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Foreseen Risks*

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Abstract

Large 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.

Keywords: Credit Bubbles, Financial Intermediaries, Financial Crises, Risk Shifting

JEL codes: G01, G18, G21, G32

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1 Introduction

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

In this paper, we propose an alternative explanation of the link between credit booms and economic crises. We build a model in which the propensity of banks to engage in "riskier lending" over the cycle is a result of exogenous variation in macroeconomic conditions and their impact on the bank's own franchise value. The main argument is that government guarantees have two opposing effects on bank risk taking, and which effect dominates depends on the economic outlook. On the one hand, government guarantees reduce depositors' incentives to monitor and so encourage risk taking. On the other hand, government guarantees are a source of economic rents to banks: they increase bank profit margins, which creates value, and reduces the incentives to take more risk. The better the economic prospects, the more likely it is that this second effect dominates. As a result, in our model, there is no concept of a *credit cycle* that "causes" the business cycle. Instead, bank credit co-moves with – and precedes – macro aggregates such as investment and output, even if these variables are, by design, fully independent of bank lending behavior. Although we characterize bank optimal policies along the business cycle, our framework can be broadly applied to analyze the risk-taking incentives of any institution that benefits from economic rents regardless of the actual source of these rents.

[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), extrapolative beliefs (Barberis, Shleifer, and Vishny, 1998; Greenwood and Hanson, 2013), diagnostic expectations (Maxted, 2022), and investors' sentiment accompanied by frictional intermediation (Krishnamurthy and Li, 2020).

Our model is motivated by a number of key facts related to banks' behavior in the lead up to the 2007–2008 crisis. First and foremost is the rising pessimism about future house prices in the lead up to the crisis (Piazzesi and Schneider, 2009; Mian and Sufi, 2019) suggesting credit risks were perceived to be rising during this period. Thus, 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 model is that banks benefit from economic rents, arising from a wedge between the expected return on assets and the cost of debt. Although this wedge is formalized as subsidized deposit insurance, alternative, and equally compelling, sources of rents could be imperfect competition in the banking sector, limited regulatory oversight relative to other entities that provide similar services, or implicit subsidies to "too-big-to-fail" institutions.[4] Our main result, however, is that regardless of their source, the economic value of these rents will fluctuate over time as local and aggregate economic conditions change and this will generally lead banks to accept more risks when franchise values are low.

Our description of the banking sector builds on Merton (1978). Specifically, we treat banks as entities with access to an exogenous supply of deposits, paying a deposit rate priced to reflect the presence of a government guarantee. To this basic structure, we add an investment decision: banks must decide in each period on the size and 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.

We define franchise value as the present value of the future profits a bank is expected to earn as a going concern. Profits are those gains beyond what is required to cover all costs,

[3] Our model requires that risks be foreseen by some but not all investors, bank executives, or bank employees. This is then consistent with evidence of Cheng, Raina, and Xiong (2014), Chernenko, Hanson, and Sunderam (2016) and Richter and Zimmermann (2019) that some within the banking sector might have been overoptimistic. The question to us is not why bank executives acted in a way that failed to avoid risk, but rather why informed equity holders did not curtail, and perhaps even encouraged, risky practices.

[4] Buser, Chen, and Kane (1981) document that deposit insurance premia are subsidized in the US. Drechsler, Savov, and Schnabl (2017) provide recent evidence for the lack of competition in the banking sector. A weak regulatory oversight may capture the shadow banking sector in the period before the crisis.

including the cost of capital. 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 particular, in our framework, government guarantees on deposits provide banks with a source of economic rents. The discounted value of this stream of rents is what we call the bank's *franchise value* and its fluctuations over the business cycle drive lending behavior.[5] 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.

Our model matches a number of key stylized facts about the behavior of US banks in the lead up to the 2007-08 crisis. Notably, shareholder payouts and leverage rise in anticipation of a crisis just as they did before 2008. Similarly market to book ratios begin to fall as the likelihood of a crisis increases, again just as was seen in 2007-08.

To study the links between bank lending and aggregate economic activity, we expand the baseline model to include a corporate sector that makes investment decisions. We assume banks lend only to households, ensuring corporate behavior remains fully independent of bank lending. We then confront our quantitative implications with recent evidence on the relationship between bank lending and financial crises. In particular, we show our model replicates the patterns in Schularick and Taylor (2012) and Jordà, Schularick, and Taylor (2016) documenting that crises often follow periods of very fast credit growth, the finding of Baron and Xiong (2017) that fast lending growth predicts bank equity crashes, and the findings in Mian, Sufi, and Verner (2017) on the strong predictability of future GDP growth by

[5] Following Demsetz, Saidenberg, and Strahan (1996), we can separate the sources of franchise values in two categories. The first source of franchise value is related to government policies. For instance, regulation may create barrier to entry, giving banks greater access to profits, or the government can provide guarantees, effectively subsidizing the bank's cost of capital. There are also bank-related factors, e.g., a bank's branch network can give it a competitive advantage in dealing with customers who prefer the convenience of full-service banking at a local branch. These bank-related factors have been shown important in a recent literature (Drechsler et al., 2017). Acknowledging that the two sources are not exclusive and may actually reinforce each other, we mainly focus on this first source of franchise value for expositional reasons.

the growth in household debt. Notably, we also document that, in the data, this predictability holds only for countries and periods with deposit insurance, thus independently validating our model's main mechanism.

Beyond these findings, our model also provides lessons for the evaluation of recent unconventional monetary policy interventions and macroprudential regulation. After the 2008 crisis, policy makers in many 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 these interventions were designed to encourage private sector lending, some banks instead preferred to invest heavily in government bonds or increase excess reserves in central banks. This behavior however is entirely consistent with our model, since these stabilization policies effectively worked as subsidies, reducing the cost of financing for banks, increasing their franchise values and reinforcing their incentives to hold 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 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 will also fluctuate endogenously over time with local and aggregate economic conditions. This in turn induces important changes in bank lending behavior over the business cycle. Within this literature, our paper is complementary to Granja, Leuz, and Rajan (2019) who examine empirically the conditions under which banks' risk taking is exacerbated. They show that, in areas with higher competition amongst banks, lending

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

standards have been far more sensitive to the economic cycle, and banks have issued more risky loans in the years preceding the financial crisis of 2008.

Our work also relates to more recent studies analyzing the specific impact of regulatory policies on bank balance sheets, lending, and 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 they explicitly model the bank's maximization problem (Van den Heuvel, 2008; De Nicoló, Gamba, and Lucchetta, 2014; 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 surveys the key patterns in US bank behavior in the lead-up to the 2007-2008 crisis that motivate our approach. Section 3 proposes a basic version of the model with constant probability of crises, which we use to characterize analytically the key theoretical results. Section 4 presents the quantitative

[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.

framework used to study the optimal composition of bank lending in the presence of deposit insurance and time variation in economic rents. We augment the model with a corporate sector and its results are quantitatively assessed in Section 5. Section 6 then studies our key policy implications while Section 7 discusses novel empirical evidence in support of the role deposit insurance in financial crises. Section 8 concludes.

2 Motivation: Beliefs and US Bank Behavior Leading up to the 2007-2008 Crisis

Our theoretical approach is motivated by a number of patterns in the behavior of US banks in the lead up to the 2007–2008 crisis. In this section we survey some of the most important ones. This evidence complements the findings of Jordà et al. (2016) and Mian et al. (2017), which we discuss later and form the basis for our quantitative analysis. While this behavior undoubtedly reflects a multitude of perhaps complementary forces, these facts help to highlight the importance of the specific mechanism we describe in this paper.

2.1 Rising Pessimism

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 “now is a bad time to buy a house” reached a peak in 2007 (Piazzesi and Schneider, 2009; Mian and Sufi, 2019). This fraction doubled in 2005 passing from 20% in 2004 to 40% in 2006. The figure also shows the fraction of households who said “prices are currently high.” About 75% of the pessimist households (i.e., 30% of total households) in 2006 claimed the reason why it is a bad time to buy a house is that prices were currently high.

A similar conclusion of rising pessimism can be drawn from looking at the Gallup’s Economic Confidence Index (Figure 1 in the Online Appendix).[8] Between January and

[8]The index is based on the combined responses to two questions, the first asking Americans to rate economic conditions in this country today and second asking whether they think economic conditions in the

September 2006 the index already took negative values, and from March 2007 up to 2014 the index has constantly been negative. In terms of magnitude, it's worth noting that the values taken by the index in 2007 were lower than the values reached by the same index more recently during the first Covid wave in 2020. Thus, while this is just suggestive evidence and 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 expectation that economic conditions would deteriorate in the build up to the crisis: macroeconomic risks were *foreseen* by many.

2.2 Bank Dividends, Leverage and Investment

As Figure 2 shows bank dividend payouts were high before and even during the crisis. Even more strikingly however, each of the 12 largest bank holding companies repurchased stock extensively just before the crisis (Hirtle, 2016).[9]

Figure 3 shows that average bank leverage increased steadily from 2004. Leverage was relatively moderate in the early 2000s but increased significantly, especially after 2006. By contrast the share of safe assets (Treasuries, agency securities, and cash) in banks' balance sheet decreased before the crisis. As Figure 4 shows the average holdings of these assets by commercial banks decreased steadily until the 3rd quarter of 2008, then spiked back after the subprime mortgage crisis spiraled into a full-blown financial collapse.

Finally, the aggregate market-to-book ratio for US bank holding companies, as documented in Figure 5, has dropped starting from 1998 and passed from a level of 3 to about 2 in 2006. Definitely, there are several factors that underlie this slow 8-year drop, and most of them are probably outside the model we present in the next section. However, in 2007, there was a precipitous drop and the market-to-book ratios reached levels below 1. Our model suggests

country as a whole are getting better or worse.

[9]Unlike broker-dealers (Adrian and Shin, 2010), commercial banks seem to actively manage equity. Figure 2 in the Online Appendix shows the relation between asset and 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.

that this *latter* dramatic drop occurred concomitant with an increased perceived probability of an economic crisis. These facts once again suggest investors perceived risks to the banking sector to be rising significantly.

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 crisis. Next, we show how these facts can be reconciled in a model of optimal bank behavior. The model matches the sharp increase in pessimism, dividend payouts, leverage, and lending and also 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). Although our aim is to provide a benchmark quantitative model that connects a wide range of facts it remains far from providing a full account of all credit-cycle related phenomena. 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 5.2.

3 A stylized framework

In this section, we describe a tractable analytical version of the more generalized model that is used for our quantitative analysis. This allows us to derive explicit conditions under which a bank decides to shift its asset allocation toward risky loans, and establish that bank value is decreasing in the probability of a crisis. These key properties are preserved in our quantitative analysis. The model presented in the text focuses only on the asset allocation decision of the bank (loan vs government bonds), and abstracts from leverage. The Online Appendix Section 1.2 extends this framework to include a leverage decision. This second margin of adjustment becomes important in the quantitative analysis when mapping the model to the data.

