies on bank franchise value. The figure shows bank franchise value scaled by deposits, $\widetilde{v}_t = \left(\widetilde{V}_t/D_t\right)$, as a function of crisis probability p_t for two different levels of bank subsidies. We set $a_{t-1} = 1.12$ and $\omega_t = 0$. The case of low subsidies is our benchmark model. For the high subsidies scenario we lower the benchmark deposit rate by 6 basis points.

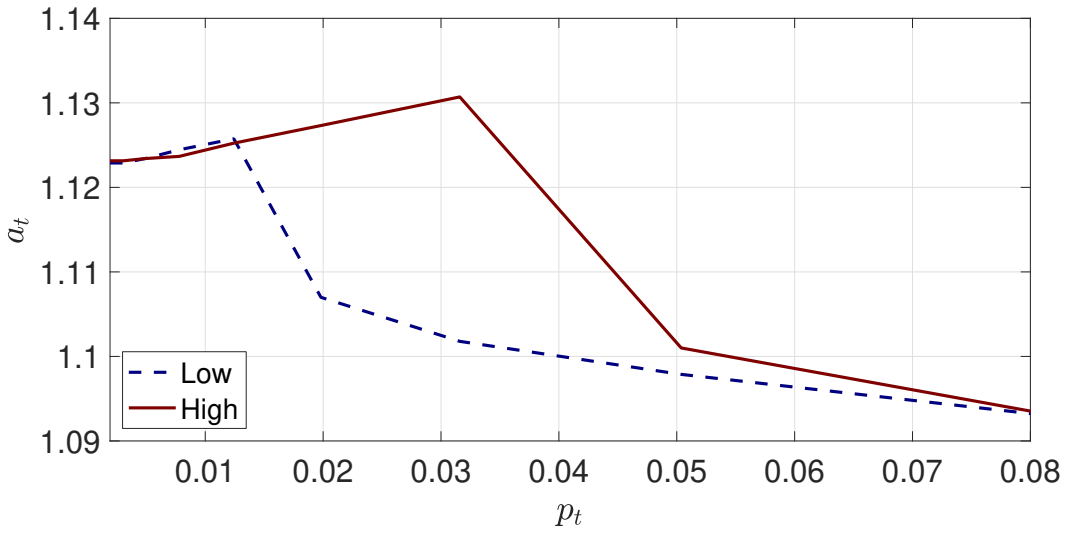


Fig. 16. Impact of subsidies on bank leverage. The figure shows the optimal ratio of assets to deposits $a_t = (A_t/D_t)$ as a function of crisis probability p_t for two different levels of bank subsidies. We set $a_{t-1} = 1.12$ and $\omega_t = 0$. The case of low subsidies is our benchmark model. For the high subsidies scenario we lower the benchmark deposit rate by 6 basis points.

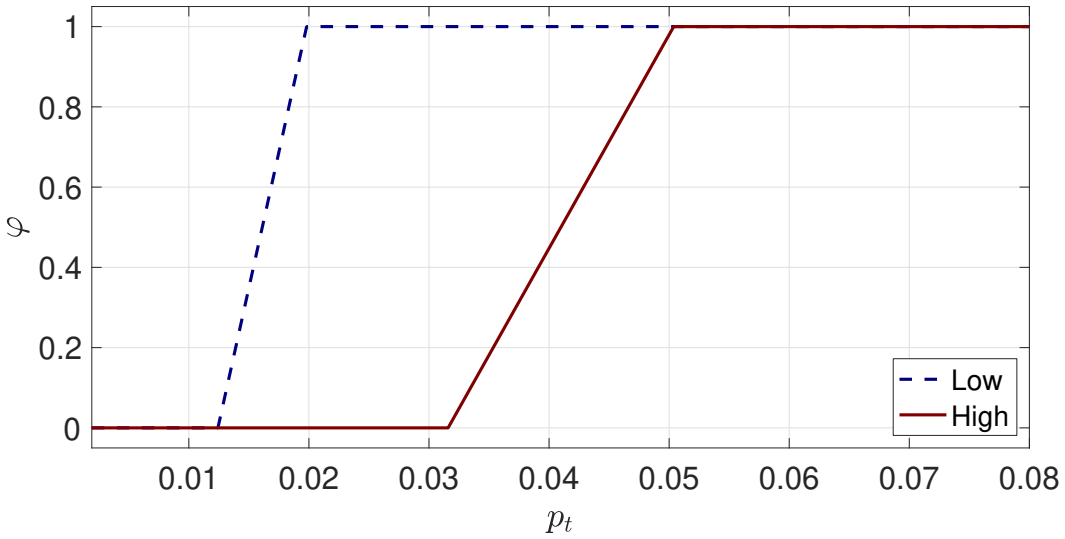


Fig. 17. Impact of subsidies on bank's optimal portfolio composition. The figure shows the portfolio allocation of an individual bank (φ_t) for high and low subsidies (solid and dashed line respectively) and different levels of the probability of criss p_t keeping fixed the last period asset-to-debt ratio $a_{t-1} = (A_{t-1}/D_{t-1})$ to 1.123, and $\omega_t = 0$. φ equal to 1 represents investment in the portfolio of household loans, while φ equal to 0 stands for investment in the government T-bill. The case of low subsidies is our benchmark model. For the high subsidies scenario we lower the benchmark deposit rate by 0.06%.