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Bank capital and uncertainty ☆

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ABSTRACT

Financial frictions in raising external finance can induce banks to self-insure against future shocks through holding more bank capital. As uncertainty about future losses increases, the above reasoning implies that they would choose to increase their capital position. This paper tests this hypothesis in a dataset with U.S. Commercial Banks by exploiting a cross-sectional variation in uncertainty to explain the distribution of bank capital ratios. I find statistically significant and robust evidence in support of a self-insurance mechanism. A counterfactual experiment suggests that a decline in uncertainty to its lowest level generates an average reduction in bank capital ratios of up to 2 percentage points. Furthermore, uncertainty explains, on average, about half of banks regulatory capital buffers.

1. Introduction

The study of banks' financial structure has long been at the core of the banking literature. Moreover, the recent crisis has provided an additional and important boost to the interest in better understanding banks' leverage choices. This increased attention follows from the growing consensus in academic and policy thinking of the need to redesign macroeconomic and financial policies to better account for leverage dynamics in the financial sector (Woodford, 2011; King, 2012, and others).

This paper contributes to the understanding of how banks make leverage decisions by looking at how they respond to uncertainty. This is an important component in a broad agenda on banks's financial structure because it has implications for the procyclicality of bank leverage.

The paper starts with a simple model in which a bank faces frictions in raising external finance. When the bank is hit by a negative shock that lowers bank capital, financial frictions intensify and it becomes much more costly for the bank to raise new deposits or debt. When the risk of these shocks increases, the forward-looking bank increases bank capital to better shield its business. The model is used to derive a theoretical measure of uncertainty borrowed from the precautionary savings literature (Kimball, 1990). In the empirical section, this measure is complemented with simple atheoretical measures of uncertainty as a robustness exercise. It is important to clarify that the analysis abstracts from distinctions between uncertainty and risk (Knight, 1921) and thus for the purpose of this paper, the terms risk and uncertainty will be used interchangeably.

In this paper, uncertainty (or risk) means that the future is unknown, and thus banks make decisions today taking into account the various outcomes that could occur in the future and their (assumed known) probability distribution. This type of uncertainty can stem from many sources, for instance, depositors may withdraw money unexpectedly, asset prices may decline, or borrowers may suddenly be unable to repay loans. Some of these sources can be idiosyncratic, and some can reflect aggregate uncertainty, common to all banks. For simplicity and illustrative purposes, the theoretical model focuses only on one source of uncertainty: lending activities (e.g. changes in borrowers' capacity to repay loans). But in the empirics, a more flexible approach is adopted to reflect the combined impact of many different sources of uncertainty on banks' business activities.

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The empirical examination is implemented using U.S. commercial banks data and the aim is to explain the crossectional variation in bank capital ratios. To address endogeneity concerns I proceed as follows: I first construct measures of bank capital shocks that are idiosyncratic to the bank (i.e., variation in bank capital in excess of the mean variation across banks, after removing common shocks). Second, I construct proxies for banks' business model by grouping banks according to a set of characteristics. After grouping banks, I construct measures of uncertainty that are specific to each bank group but not to the individual bank, using data from 1985 to 1998. I use these measures of uncertainty to explain the crossectional distribution of bank capital ratios in the period after 2000. Endogeneity concerns are thus mitigated substantially because (i) the measures of risk are constructed for groups of equally weighted banks, and thus no individual bank influences the measure for the group, and (ii) the measures of risk are computed in a sample period that does not overlap with the one used in the regressions.

The empirical analysis results in significant and robust support for the hypothesis that banks facing higher uncertainty also maintain higher capital-to-assets ratios. The results are highly statistically and economically significant. A counterfactual experiment using the baseline estimates suggests that if uncertainty were to decline to the lowest value observed in the sample, a weighted average reduction of up to 2 percentage points in bank capital ratios would follow. Moreover, an additional counterfactual experiment suggests that the baseline measure of uncertainty explains on average 50% of banks' regulatory capital buffers. It is important to keep in mind that this is only one channel through which banks could mitigate the effects of uncertainty. Alternatively, banks can also securitize assets, alter the composition of liabilities, assets, off balance sheet positions, etc. Consequently, the impact of uncertainty on banks' behavior could go way beyond their leverage choices.