For simplicity, we specify the model dynamics directly under risk neutral probabilities and normalize the risk-free rate R^f to 1. Both assumptions are generalized in our quantitative analysis. Similar to Merton (1978), we assume that regulators monitoring the bank intervene and seize the bank's operating license whenever the returns on the bank portfolio are insufficient to pay back depositors. This is equivalent to assuming that equity injections are prohibitively costly during periods of distress, an assumption that is not too far from reality.

A bank can invest, at any time t, in loans to the private sector, with a stochastic return R^L_{t+1} in period t+1, and/or government bonds that pay R^G_{t+1}. We assume that there are 3 possible states of the world, denoted u, m, d (for up, medium, down). Next-period realized returns for loans and bonds can be

$$R^L_{t+1}, R^G_{t+1} = \begin{cases} \overline{R}^L, \overline{R}^G, \text{ in state } u \text{ with prob. } 1-p; \\ \zeta_L, \zeta_{Gm}, \text{ in state } m \text{ with prob. } p(1-q) \\ \zeta_L, \zeta_{Gd}, \text{ in state } d \text{ with prob. } pq, \end{cases} \tag{1}$$

where $p \in (0,1)$ and $q \in (0,1)$ are the probabilities defining corporate and government default, respectively and we denote the default recovery values for private loans as ζ_L and for government bonds as ζ_{Gd}. We assume (a) $\zeta_L < \zeta_{Gd} < R^D$, implying that banks will always default in state d no matter their portfolio allocation, and (b) $\zeta_{Gm} \geq R^D$ so only a bank over-exposed to private loans will default in state m.

Given ζ_L, ζ_{Gm}, ζ_{Gd}, R^f we can use the no-arbitrage conditions to solve for the equilibrium values of $\overline{R}^L$, and $\overline{R}^G$,

$$(1-p)\overline{R}^L + p\zeta_L = 1 \tag{2}$$

$$(1-p)\overline{R}^G + p(1-q)\zeta_{Gm} + pq\zeta_{Gd} = 1 \tag{3}$$

or

$$\overline{R}^L = \frac{1-p\zeta_L}{1-p} \tag{4}$$

$$\overline{R}^G = \frac{1-p(1-q)\zeta_{Gm} - pq\zeta_{Gd}}{1-p}, \tag{5}$$

which implies that $\overline{R}^L > \overline{R}^G$.

It is straightforward to show that both $\overline{R}^L$ and $\overline{R}^G$ are increasing in p so that both assets pay larger returns in the u state in which the bank survives. In addition,

$$\frac{\partial \overline{R}^L}{\partial p} = \frac{1-\zeta_L}{(1-p)^2} \tag{6}$$

$$\frac{\partial \overline{R}^G}{\partial p} = \frac{1-\zeta_{Gm}(1-q)-q\zeta_{Gd}}{(1-p)^2}, \tag{7}$$

which, given our assumptions, implies $\frac{\partial \overline{R}^L}{\partial p} > \frac{\partial \overline{R}^G}{\partial p}$ for any p. The fact that the difference between $\overline{R}^L$ and $\overline{R}^G$ increases for larger p incentivizes banks to tilt their portfolio allocation towards loans for larger values of p.

The model is fully solved in the Online Appendix Section 1. Here, we discuss its main results. Define φ to be the fraction of bank's assets invested in private loans. The bank faces the following trade-off: on one side, it can invest more in loans to generate greater profits in state u, but on the other side, this raises the likelihood of default and the potential loss of continuation value. We show that for a given level of p, the bank either sets its loan allocation to fully avoid default in state m, i.e., $\varphi = \overline{\varphi} < 1$ or is fully invested in loans, i.e., $\varphi = 1$. In the latter case the bank defaults with certainty if state m realizes.

When p increases the bank manager's incentives change. The following happens for larger p: 1) loans become more attractive from the bank's perspective because they yield even greater returns in state u compared to government bonds; 2) the probability of default rises leading to a drop in the continuation value of the bank, which in turn makes survival in state m less attractive. These two effects ultimately make it more appealing for the bank to be fully invested in loans for large enough values of p. We formalize this intuition in the following two propositions.

Proposition 1. *There exists a $\overline{p}$ such that a bank invests $\overline{\varphi} < 1$ of its assets in loans for values of $p < \overline{p}$, whereas for values of $p \geq \overline{p}$ the bank is fully invested in loans.*

In this model $\overline{p}$ is defined as

$$\overline{p} = \frac{(1-R^D)(\zeta_{Gm}-\zeta_L)(1-q)}{(R^D-\zeta_L)(\zeta_{Gd}-\zeta_L)q}. \tag{8}$$

A necessary condition for this result is that the bank enjoys a subsidized cost of debt, which following our normalization of the risk-free rate implies $R^D < 1$. If $R^D = R^f = 1$, $\overline{p} = 0$, i.e., the bank is always fully invested in loans.[10]

Proposition 2. *Assume $R^D < R^f = 1$ and let V^* be the value of the bank at the optimum, then*

$$\frac{\partial V^*}{\partial p} = \begin{cases} \dfrac{R^D-1}{qp^2}, & \textit{for } p < \overline{p}; \\ \dfrac{R^D-1}{p^2}, & \textit{for } p \geq \overline{p}. \end{cases} \tag{9}$$

Economically, this result means that in the presence of subsidized cost of debt, the equilibrium increase in $\overline{R}^L$ and $\overline{R}^G$ following an increase in p does not fully compensate the bank for the loss of continuation value.

4 Quantitative Model

The 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

[10]What is necessary for franchise value to exist in equilibrium is for the deposit rate to be lower than the risk-free rate in profitable states of the world for the bank. We interpret this condition as *government subsidies*.

the firms in the productive sector. However, the productive sector faces no financial frictions and may equivalently be financed with equity alone.

4.1 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.

4.2 Consumption and Uncertainty

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

$$C_{t+1} = C_t e^{\mu_c + \sigma_c \epsilon_{c,t+1} + \xi x_{t+1}}, \tag{10}$$

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) and 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 Markov chain approximating a first-order autoregressive process with persistence ρ_p and mean $\log \bar{p}$:

$$\log p_{t+1} = (1-\rho_p)\log \bar{p} + \rho_p \log p_t + \sigma_p \epsilon_{p,t+1}, \tag{11}$$

where ϵ_{pt} is standard normal, iid over time, and independent of ϵ_{ct} and x_t.[11] Let $S(p_t)$ denote the ratio of aggregate wealth to aggregate consumption. It is well-known that the stochastic

[11] In our simulations, we discretize the process (11) so that $p_t < 1$.

discount factor (SDF) satisfies

$$M_{t,t+1} = \beta^{\theta} e^{-\gamma(\mu_c + \sigma_c \epsilon_{c,t+1} + \xi x_{t+1})} \left(\frac{S(p_{t+1}) + 1}{S(p_t)} \right)^{-1+\theta}, \tag{12}$$

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

$$\mathrm{E}_t \left[\beta^{\theta} \left(\frac{C_{t+1}}{C_t} \right)^{1-\gamma} \left(S(p_{t+1}) + 1 \right)^{\theta} \right] = S(p_t)^{\theta} \tag{13}$$

and $\theta = \frac{1-\gamma}{1-\frac{1}{\psi}}$.

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

$$P_{Gt} \quad = \quad \mathrm{E}_t[M_{t,t+1}(1 - q x_{t+1})]. \tag{14}$$

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

$$r^G_{t+1} = \frac{1 - q x_{t+1}}{P_{Gt}} - 1. \tag{15}$$

4.3 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.[12]

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

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.

4.3.1 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.[13,14]

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}.[15] A bank must also pay operational, or non-interest expenses, Φ_{it} in every period, so that its resource constraint at time t is:

$$A_{it} = BE_{it} + D_{it} - Div_{it} - \Phi_{it}. \tag{17}$$

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

$$BE_{i,t+1} = (1 + r^{A}_{i,t+1})A_{it} - (1 + r^{D}_{t+1})D_{it}. \tag{18}$$

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

[14]We set g to equal expected consumption growth:

$$g = \log((1 - \mathrm{E}p_t)e^{\mu_c + \sigma_c^2/2} + \mathrm{E}p_t e^{\mu_c + \sigma_c^2/2 + \xi}). \tag{16}$$

[15]Allowing banks to optimally choose their asset size/leverage, rather than the portfolio allocation alone, is only important when mapping the model to the data.

4.3.2 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:

$$r^A_{i,t+1} = \varphi_{it} r^L_{i,t+1} + (1 - \varphi_{it}) r^G_{t+1}. \tag{19}$$

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.[16] We let the time-t collateral value for each individual loan $j = 1, \ldots, n$ of bank i equal

$$W_{ijt} = e^{\sigma_c \epsilon_{ct} + \xi x_t + \omega_{it} + \sigma_j \epsilon_{jt}}. \tag{20}$$

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}.

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:

$$\omega_{i,t+1} = \rho_\omega \omega_{it} + \sigma_\omega \epsilon_{\omega_i,t+1}. \tag{21}$$

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

[16] 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.

value. In Appendix A we use the law of large numbers 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 6 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.

4.3.3 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 et al., 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 7 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.

4.3.4 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.[17] We calibrate f to such a large value that this constraint is equivalent to a hard regulatory constraint on leverage: banks never breach the regulatory threshold.

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: shareholders are not allowed to make up for negative book equity. As a result, from the perspective of its equity holders, excessive risk taking by the bank may result in sub-optimal termination.

4.3.5 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:

$$V_{it} = \begin{cases} \mathrm{E}_t\left[\sum_{s=t}^{T_i^*-1} M_{t,t+s} Div_{is}\right], & t < T_i^* \\ 0, & t \geq T_i^* \end{cases} \tag{22}$$

where

$$T_i^* = \inf\{t : BE_{it} < 0\} \tag{23}$$

denotes bank i's (stochastic) termination time, and $M_{t,t+s}$ denotes the SDF between times t and $t+s$.[18]

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

$$V_i(BE_{it}, A_{i,t-1}, D_{it}, p_t, \omega_{it}) = \\ \max_{\varphi_{it}, Div_{it}} Div_{it} + \mathrm{E}_t\left[M_{t,t+1} V_i(BE_{i,t+1}, A_{it}, e^g D_{it}, p_{t+1}, \omega_{i,t+1}) \mathbb{1}_{BE_{i,t+1}>0}\right], \tag{24}$$

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

[18]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 (12).

subject to (18),

$$\begin{aligned} r^A_{i,t+1} &= \varphi_{it} r^L_{i,t+1} + (1-\varphi_{it}) r^G_{t+1} \\ \log p_{t+1} &= (1-\rho_p)\log \bar{p} + \rho_p \log p_t + \sigma_p \epsilon_{p,t+1} \\ \omega_{i,t+1} &= \rho_\omega \omega_{it} + \sigma_\omega \epsilon_{\omega_i,t+1}, \end{aligned} \tag{25}$$

and

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

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 of 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:

$$\widetilde{v}(a_{i,t-1}, p_t, \omega_{it}) = \frac{V_i(BE_{it}, A_{i,t-1}, D_{it}, p_t, \omega_{it}) - BE_{it}}{D_{it}}, \tag{26}$$

where $a_{it} = \frac{A_{it}}{D_{it}}$ and $be_{it} = \frac{BE_{it}}{D_{it}}$. Appendix B shows that (26) is indeed a function of lagged scaled assets ($a_{i,t-1}$), crisis probability (p_t), and local conditions (ω_{it}).[19] We refer to (26), 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

[19] Technically, (26) is well-defined only when $BE_{it} \geq 0$. See Appendix B for details.

moral hazard problem resulting from deposit insurance.[20] When franchise value falls, however, incentives change.