This paper complements existing literature on bank capital adjustment in the short-run, for instance Berger et al. (2008) and Flannery and Rangan (2008), by assessing instead an important determinant of the target level of bank capital. The results presented in this paper are consistent with a number of theoretical papers in which a precautionary motive arises. These models build on the idea that capital markets are imperfect, invalidating the implications of the Modigliani and Miller (1958) theorem. Examples include Van Den Heuvel (2009), Peura and Keppo (2005), Valencia (2014a), Estrella (2004), Furfine (2001), Brunnermeier and Sannikov (2014), and Jokivuolle and Peura (2004). It also provides formal evidence of a behavior that is often mentioned in the banking literature, but for which evidence remains scarce, for instance in Hancock and Wilcox (1994a,b), Berger and Udell (1994), and Peek and Rosengren (1995).

The empirical results presented in this paper also offer support to theoretical contributions that aim at explaining fluctuations in leverage, for instance Fostel and Geanakoplos (2008) and Adrian and Shin (2008), in which reduced volatility implies an increase in leverage. The results have also implications for the ongoing debate on macroprudential regulation. Because uncertainty tends to be countercyclical (Jurado et al., 2013), the results presented in this paper suggest that countercyclical capital requirements may turn out to be effective in restraining credit during good times. However, it may not provide the needed relief during bad times because banks may want to decrease leverage as a response to increased uncertainty.

The paper is organized as follows: Section 2 presents the theoretical framework. Section 3 describes the data, the measurement of uncertainty, the empirical strategy, and the main results of the paper. Section 5 conducts additional empirical exercises as robustness and Section 6 concludes.

2. Theoretical framework

The point of departure for this paper is a variant of the model presented in Valencia (2014a). This simple model serves the purpose of motivating the analysis and deriving a theoretical measure of uncertainty.

The problem is dynamic in nature. The bank has some bank capital at the beginning of the period, makes decisions on how much to lend and distribute dividends, but it faces uncertainty (of the nature described in the introduction) regarding the realization of loan returns. The bank knows the probability distribution of these returns when making decisions. After decisions are made, uncertainty about loan returns is realized, and the bank collects loans and repays depositors. Bank capital after all these transactions are finalized, becomes the initial level of capital for the following period, and so on. This simple description is now formalized in the subsequent lines.

Consider a bank managed by risk-neutral shareholders who maximize the present discounted value of dividends.

$$\underset{\{c_t,l_t\}_s^\infty}{Max}\ E_s\sum_{t=s}^{\infty}\beta^{t-s}c_t \tag{1}$$

where β denotes the discount factor, c_t denotes dividends, and l_t denotes total lending. The problem is subject to a balance sheet constraint given by

$$l_t = \underbrace{n_t - c_t}_{q_t} + d_t \tag{2}$$

where d_t denotes bank debt, n_t bank capital, and q_t bank capital net of dividends. It is also subject to a transition equation for bank capital of the following form:

$$n_{t+1} = \alpha_{t+1} r l_t - (l_t - q_t) i_t \tag{3}$$

where r denotes the expected return on the loans portfolio. i_t denotes the average return on deposits, assumed to be a function of bank leverage, to be defined in a moment. l_t denotes total loans, and α denotes random shocks that affect the average or expected rate of return on the loans portfolio. The timing convention adopted in this paper is such that the subscript $t+1$ denotes values after uncertainty is resolved, which are unknown at the moment of making decisions. Thus $\alpha_{t+1} r$ denotes the total ex-post return on loans. Notice that the ex-post return can exceed the expected ex-ante return r, reflecting the realization of shocks. In other words, if a bank expects on average a return of 5% on its loans, the actual return may be above or below 5%, depending on the realization of factors that were unknown at the moment of granting the loans.