Figure 8 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. The negative relation between the franchise value and the crisis probability arises 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.

4.4 Bank Risk-Taking

Figures 9 and 10 illustrate the two key choices of a bank. Figure 9 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 9 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 9 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, for highly levered banks, optimal assets in the next

[20] In their influential paper, Kareken and Wallace (1978) argued that "if bank liabilities are insured, as under the FDIC scheme, at a premium that is independent of portfolio risk and if banks are not regulated, then they hold risky portfolios, and in some future states of the world there are numerous bankruptcies." In our framework, whether this behavior realizes is dependent on the state of the economy.

period are virtually flat in p_t.

How does the relatively simple model of Section 4 generate these patterns? All else equal, assets are costly to the bank (this is modeled through the cost function Φ). 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 the (stochastic) steady state.[21] This is shown by the dotted line in Figure 9. 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 9, 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 investments and seeking to stay in business, to being a "bad bank," in effect taking advantage of the subsidy offered to depositors. This is illustrated for a simulated bank in Figure 6 in the Online Appendix.[22] This is also illustrated by the policy functions shown in Figure 9 where we keep fixed ω to its average value. The threshold for p_t at which the shift occurs depends on leverage from the previous period (and ω). For the bank with low leverage the shift does not occur until the probability of a crisis is as high as 3.5%. For the bank with the middle value, it occurs at about 2%. For the bank

[21] 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.

[22] Figure 7 in the Online Appendix shows the new leverage level at which the bank moves when it passes from being a bad bank to a good bank.

with the highest leverage, all values of p_t lead it to maintain assets at their lowest value.[23]

We can see the same mechanisms at work in the optimal portfolio allocation of the bank, as Figure 10 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 9). 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 9.

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.[24] 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 assets do 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, 2020; Richter and Zimmermann, 2019).

Figure 11 summarizes our findings by showing the implications of optimal bank behavior

[23] Recall that this maximum leverage position is defined by need to pay a fine proportional to deposits when leverage exceeds this value.

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

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.

4.5 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 (12) as given. We assume this sector faces no financial frictions, and is all-equity financed.

4.5.1 Technology

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

$$Y_t = z_t^{1-\alpha} K_t^{\alpha}, \tag{27}$$

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

$$\log z_{t+1} = \log z_t + \mu_c + \epsilon_{c,t+1} + \phi \xi x_{t+1}. \tag{28}$$

During normal-times, productivity grows at rate μ_c 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.

4.5.2 Investment Opportunities

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

$$K_{t+1} = \Big[(1-\delta)K_t + I_t\Big] e^{\phi\xi x_{t+1}}, \tag{29}$$

where δ is depreciation and I_t is firm's investment at time t. Equation (29) 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

$$\lambda\left(I_t, K_t\right) = \eta_F \left(\frac{I_t}{K_t}\right)^2 K_t, \tag{30}$$

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

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

subject to (29) and (30).

5 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.

5.1 Parameter Values

We begin by selecting a set of values for our model's parameters. We calibrate the model at an annual frequency. Table 1 summarizes our choices for the parameters used to solve the problems of investors, banks and firms. Several of our parameters come from previous works by Gourio (2012) and Gomes, Grotteria, and Wachter (2018).

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. A value of γ equal to 3 and ψ equal to 2 are 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 (0.01, 0.015, and 0.987, respectively) follow from the extant macro literature that uses these parameters to match U.S. consumption data moments (e.g. Cooley and Prescott, 1995). Parameter values used to solve the problem of the firm are also in line with standard choices in the macroeconomics literature (α and δ are equal to 0.4 and 0.08, respectively) or chosen to match the relative drop in output during crises (a ϕ equal to 2) or the volatility of investment growth relative to the volatility of output growth in the data (η_F equal to 5).

Due to the rare nature of disasters, precise calculations of the probabilities and distributions implied by (11) are difficult. We generally follow Barro and Ursua (2008) and set the average probability of an economic collapse $\bar{p}$ to 2% per annum and an associated drop in consumption of $\xi = 30\%$.[25] These values are also conservative given that 30% is close to the average disaster size, and that the distribution of disasters appears to have a tail that is much fatter than that implied by the normal distribution. Next, we set the autoregressive coefficient (ρ_p) to be 0.8 (annually) with a conditional standard deviation (σ_p) of 0.42, values that are consistent with those used by 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 (0.01 and 0.90, respectively), are determined from volatility and persistence U.S. house prices, at the individual state level. A value for the idiosyncratic component of volatility, σ_j, equal to 10% 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, and the parameter f is calibrated to be so large that the bank does never find it optimal to pay the fee (i.e., this makes it equivalent to a hard regulatory constraint on leverage). Finally, a value of 3 for 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.

5.2 *Quantitative Results*

To 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 an increase in credit and poor subsequent economic performance (e.g. Gennaioli

[25]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.

and Shleifer (2018)). We show that our model can quantitatively account for these findings, though the interpretation is quite different.

To do this, we first simulate 10,000 years of artificial data from our model economy with a cross-section of 1,000 (ex-ante identical) banks (see Appendix C for details). Following Schularick and Taylor (2012) we next define a crisis as an event where realized GDP growth is in the bottom 4% of our simulated time series. This definition captures not only periods in which $x_t = 1$ but also a number during which the probability of a crisis, p_t, rose sharply, leading firms to reduce investment and thus output to fall. Importantly, it addresses the key 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.[26]

In what follows we define aggregate bank lending to the private sector as

$$L_t = \sum_i \varphi_{it} a_{i,t}$$

where $\varphi_{it} a_{it}$ is the dollar value of the private loans made by bank i in period t.[27]

Table 2 compares our model's results with those in Schularick and Taylor (2012) regarding the relation between increases in lending and the probability of a crisis event, by regressing crisis occurrences on lagged values of bank loans. Both in the model and the data we see that an increase in lending is a statistically significant predictor of a crisis with similar economic magnitudes. The standard interpretation of the empirical evidence is that increased bank lending causes a crisis. In our model, however, time-varying exogenous risk drives both, and the relation between lagged bank lending and crises is merely a correlation.

Figure 12 compares our model's findings with the related evidence in Jordà, Schularick, and Taylor (2016) showing that financial crises often follow periods of very fast credit growth.

[26] 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 $x_t = 1$.

[27] The model has clear implications for the portfolio share of loans, but less clear implications for total lending: e.g., when p is above the value at which the bank has already switched to a full-loan policy, total lending being $a \times \varphi$ can even go down for an individual bank.

Here we break down the frequency of a crisis across quintiles of lagged credit growth by country. As the figure shows, both in the model and in the data, crises frequencies increase significantly after periods of fast credit-to-GDP growth. Panel B, taken from our artificial dataset, confirms that we can substantively replicate these same facts, even if we assume the crisis is *independent* of changes in bank lending.[28,29]

Finally, Table 3 compares predictions of the model with evidence in Baron and Xiong (2017) that an increase in lending are associated with higher probability of bank crashes. A probit regression of bank equity crashes on lagged increases in lending yields significant coefficients in the data. Model coefficients are similar in magnitude. Thus in both model and data, increases in lending significantly predict sharp declines in bank stock market valuations.

Why is the model able to match this evidence? The key mechanism is the endogenous fluctuating value of the bank's franchise, which falls during periods of high probability of crises. As a result, 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 (Schularick and Taylor, 2012), and future sharp declines in bank stocks (Baron and Xiong, 2017). It also predicts lower GDP growth because non-financial firms, perceiving the same economic instability, reduce their investment, leading to lower output (Mian et al., 2017).

More broadly, our model is qualitatively consistent with a number of other recent findings linking credit growth, valuations, and financial crises. Consistent with Muir (2017), the model predicts that when banks are close to default, equity valuations are low, and future

[28]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 it, credit growth is stationary. However, theoretically, the ratio of loans to GDP may not be stationary in our model.

[29]In the Online Appendix, we 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. Panel A of Figure 8 in the Online Appendix 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. Once again, this empirical exercise has no explicit link to financial crises. In our model it is the increased probability of a crisis that leads to lower growth. To make this point clearer, in the model scatterplot (panel B of Figure 8 in the Online Appendix) we explicitly exclude realized disasters.

risk premia are high. 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 crisis probability, 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.

Our model makes also cross-sectional predictions, which are indeed consistent with the recent evidence by Meiselman et al. (2020) and Fahlenbrach, Prilmeier, and Stulz (2017). Meiselman et al. (2020) have shown that the higher the expected payoff of banks' portfolios in good times, the higher must be their exposure to systematic risk, that is, riskier banks have larger profits in good times. The cross-sectional predictions in our framework are driven by variation in the bank-specific determinant of loan performance (ω). For a given p and a, a larger ω is associated to lower excess returns on loans (Figure 6), a lower share of loans in the bank's portfolio (therefore a lower expected payoff in good time) and a lower bank's value (Figures 9 and 10 in the Online Appendix). Once a crisis is realized, it is those banks that lent the most that are most affected, as documented by Fahlenbrach et al. (2017).

Our model has also limitations. Indeed, it predicts that, on average, declines in bank equity valuations co-occur with rising household credit, and that both should forecast higher returns (and higher future crash risk). In the data rising household credit has been shown to forecast declining valuations (Baron and Xiong, 2017). Our model can only replicate this finding in small samples with overrepresented disasters. In fact, given that in our model investors are rational and risk-averse, an increase in the probability of an economic crisis, that we have shown is associated to larger credit expansions and lower market valuations of banks, is related to larger equity premia and larger expected (and on average realized) excess returns for bank's shareholders.

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.

6 Policy Evaluation

Unconventional monetary policy and macroprudential regulation. In response to the recent financial crisis, fiscal and monetary authorities implemented various policies to influence the behavior of the banking sector. These measures included the Capital Purchase Program (CPP) and the first round of quantitative easing (QE1) in the United States, as well as the long-term refinancing operations (LTRO) in Europe. Under complete and perfect markets, unconventional monetary policy is irrelevant, that is, the market undoes the financial policy of the monetary authority (Wallace, 1981). The theoretical literature has then introduced financial frictions or incomplete markets to argue the unconventional monetary policy can affect interest rates, the amount of lending and finally equilibrium consumption. In fact, much of the recent theoretical literature on unconventional interventions highlights 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).

These frameworks have given rise to numerous empirical studies intending to clarify the channels through which unconventional monetary policy has real effects. The three channels that have found the largest support are : a) a signaling channel that works trough changes in investors' expectations about future monetary policy; b) a portfolio substitution channel where changes in the quantity of marketable assets affect their prices and yields; c) a refinancing channel whereby the banks' cost of capital is lowered. We now evaluate our model implications in light of these three channels.

Some scholars argue the impact of quantitative easing or asset purchase programs is primarily due to a combination of expectations and portfolio substitution channels, i.e., the first and the second channel. When central banks purchase long-term government bonds, the yields on these assets decrease, leading to increased lending by banks as loans become more attractive compared to government bonds (Krishnamurthy and Vissing-Jorgensen, 2011 for US; or Motto, Altavilla, and Carboni, 2015 for Euro area). This aligns with the predictions of our framework, where lowering government bond yields exogenously leads banks to shift their portfolio towards more loans.

Other scholars propose that quantitative easing or asset purchase programs have an effect on banks' refinancing. One hypothesis is that when a central bank purchases MBS from banks, it increases the liquidity and marketability of these assets, reducing banks' cost of capital and potentially increasing their profits and franchise value. Our model implies this channel could lead to banks shifting their portfolios towards safer government bonds and reducing lending. An alternative (not mutually exclusive) hypothesis is that when central banks purchase non-government debt, non-banks sell public debt to central banks and deposit money at banks, providing cheap financing and increasing banks' profits. Our model implies also in this case, banks to shift their portfolios towards safer government bonds and reduce lending. 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; besides, Crosignani, Faria-e Castro, and Fonseca (2019) suggest that European banks used the cheap loans from LTROs to buy domestic government bonds yielding returns that exceeded the cost of those loans.[30]

All three channels mentioned above have found empirical support in different phases of the programs. While the debate continues regarding which channel is the most influential, our model underscores the importance of examining unconventional monetary policies through their impact on bank franchise value. By presenting an alternative mechanism that aligns with

[30] A large literature argues that domestic sovereign debt is an obvious form of safe asset from the bank shareholders' perspective because once the government defaults domestic banks would be likely to be insolvent anyway (Myerson, 2014). Following the same argument, Andreeva and Vlassopoulos (2019) claim that during the recent European crisis banks did not fully price their own sovereign's credit risk when making portfolio allocation decisions.

the available evidence, our paper offers a fresh perspective on the effects of unconventional monetary policies on banks.

Our findings also contribute to extensive discussions on the role of macroprudential regulation. While in our model credit growth does not cause crises by construction, it remains possible that credit growth may be socially excessive during booms and indeed a more complete model that allows for significant social costs associated with bank defaults may amplify the magnitude of the disasters. Even in this case, our analysis suggests that macroprudential regulation should move beyond a broad-based focus on constraining credit growth as a means of preventing crises, which is also potentially welfare-reducing, and instead prioritize mitigating the potential for systemic defaults such as interconnectedness of financial institutions, the concentration of risk within a few large banks or speedy resolution processes for troubled banks.

The effects of reducing banks' cost of funding. We formally examine the impact of a particular government intervention that reduces banks' cost of funding below its current value, $\widetilde{r}^D < r^D$, which we believe can be used to interpret the consequences of several recent policy measures.[31] Unsurprisingly, in our model, as Figure 13 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 14 shows that after this intervention banks rely (relatively) more on equity. This is because with increased franchise values, default will 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 15 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 to tap debt

[31]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.

markets at below-market rates lead many banks to reduce overall risk taking. Moreover, Figures 14 and 15 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. Our results are also consistent with the evidence of Rodnyansky and Darmouni (2017), who find that U.S. banks with mortgage-backed securities on 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.

7 Evidence on the Role of Deposit Insurance

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.[32]

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 4, reports the estimates for the following equation:

$$\Delta_3 y_{i,t+h} = \alpha_i + \beta_H \Delta_3 d^{HH}_{i,t-1} + \beta_F \Delta_3 d^{F}_{i,t-1} + u_{it}, \tag{31}$$

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.[33] 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 (31) and estimate the following equation:

$$\Delta_3 y_{i,t+h} = \alpha_i + (\beta_{HH} + \beta^{DI}_{HH} \mathbb{1}_{DI}) \Delta_3 d^{HH}_{i,t-1} + (\beta_F + \beta^{DI}_{F} \mathbb{1}_{DI}) \Delta_3 d^{F}_{i,t-1} + u_{it}, \tag{32}$$

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

Panel B in Table 4 shows that the coefficients on the interaction between growth in household credit and the presence of deposit insurance are generally statistically significant, suggesting that the variation captured by our regressors is mostly concentrated in periods and

[32] 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.

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

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.[34] By contrast, 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 crises is outside the scope of this paper, Table 4 strongly suggests that the relation between credit growth and crises is mediated through deposit insurance.

8 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 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

[34]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.

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.

These results are important in light of the findings by Sarin and Summers (2016). These authors have shown that, despite the stricter rules imposed on banks after the financial crisis as far as regulatory requirements and stress-testing procedures were concerned, and the fact that standard financial theories predict that such changes should have led to substantial declines in financial market measures of risk, financial market measures of bank risk have actually increased in the aftermath of the new regulation. Our model can justify this finding. If higher regulation decreases banks' rents, this would lead to a drop in franchise value and a contemporaneous optimal bank decision to undertake riskier investments. Again, ignoring the incentive effects of policy on banks, which operate through variation in franchise values, can lead to wrong conclusions and sub-optimal policy implementations.

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Appendix A Bank Lending

Following Vasicek (2002), Gornall and Strebulaev (2018), 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

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

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

Define

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

It follows from the law of large numbers that

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

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

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

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

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

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 (17) into (24) 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 (18) and (25). 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 (25), for $be_{it} \geq 0$; otherwise $v_{it} = 0$. Dividing both sides of (24) 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 (25). 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 20-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 (13). 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 (12). Prices and returns for the Treasury bill and the loans to households are derived from the Euler equations presented in (14) and (A.5), respectively.

With this information at hand, we solve the problem of the bank.[35] 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 2,000 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.[36] 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.

[35]The problem of the bank is solved with a tolerance of 10^{-4}. We have also solved it with a tolerance of 10^{-10} and quantitative results are very similar.

[36]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. The stationarity of our model can be visualized using Figure 4 and 5 in the Online Appendix that show for a very long simulated sample the cross-sectional average and cross-sectional standard deviation of bank leverage forcing p to 1.84% and ϵ_{t+1} to 0 in the simulated sample and letting only ω vary.

Table 1. Parameter Values

Description	Parameter	Value
Representative Investor		
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
Bank		
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	0.009
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
Punishment under no compliance	f	10^4
Adjustment cost on capital	η_B	3
Representative Firm		
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 problem of the representative investor's, an individual bank, and the representative firm. The model presented in Section 4 is calibrated at annual frequency. The parameters are discussed in more detail in Section 5.1.

Table 2. Predicting crises in data and model

	LPM – Data	LPM – Model	Logit – Data	Logit – Model
ΔL_{t-1}	-0.0182	0.2382	-0.0917	4.8195
ΔL_{t-2}	0.260	0.1580	6.641	3.5435
ΔL_{t-3}	0.0638	0.0433	1.675	1.2271
ΔL_{t-4}	-0.00423	0.0372	0.0881	1.0196
ΔL_{t-5}	0.0443	-0.0013	0.998	0.0974
Sum of lag coefficients	0.345	0.4755	9.311	10.7071
R^2	0.0126	0.0076	0.0379	0.0070

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 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 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 3. 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	0.048	0.044	0.039
50th pct	0.125	0.128	0.123
95th pct	0.197	0.207	0.206

Notes: This table reports coefficients from a probit regression of bank equity index crashes on lagged credit expansion. We examine horizons of 1, 2, and 3 years. The crash dummy takes value 1 if there is a drop of -30% in the next 1, 2 or 3 years 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 (2017). 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.

Table 4. 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)	(0.08)	(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	0.05	0.08	0.10	0.14	0.14	0.12
	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)	(0.18)	(0.13)	(0.12)	(0.12)	(0.13)
$\Delta_3 d^{F}_{i,t-1}$	-0.03	-0.13	-0.15**	-0.12**	-0.07	-0.02	0.02
	(0.09)	(0.09)	(0.07)	(0.05)	(0.05)	(0.06)	(0.06)
$\Delta_3 d^{HH}_{i,t-1}\mathbb{1}_{DI}$	-0.18	-0.28	-0.36*	-0.44***	-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 double-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.

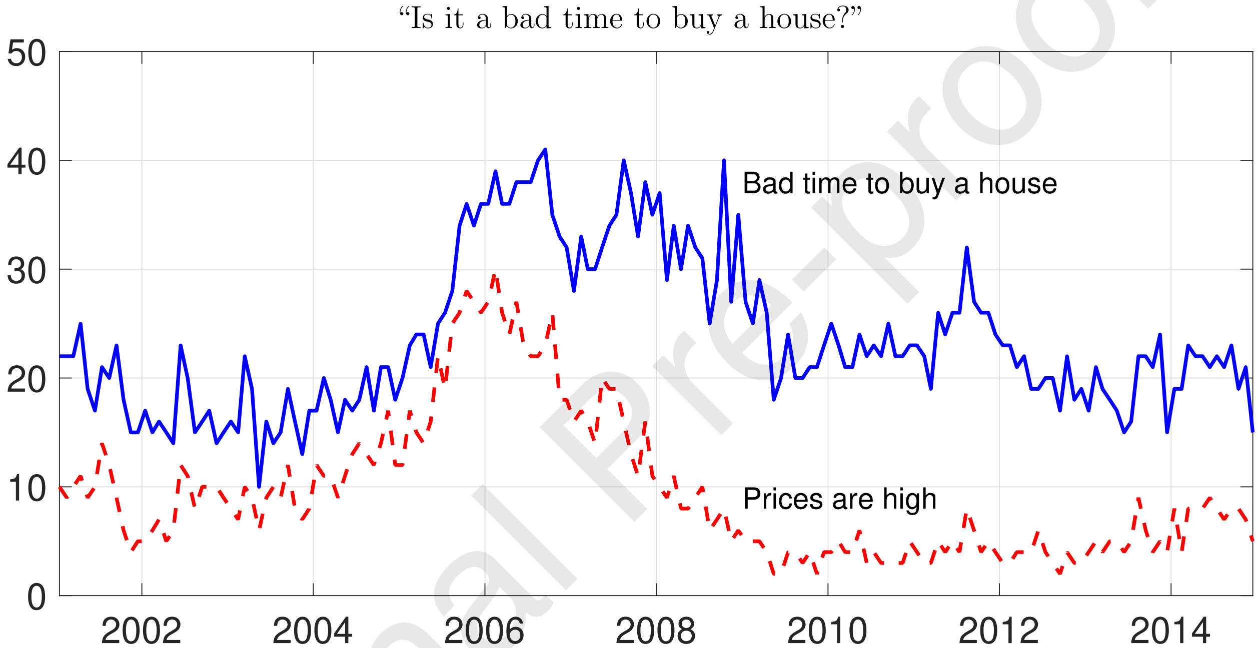

Fig. 1. Rising Pessimism. The figure shows the fraction of households answering the question "Generally speaking, do you think now is a good time or a bad time to buy a house?" with "now is a bad time." Data are from the Michigan Survey of Consumers.