One possible microeconomic interpretation for the stochastic nature of loan revenues is unknown ability of managers in screening and/or monitoring loans, and their ability in making sound loans has an impact on loan repayments. An alternative macroeconomic interpretation is the response of the bank's loans portfolio to variations in regional or national financial and economic conditions. For instance, if asset prices improve borrowers' conditions across the board and thus lowers the fraction of loans that the bank expected to go bad. In the simple model developed here, the distinction between idiosyncratic and aggregate uncertainty is irrelevant, and hence both examples above are valid. However, this distinction will matter in the empirical section for identification purposes.

The problem, written in Bellman's equation form is given by

$$V(n_t) = \underset{\{q_t,l_t\}}{Max}\left[n_t - q_t + E_t\beta V(n_{t+1})\right] \tag{4}$$

$$n_{t+1} = \alpha_{t+1} r l_t - (l_t - q_t) i_t \tag{5}$$

$$q_t \leqslant n_t \tag{6}$$

The last equation is a restriction on equity financing. It tells us that the bank cannot issue equity beyond what is done through retained earnings. It is written as a restriction on capital after distributing dividends, q, imposing that it cannot exceed what the bank had at the beginning of the period. In reality, banks do issue equity, but it is costly. The extreme assumption above is made just for simplicity. As long as it is costly to raise capital, the difference between a finite cost of raising equity and an infinite cost in doing so (as above) is just a matter of magnitudes. A bank able to issue equity will replenish capital more rapidly than one that is not. However, what matters is that as long as there is a cost in issuing equity, a bank cannot replenish capital instantaneously as it would be the case when the bank faces no costs in doing so. For instance, in Valencia (2014b), the bank can issue equity, but shareholders wish to smooth dividends. In Peura and Keppo (2005), equity injections are costly and arrive with a delay. In both cases, the bank replenishes capital only gradually.

Capital market imperfections manifest themselves in this simple model in two ways: the bank cannot issue equity and funding costs are a function of bank leverage. In Appendix A I show how this function can be derived endogenously from imposing information asymmetries between creditors and the bank using Townsend (1979) costly state verification. In this case, bank creditors do not observe the realization of the return on loans, which is private information to the banker. When the realization is low enough, because of limited liability, the bank defaults and bank creditors keep the bank's residual value, but they pay a cost to learn the value of assets. Since bank creditors demand to be compensated ex-ante for the risk of default, and the latter rises with leverage, funding costs become an increasing function of leverage. Conveniently for analytical purposes, a twice differentiable function satisfies with minimal ingredients the properties of borrowing costs under this modeling approach, as shown in Appendix A. The interaction between these information problems and the bank's risk of default invalidate Modigliani and Miller's (1958) implications because the average cost of capital for the bank changes as bank leverage changes. This final assumption involves decomposing the yield on deposits into two subcomponents $i_t = \rho + \Omega_t$, where ρ is the risk-free rate and Ω_t is the spread between the deposit or bank debt rate and the risk-free rate, which as discussed above, it is assumed to be a twice continuously differentiable function of bank leverage.

The assumptions on Ω_t generate increasing marginal costs of borrowing and thus deliver an interior solution. While the model is too simple to yield quantitative implications, it serves the purpose of illustrating the relationship between capital and uncertainty.

The corresponding first order conditions are given by

$$1 = \beta E_t V'(n_{t+1})\left[\rho + \Omega_t - (l_t - q_t)\frac{d\Omega_t}{dq}\right] \tag{7}$$

$$0 = E_t V'(n_{t+1})\left[\alpha_{t+1} r - (\rho + \Omega_t) - (l_t - q_t)\frac{d\Omega_t}{dl}\right] \tag{8}$$