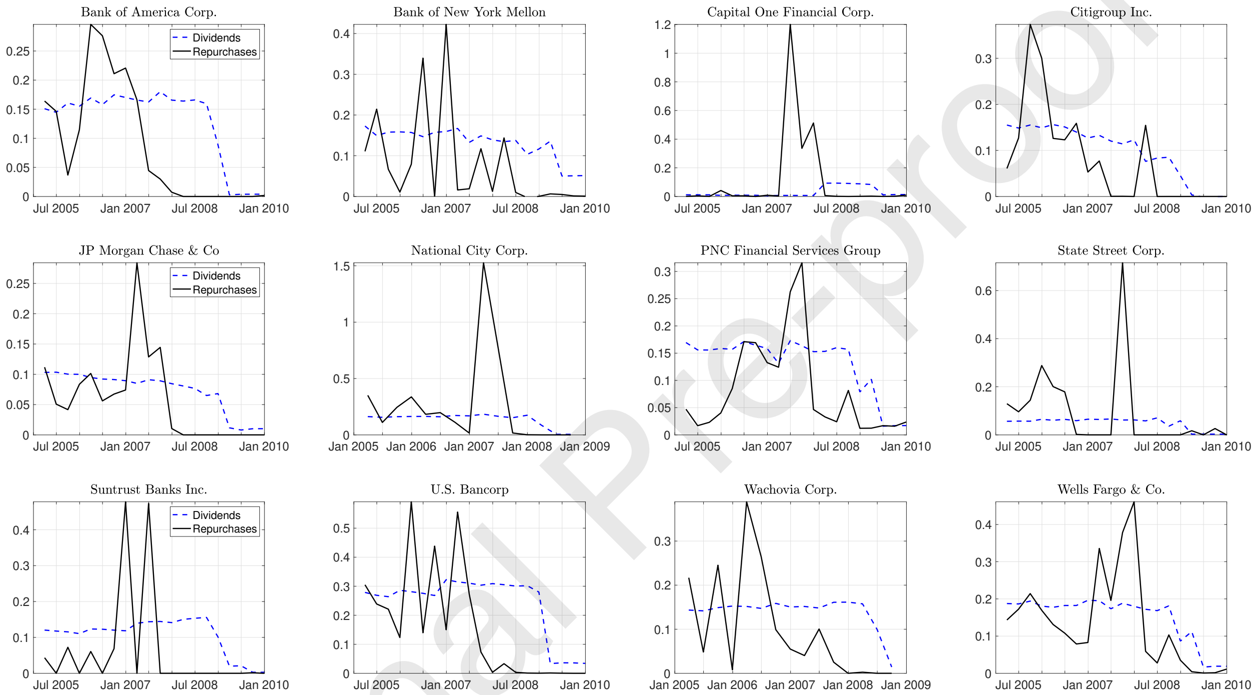

Fig. 2. Dividends and Repurchases by large bank holding companies. The figure shows the dividends and share repurchases made by large bank holding companies in the United States between 2005 and 2009. Values are in percentage of the total assets.

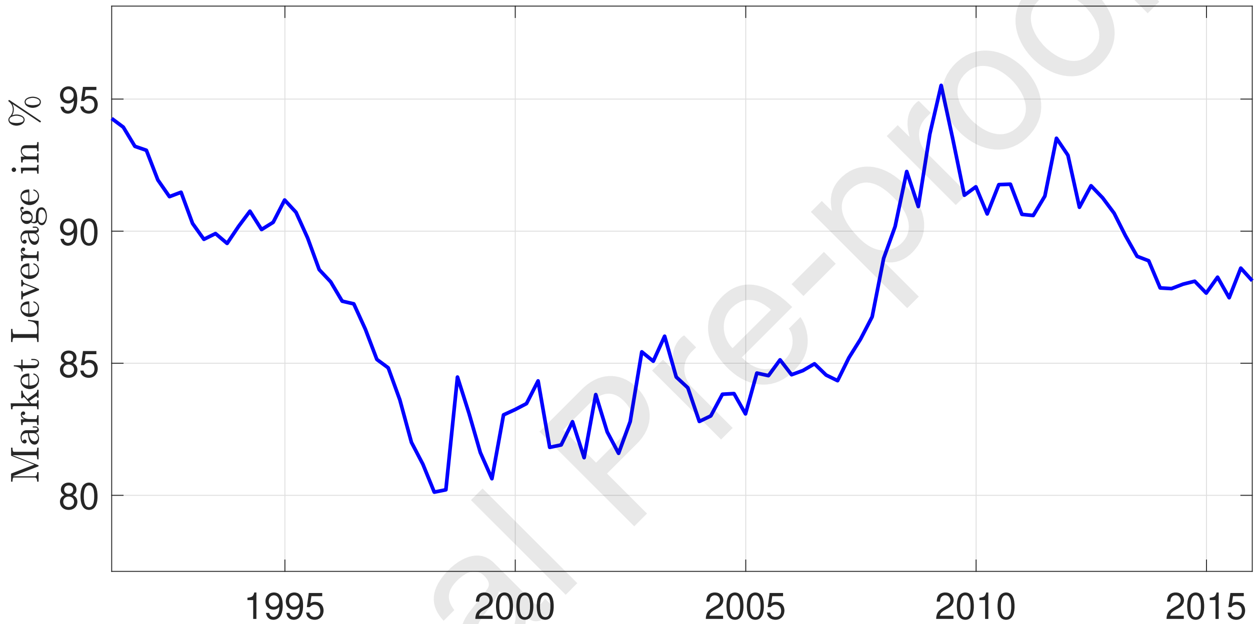

Fig. 3. Market Leverage for Bank Holding Companies. The figure shows the aggregate market leverage for bank holding companies. Leverage is computed as the sum of total liabilities across banks divided by the sum of market capitalization and total liabilities across banks.

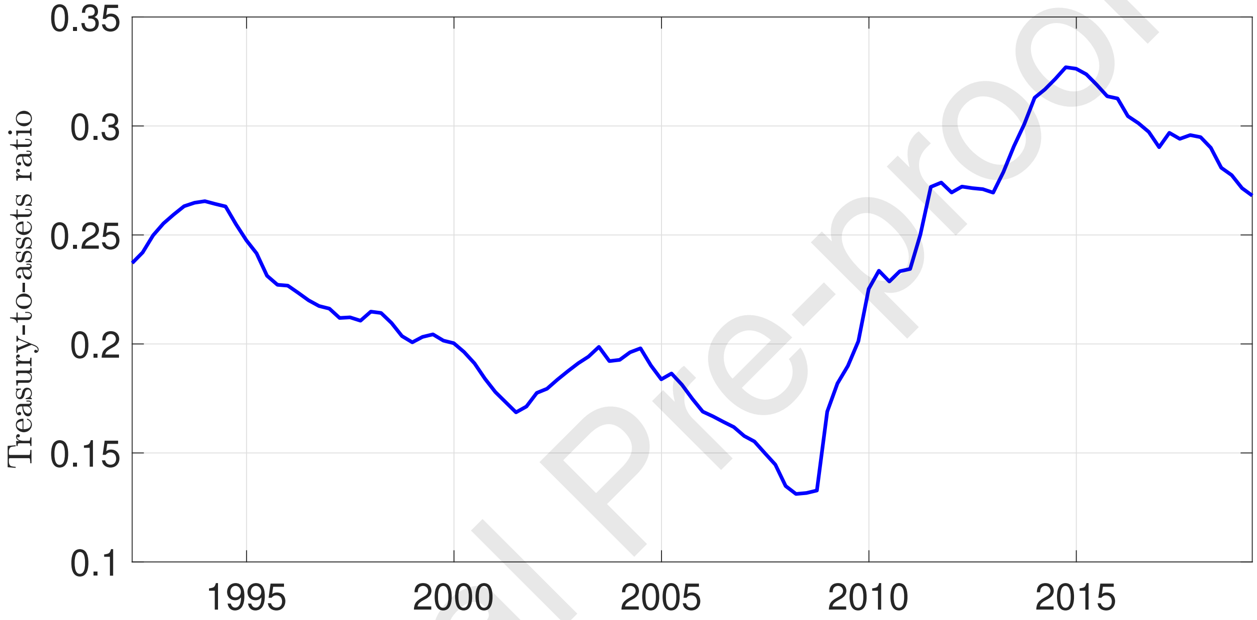

Fig. 4. Relative size of Treasury and cash in the bank portfolio. The ratio is computed as the sum of Treasury and agency securities and cash assets divided by the sum of total assets across commercial banks in the United States. Data are from the Federal Reserve H.8 Assets and Liabilities of Commercial Banks in the United States, and refer to the period ranging from 1992 to 2019.

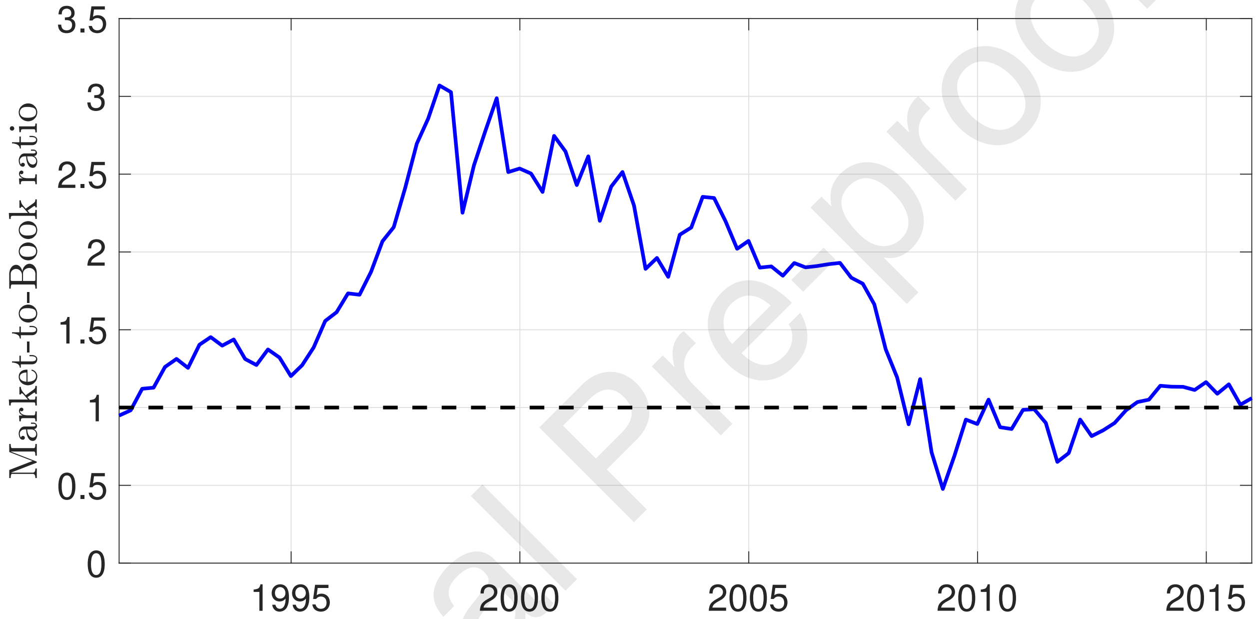

Fig. 5. Market to Book Value of Equity for Bank Holding Companies. The market to book ratio is the sum of market capitalization across bank holding companies divided by the sum of equity book value across bank holding companies.

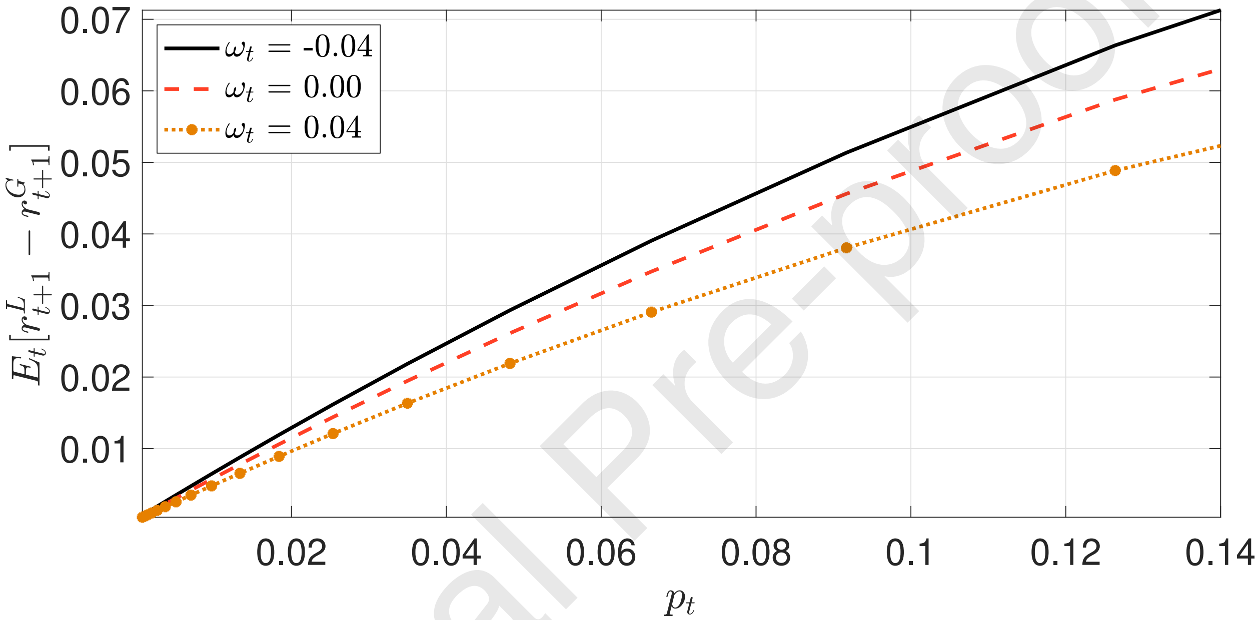

Fig. 6. Excess Return on Private Loans. The figure shows the ex-ante expected rate of return on bank loans, r^L_{t+1}, relative to the rate of return earned on a one-year government bill, r^G_{t+1} for each level of the probability of crisis, p_t, and alternative values of the current-period collateral, ω_t. The expected return and the probability are in annual terms.

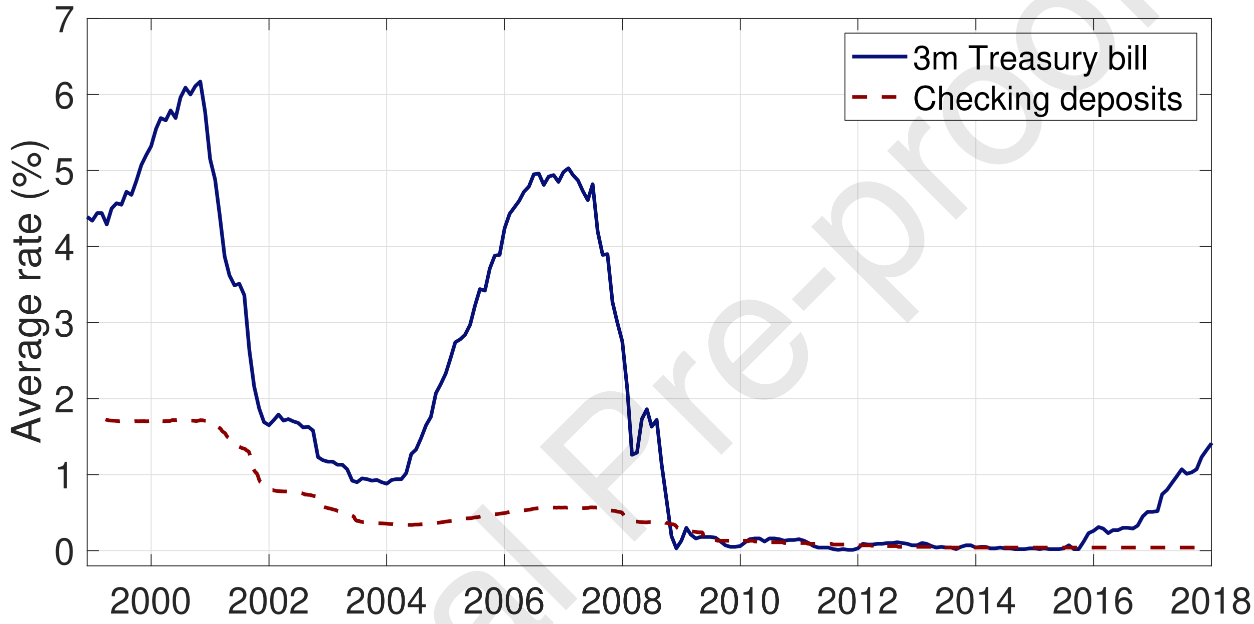

Fig. 7. Rates on deposits and Treasury bills The figure shows the deposit rate on checking accounts (US average) and the yield on the 3-month Treasury bill from 1999 to 2018. Treasury bill rates are from FRED. Data on checking deposits before 2009 are from Drechsler et al. (2017) while after 2009 are from FDIC.

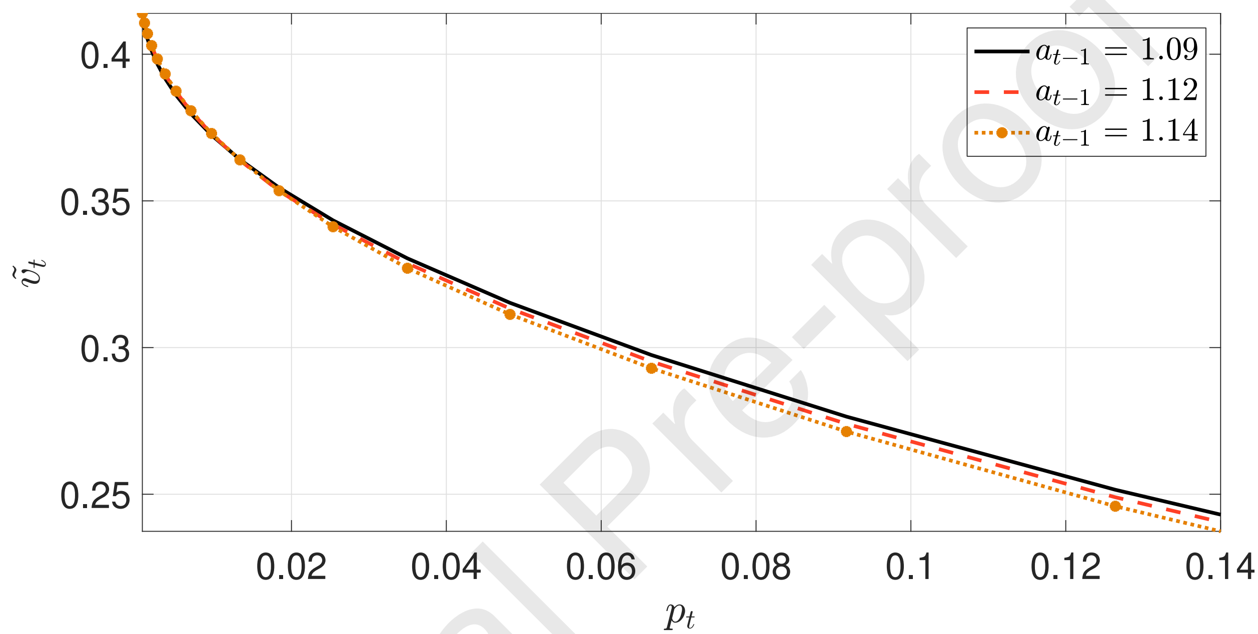

Fig. 8. Bank Franchise Value. The figure shows the bank's franchise value, scaled by deposits, $\widetilde{v}_t = \left(\frac{\widetilde{V}_t}{D_t}\right)$. Alternative levels of crises probability p_t are plotted on the x-axis. Different lines represent different lagged asset-to-debt ratio $a_{t-1} = \left(\frac{A_{t-1}}{D_{t-1}}\right)$. ω_t is fixed to 0.