The right hand-side of Eq. (7) corresponds to the marginal value of holding capital, determined by how much the bank would increase profits today by reducing interest costs on deposits $\left(\rho + \Omega_t - (l_t - q_t)\frac{d\Omega_t}{dq}\right)$ and by how much it would increase profitability in the future by reducing future interest costs $V'(n_{t+1})$, if it had one additional dollar in bank capital. The left-hand side is the marginal value of dividends. The amount of dividends distributed is such that it equals the marginal value of bank capital. Uncertainty affects bank decisions because the bank takes into account the future realization of the stochastic shocks through $V'(n_{t+1})$. For instance, if the standard deviation of α increases, the standard deviation of future bank capital also increases. If the marginal value function $V'(n_{t+1})$ were linear, then this increase in uncertainty would not matter. Therefore, for uncertainty to matter, $V'(n_{t+1})$ has to be non-linear, which is the outcome of assuming that $\Omega(\cdot)$ is not linear.

Eq. (8) tells us that the optimal amount of lending is such that expected marginal profits are zero. Notice that lending and dividends decisions depend on the leverage level of the bank through the derivatives of $\Omega(\cdot)$ with respect to lending and capital, because changes in leverage affect the marginal costs of borrowing. As with dividends, the bank makes lending decisions taking into account future profitability.

The model generates a precautionary motive because for a given level of bank capital, a sufficiently large negative shock causes funding costs to increase sharply, because of the assumed shape of Ω_t, hurting profitability. This negative impact persists for some time because the bank cannot issue equity to replenish capital instantaneously (Valencia, 2014a). When uncertainty increases, for a given level of capital, a negative shock capable of generating the above effects becomes more likely. The bank reacts by increasing bank capital to mitigate the potential losses incurred from more volatile loans' profitability.

2.1. A theoretical measure of uncertainty

There is no theoretical framework that is widely accepted in the literature as a standard way to measure uncertainty. Jurado et al. (2013) present a discussion of existing empirical approaches to measure macroeconomic uncertainty and propose a new one based on factor analysis. However, because in this paper the issue on hand is to explain the crossectional distribution of bank capital, ideally one needs a measure of idiosyncratic uncertainty.

One theoretically appealing option to measure uncertainty in a way that is relevant for the purpose of this paper is Kimball (1990). He develops a theoretical framework which builds on Rothschild and Stiglitz (1971) and applies it to the specific case of precautionary saving in consumption theory. At the empirical level, this measure has been used by Carroll and Samwick (1998) to quantify the importance of precautionary savings in U.S. data. Kimball's (1990) measure of interest is the equivalent precautionary premium and is a conceptual framework applicable to any problem involving an agent making decisions under uncertainty. The general idea is that one could derive the optimality conditions in a model with uncertainty and compare them with those from the same model without uncertainty. One can find an increase in the value of the choice variable in the model without uncertainty that would be equivalent to the increase in the value of the choice variable that would follow from adding uncertainty in the model. For example, in the case of a precautionary savings consumer, one can compute the amount of savings that when added to the optimal savings in a model without uncertainty, yields a total amount of savings equivalent to the optimal amount that arises in a model with uncertainty.

The application of Kimball's (1990) conceptual framework to the model presented in this paper is straightforward. The equivalent precautionary premium would be determined by the certain reduction in dividends (or alternatively, the certain increase in capital) in a version of the model without uncertainty that yields the same total amount of capital net of dividends that arises when uncertainty is added to the model.

Formally, let q^* denote the target level of bank capital the bank wishes to hold in a world with uncertainty, and $q^* - \Psi$ the amount of bank capital the bank would hold in absence of uncertainty. Then Ψ denotes the equivalent precautionary premium because it represents the increase in optimal bank capital that would result from adding uncertainty to the model. Assume also for analytical convenience that $\Omega_t = (\frac{l_t - q_t}{\alpha_{t+1} r l_t})^2$ and denote * the optimal amount of lending that satisfies Eq. (8). As discussed in the theoretical model section, a quadratic function is the minimum condition on the shape of Ω that is needed to guarantee that the marginal value function $V'(n_{t+1})$ is not linear.

The definition of the equivalent precautionary premium implies[1]

$$\beta E_t\left[\rho + 3\left(\frac{l^* - q^*}{\alpha_{t+1} r l^*}\right)^2\right] = \beta\left[\rho + 3\left(\frac{l^* - (q^* - \Psi)}{r l^*}\right)^2\right] \tag{9}$$

$$E_t\left[\left(\frac{l^* - q^*}{\alpha_{t+1} r l^*}\right)^2\right] = \left[\left(\frac{l^* - (q^* - \Psi)}{r l^*}\right)^2\right] \tag{10}$$

$$(l^* - q^*)\sqrt{E_t\left(\frac{1}{\alpha_{t+1}}\right)^2} = l^* - q^* + \Psi \tag{11}$$

$$\sqrt{E_t\left(\frac{1}{\alpha_{t+1}}\right)^2} - 1 = \frac{\Psi}{l^* - q^*} \tag{12}$$

where the first step equates the right-hand side of Eq. (7) under two scenarios, one with uncertainty (left) to the equivalent one without. The last step gives us a scaleless measure, which from now on will be referred to as the relative equivalent precautionary premium, or simply REPP. The non-linearity of Ω_t implies that REPP is a non-linear function of the stochastic shock, implying that increases in the variance of the shock affect REPP. In the model, to keep things simple I allowed only for one source of uncertainty stemming from lending activities through the stochastic factor α. I take a more flexible approach in the empirics and focus on bank capital shocks. Therefore, I interpret α now as realizations of bank capital shocks.

3. Empirical analysis

This section begins by discussing the data and methodology to measure uncertainty and then it elaborates on the estimation strategy and robustness exercises.

4. Data

The dataset in question is the universe of U.S. commercial banks filing Call Reports, Consolidated Reports of Condition and Income for a Bank with Domestic and Foreign Offices (FFIEC031 reporting forms), over the period 1985q1–2009q4, which includes all federally-insured banks. We start our sample in 1985 because starting in 1984, banks were in general required to provide more detail concerning assets and liabilities, resulting in discontinuities in many series with respect to earlier periods. We use consolidated financial statements (RCFD series) because the largest banks only provide consolidated information.

I filter the data in line with what other authors working with Call Reports have done (e.g. Kashyap and Stein, 2000 and others) as follows:

- I keep only federally insured institutions chartered as commercial banks, and located in the 50 contiguous U.S. states plus the District of Columbia.
- I correct for mergers by first collecting information on the date mergers took place from SNL Financial Database. I set to missing the observations on loans in quarters where mergers took place.
- I remove reporting errors such as negative assets and negative loans.
- The Call Report content and structure is occasionally revised to reflect developments in the banking industry and supervisory, regulatory and analytical changes. These changes result in breaks in 1978, 1984, and 1994. The first two are outside our sample period. I follow Kashyap and Stein (2000) to construct a consistent time series to avoid a jump in 1994.

I construct yearly balance sheet observations by averaging end-of-quarter balances in order to reduce the impact of seasonal effects. Income-related variables are simply end-of-year values. I define liquidity as in Kashyap and Stein (2000), that is, the ratio of securities holdings to total assets. As in their study, we do not include cash in the numerator because for most of the sample, it may largely reflect required reserves, which cannot be freely drawn down. However, results are not affected if cash is included. The capital-to-assets ratio used in the regressions corresponds to total equity to assets. In the regressions with regulatory capital buffers as dependent variable, I use total regulatory capital, where the buffer is computed as the difference between this variable and 8%, the minimum required. All variables are winzorized at their corresponding 1st and 99th percentiles.

4.1. An empirical measure of REPP

With the data on hand, the next step is to construct an empirical measure of REPP. One approach could be to use a long time series on each bank and compute a bank-specific REPP. However, under this approach one would worry about reverse causality because a bank with high capital could choose to take on more risk and thus influence its value of REPP. At the same time, this approach would mix uncertainty with heterogeneity across banks, for instance, different degrees of risk aversion. While these considerations were not relevant in the simple model developed earlier because there was only one representative bank, they may matter in the data which encompass a great deal of heterogeneity. A way around these problems is to compute REPP for a pre-determined group of banks. To proceed along these lines, the first step is then to choose the criteria to group banks. REPP would then be computed for the group, reducing the influence of bank specific factors and of reverse causality since an individual bank cannot influence the value of REPP for the group.