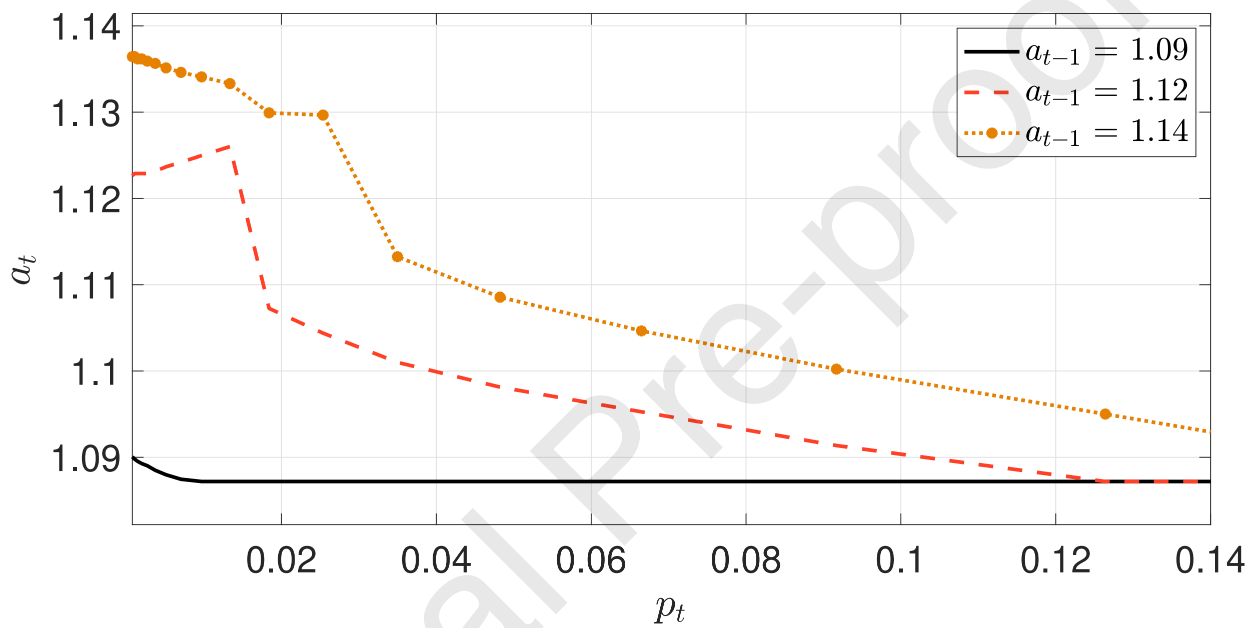

Fig. 9. Optimal Bank Lending. The figure shows the optimal amount of bank assets (lending), scaled by deposits. Alternative levels of crises probability p_t are plotted on the x-axis. Different lines represent different lagged asset-to-debt ratio $a_{t-1} = \left(\frac{A_{t-1}}{D_{t-1}}\right)$. ω_t is fixed to 0.

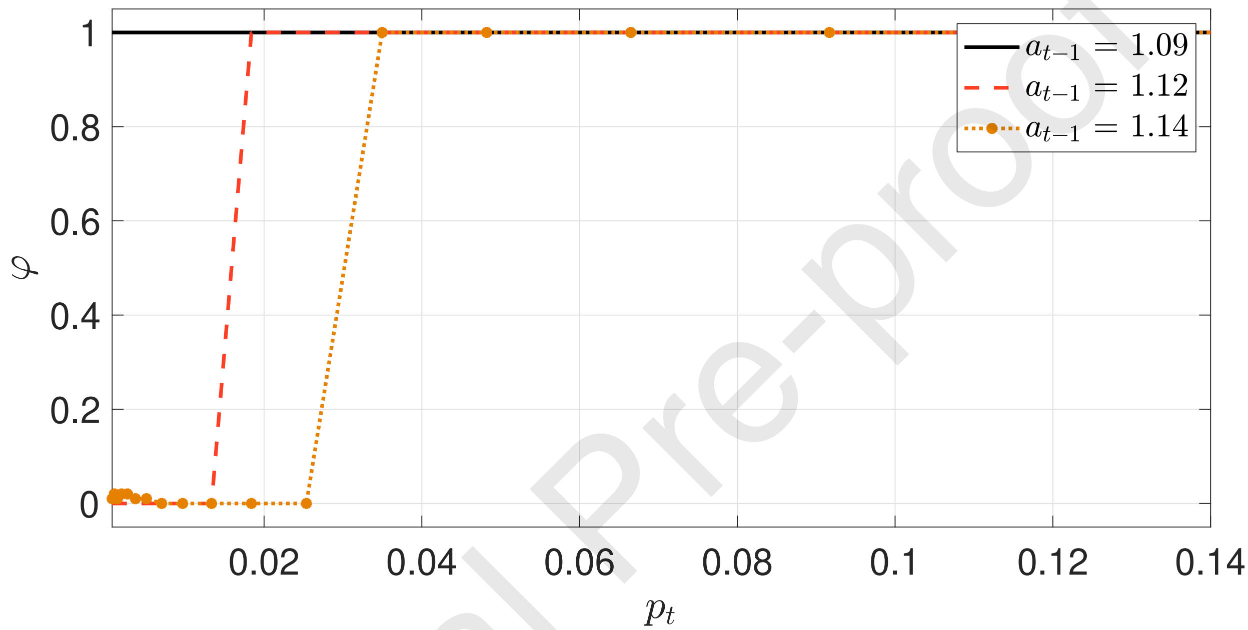

Fig. 10. Portfolio Allocation. The figure shows the policy for portfolio allocation of an individual bank (φ_t). Alternative levels of crises probability p_t are plotted on the x-axis. Different lines represent different lagged asset-to-debt ratio $a_{t-1} = \left(\frac{A_{t-1}}{D_{t-1}}\right)$. ω_t 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.

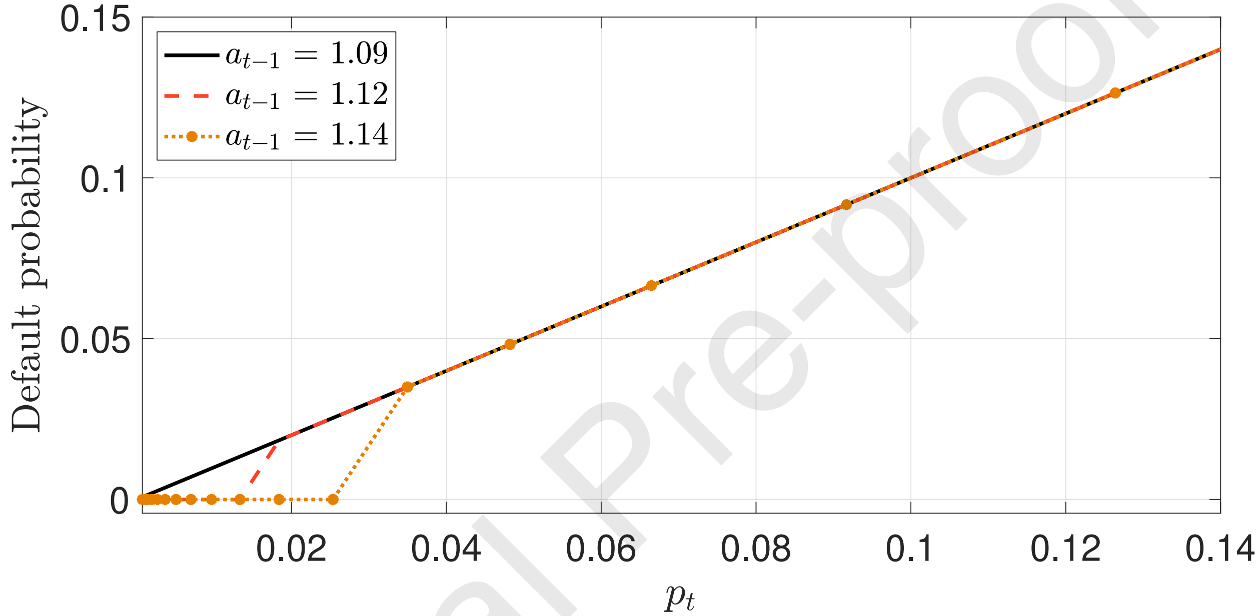

Fig. 11. Bank default probability. The figure shows the endogenous default probability of an individual bank after optimally deciding on the amount of capital and its portfolio allocation. Alternative levels of crises probability p_t are plotted on the x-axis. Different lines represent different lagged asset-to-debt ratio $a_{t-1} = \left(\frac{A_{t-1}}{D_{t-1}}\right)$. ω_t is fixed to 0.