The set of bank characteristics used for classifying banks includes: size (natural logarithm of total assets), location (state where located), exposure to real estate loans (fraction of real estate loans to total loans), exposure to household loans (fraction of loans to individuals to total loans), exposure to commercial and industrial loans (fraction of C&I loans to total loans), non-lending business (fraction of non-interest income to total income), liquidity (fraction of liquid assets to total assets), and if it is the largest institution in the bank holding corporation (1 if yes, 0 otherwise). These characteristics are aimed at capturing different banks' business models.

For each bank variable listed above, I compute deciles of the corresponding variable, except in the case of the location variable and the indicator if the bank is the largest in the bank holding corporation. I first remove the effect of common shocks by computing a relative capital-to-assets indicator denoted by $\chi_{t,ji} = \frac{s_{t,ji}}{S_t}$, where $s_{t,ji}$ denotes the capital-to-assets ratio for bank i, in year t, in group j, and S_t denotes the average capital-to-assets ratio in period t for the entire banking industry. With this variable on hand, realiza-

[1] A requirement for the problem to have a well-defined solution is that $\beta^{-1} > \rho$. With this assumption, the bank does not have the incentive to accumulate capital forever because as leverage decreases, the cost of funds approach ρ, but with $\beta^{-1} > \rho$, the outside return on dividends exceeds the savings in interest costs the bank would obtain if instead it kept an additional dollar as bank capital. This also implies that the non-negativity constraint on dividends does not bind in equilibrium because otherwise the bank would accumulates bank capital forever. Therefore, at the optimal solution for lending and bank capital $1 = \frac{dV(n_{t+1})}{dn_{t+1}}$.

tions of $\alpha_{t,ji}$ are computed as $\alpha_{t,ji} = \frac{\chi_{t,ji}}{\chi_{t-1,ji}}$, that is, the change in period t of the capital ratio–normalized by the industry capital ratio–relative to its value in period $t-1$. Fig. 1 shows the distribution of capital shocks according to this procedure for the entire sample, including the normal density.

There are TxN_j values of α for each group j, where T is the number of years, and N is the number of banks in group j. For each group j, the TxN_j available points are used to estimate the empirical distribution of α using a 20-point kernel estimator. As shown in Fig. 1 a normal density does not capture well the distribution of shocks and for that reason I proceed with a non-parametric approach. With the estimated empirical distribution of α I compute REPP following Eq. (12).

Alternative measures of uncertainty include a-theoretical alternatives such as the volatility of the return over assets (ROA), denoted as VOLROA, and the capital-to-assets ratio (CAR), denoted as VOLCAR. These alternative measures are computed for each of the bank groups created above. For instance, the volatility of the return over assets is computed as the variance of all observed values for ROA over the period 1985–1998 for the banks in the corresponding group.

Table 1 shows summary statistics for all variables described here and used in the regressions, except for the geographic location dummies, for the period 2001–2009, which is the one used in the cross-sectional regressions.

4.2. Estimation strategy

With the data on hand, the objective is to determine how much of the cross-sectional distribution of capital-to-assets ratios can be

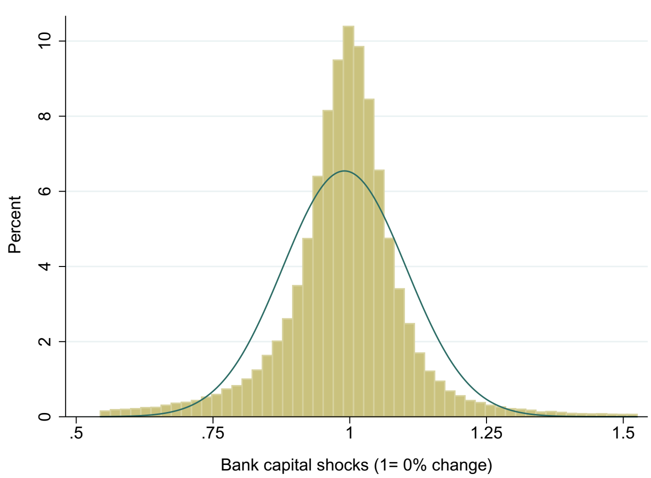

Fig. 1. Distribution of bank capital shocks. *Note.* Capital shocks defined as the change in the capital-to-assets ratio, after removing common shocks.

explained by uncertainty. The empirical exercise uses a linear specification of the following form:

$$s_i = \gamma_0 + \gamma_1 Unc_i + \gamma_2 X_i + \epsilon_i \tag{13}$$

where s_i denotes the capital-to-assets ratio of bank i measured as of 2006, long after the 2001 recession was over, but before the 2007 recession started. Importantly, it is a period outside the sample in which the measures of uncertainty were constructed. Unc_i denotes the measure of uncertainty. The vector of controls, X_i, includes all the variables employed in classifying banks for the construction of the measures of uncertainty to reduce concerns about omitted variables. This vector includes size (natural logarithm of total assets), location (state where located), exposure to real estate loans (fraction of real estate loans to total loans), exposure to household loans (fraction of loans to individuals to total loans), exposure to commercial and industrial loans (fraction of C&I loans to total loans), non-lending business (fraction of non-interest income to total income), liquidity (fraction of liquid assets to total assets), and if it is the largest institution in the bank holding corporation (1 if yes, 0 otherwise). All these variables, except for the geographic variable and bank holding company indicator are measured as of 2005, to further mitigate concerns of reverse causality. ϵ_i is a zero-mean random disturbance.

Recall that the measures of uncertainty are constructed using data from 1985 until 1998 and are specific to the bank group. To compute the measure of uncertainty in 2006 that would correspond to bank i, I repeat the process of grouping banks using the same categories as before, but now with 2006 data. For each of these groups I assign the value of uncertainty that corresponds to the group, computed with data from 1985–98. For instance, banks in the 9th decile according to total assets using 2006 data are assigned the value of REPP that was computed earlier for banks in the 9th decile using earlier data. This strengthens identification because the banks used to compute REPP in 1985–1998 are not necessarily the same as those in 2006. The original banks may have exited, or grew larger and migrated to a different group, etc. Since a bank can appear in various groups at the same time, the value of Unc_i for bank i is the average measure of uncertainty for that bank across all the values of uncertainty corresponding to the groups where bank i appears.

By focusing on cross-sectional regressions we avoid the problem of simulteneity caused by changes in aggregate condition that affect both, uncertainty and bank capital.

4.3. Estimation results

Table 2 shows the estimation results, where for brevity, the coefficients on the location dummies are omitted. The columns correspond to the different measures of uncertainty used in the regressions. The first column corresponds to the baseline measure,

Table 1
Summary statistics.

Variable	Units	Mean	Std. Dev.	p25	p50	p75	Min	Max
Capital to assets	Fraction	0.108	0.033	0.086	0.099	0.120	0.065	0.243
Regulatory capital buffers	Fraction	0.084	0.068	0.039	0.062	0.104	0.016	0.383
Total Assets	Logs	11.660	1.269	10.837	11.525	12.307	7.686	21.177
Real Estate loans	Fraction	0.639	0.184	0.521	0.665	0.778	0.126	0.959
C&I loans	Fraction	0.157	0.099	0.087	0.136	0.203	0.005	0.525
Individual loans	Fraction	0.101	0.091	0.038	0.075	0.135	0.001	0.510
Liquid assets	Fraction	0.231	0.143	0.124	0.209	0.317	0	0.655
Non-interest income	Fraction	0.137	0.128	0.069	0.107	0.162	0.009	1.001
Largest in BHC	Dummy	.682	.465	0	1	1	0	1
REPP		0.896	0.002	0.894	0.896	0.898	0.892	0.909
VOLROA		0.007	0.002	0.006	0.007	0.008	0.004	0.028
VOLCAR		0.084	0.009	0.077	0.082	0.089	0.062	0.139

Table 2
Regression results.