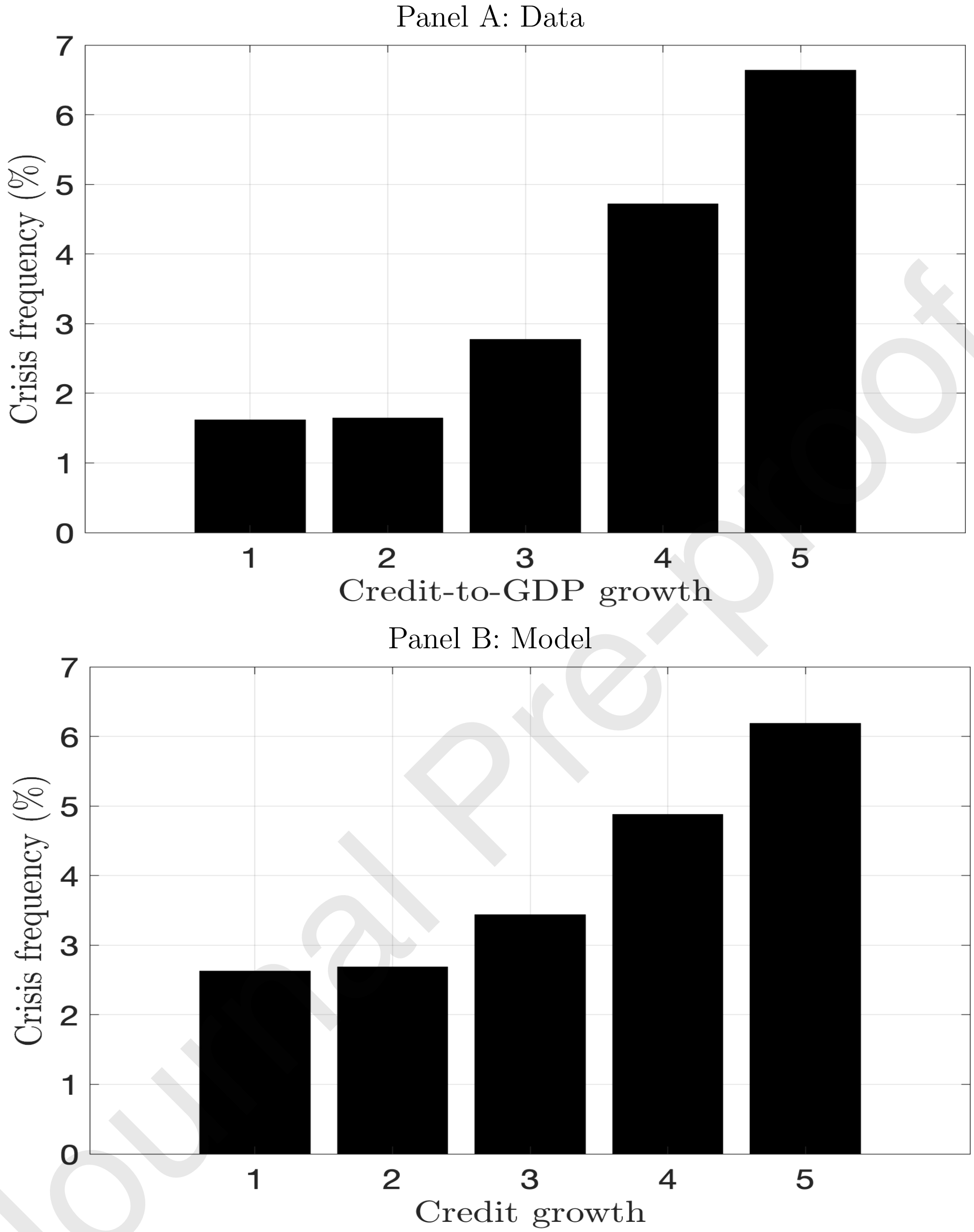

Fig. 12. Frequency of crises by credit growth. The top figure shows the empirical average frequency of a crisis in year $t+1$ conditioning on a given quintile of credit-to-GDP growth rates from year $t-5$ to t. Data are from Jordà, Schularick, and Taylor (2016). For each country, we compute the growth 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.

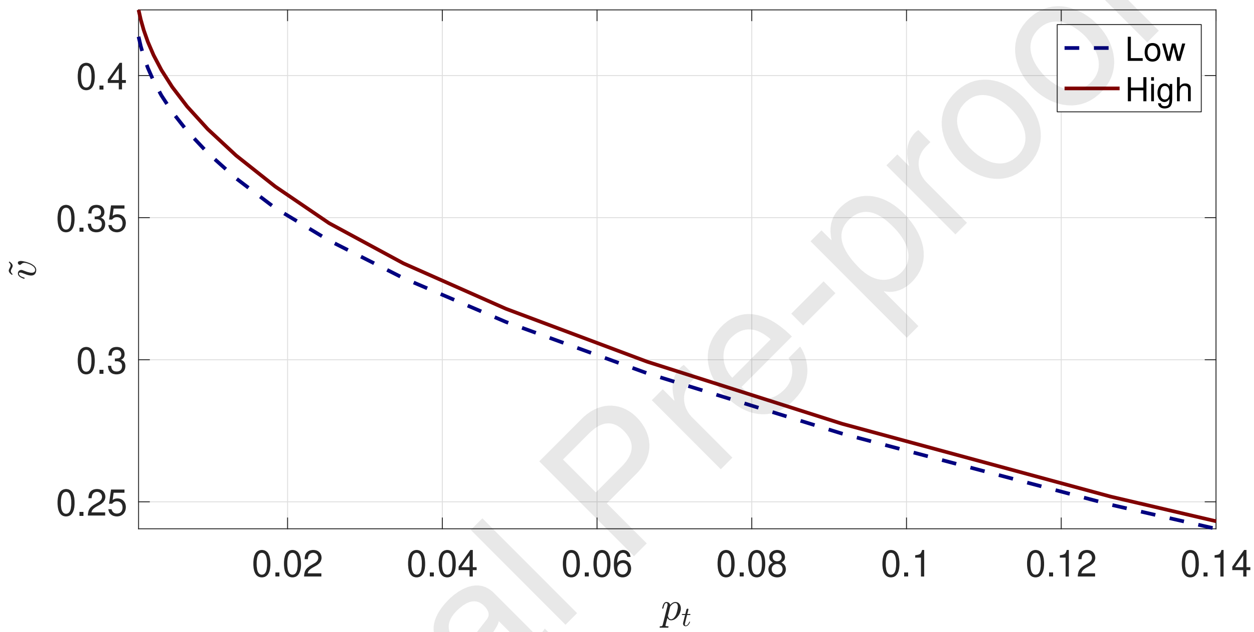

Fig. 13. Impact of subsidies on bank franchise value. The figure shows bank franchise value scaled by deposits, $\widetilde{v}_t = \left(\widetilde{V}_t / D_t\right)$, as a function of crisis probability p_t for two different levels of bank subsidies. We set $a_{t-1} = 1.12$ and $\omega_t = 0$. The case of low subsidies is our benchmark model. For the high subsidies scenario we lower the benchmark deposit rate by 3 basis points.

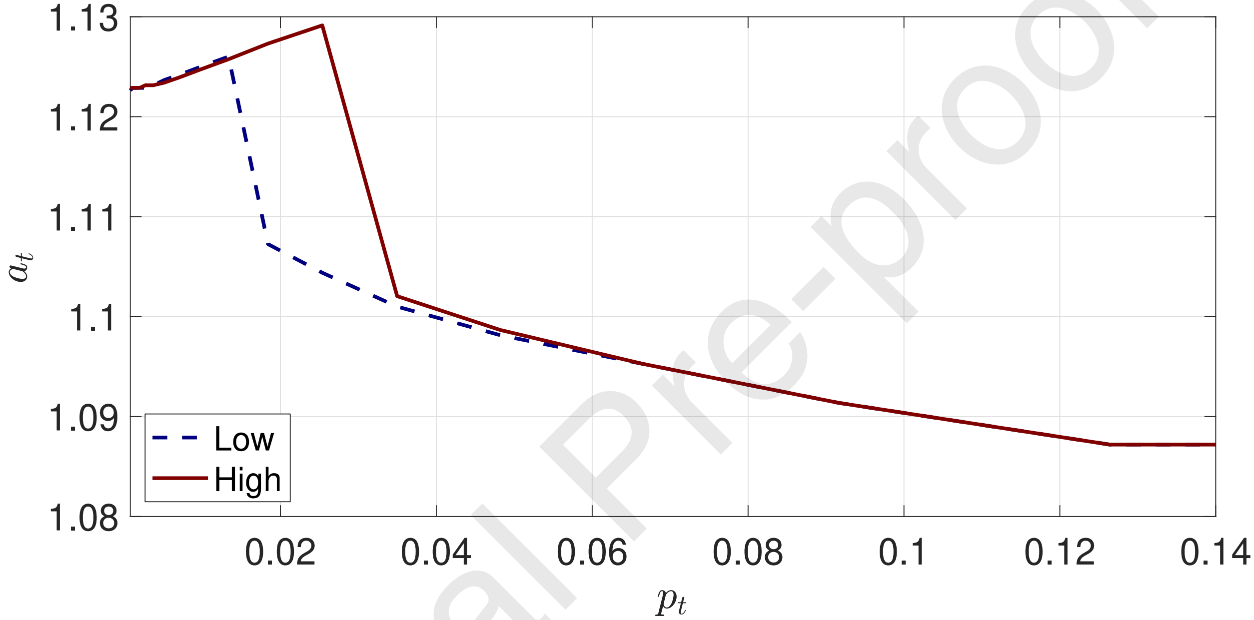

Fig. 14. Impact of subsidies on bank leverage. The figure shows the optimal ratio of assets to deposits $a_t = (A_t/D_t)$ as a function of crisis probability p_t for two different levels of bank subsidies. We set $a_{t-1} = 1.12$ and $\omega_t = 0$. The case of low subsidies is our benchmark model. For the high subsidies scenario we lower the benchmark deposit rate by 3 basis points.

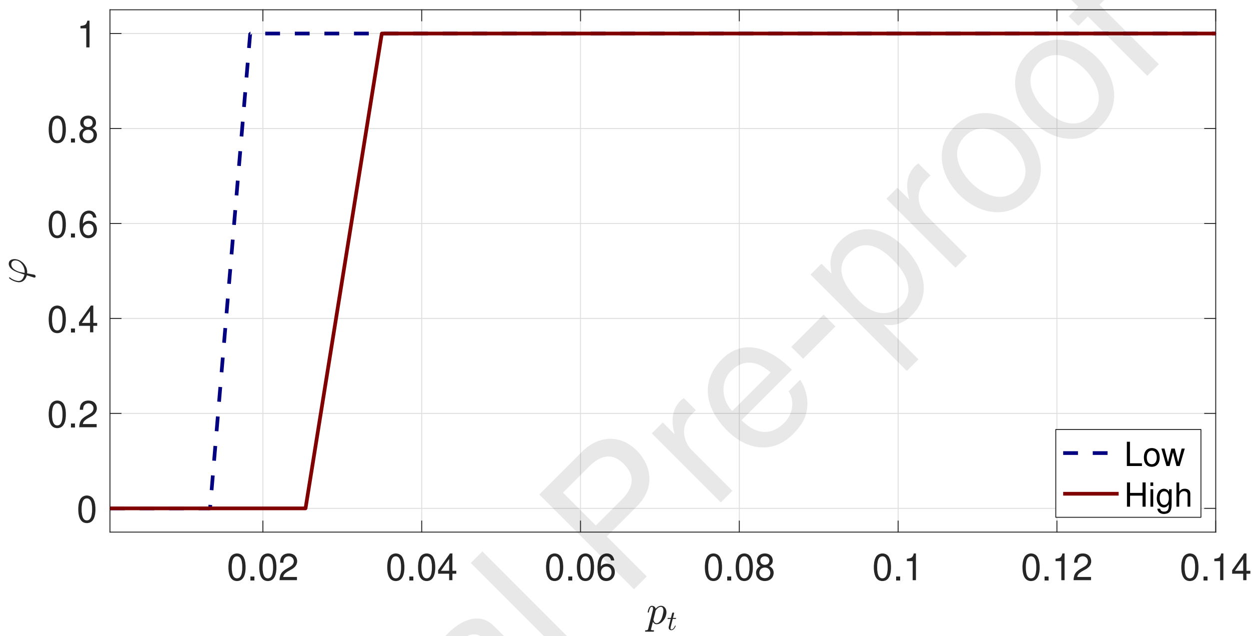

Fig. 15. Impact of subsidies on bank's optimal portfolio composition. The figure shows the portfolio allocation of an individual bank (φ_t) for high and low subsidies (solid and dashed line respectively) and different levels of the probability of criss p_t keeping fixed the last period asset-to-debt 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 3 basis points.

I, Joao Gomes, declare that I have no relevant or material financial interests in this paper.

I, Jessica Wachter, declare that I have no relevant or material financial interests in this paper.

I, Marco Grotteria, declare that I have no relevant or material financial interests in this paper.