Dep. var.: CAR	Uncertainty measure		
	REPP	VOLCAR	VOLROA
Uncertainty	2.876***	0.946***	2.592***
	(0.372)	(0.071)	(0.361)
Liquidity	0.050***	0.021***	0.043***
	(0.004)	(0.003)	(0.004)
Non-interest income	−0.001	0.010**	−0.002
	(0.005)	(0.004)	(0.005)
Individual loans	−0.002	−0.005	−0.004
	(0.009)	(0.008)	(0.009)
C&I loans	−0.042***	−0.014**	−0.026***
	(0.007)	(0.007)	(0.007)
Real estate loans	−0.027***	−0.013**	−0.027***
	(0.005)	(0.004)	(0.005)
Total assets	−0.004***	−0.002***	−0.004***
	(0.0004)	(0.0004)	(0.0004)
Largest in BHC	−0.007***	−0.006***	−0.009***
	(0.001)	(0.001)	(0.001)
Constant	−2.385***	0.079***	0.175***
	(0.334)	(0.017)	(0.015)
Observations	6526	6526	6526
R^2	0.147	0.168	0.146
Time period	2006	2006	2006

Note: OLS regressions with robust standard errors in parenthesis.
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. REPP denotes the relative precautionary premium as defined in Eq. (12), VOLCAR is the volatility of capital-to-asset ratios,while VOLROA is the volatility of ROA.

REPP, while the other two correspond to VOLCAR and VOLROA. The coefficients on uncertainty measures come up highly statistically significant and with the expected sign, banks exposed to riskier or more uncertain returns hold more capital as a buffer. It is interesting to note that liquidity comes up significant and positive, suggesting that better capitalized banks are also more liquid. The positive correlation could also explain a complementary way in which banks self-insure, through holding more liquid assets.

Among the remaining variables, size and being the largest in the bank holding corporation are statistically significant and negative, suggesting that larger institutions hold less capital, after controlling for uncertainty and the other variables included in the regression. Greater exposure to commercial and industrial lending as well as real estate lending are also associated with lower capital holding and come up with statistically significant coefficients. The coefficients on individual loans or non-interest income are mostly negative but insignificant, except when uncertainty is measured as VOLCAR, in which case non-interest income is positive and significant. Some of these results may be explained by regulatory reasons, for instance, real estate loans receive a lower risk weight for regulatory capital purposes, in which case, banks naturally would hold less capital if they were more exposed to real estate lending. I explore this regulatory explanation in the next section.

To be sure that the above results are not sensitive to the choice of base year for the regressions, Table 3 shows the resulting coefficients for uncertainty from year by year regressions, starting in 2000 up to 2009 for each of the measures of uncertainty. For brevity, I omit reporting the coefficients on the other variables because their coefficients do not change materially when compared to those shown in Table 2. The specification, however, is identical to the one used in Table 2.

The coefficients are highly statistically significant in all years. However, the coefficients vary over time. They seem larger right before a recession, as it is the case for the coefficients before 2001 and 2007. Clearly there are two factors at play once time-variation enters the analysis: whether risk changed or whether the attitude toward risk changed. Since REPP is not changing over time, one would be tempted to conclude then that the self-insurance motive intensifies before a recession. However, a more rigorous exploration of this hypothesis is left for future research. Note also that an alternative, simple mechanical explanation is just the inertial variation in profits. However, evidence presented in Berger et al. (2008) shows that banks actively manage their capital ratios, concluding that they are not just the inertial consequence of variation in profits.

To assess how quantitatively important the above coefficients are, I ask the question: How would the cross-sectional distribution of bank capital-to-asset ratios change if uncertainty declined for all banks? The experiment is implemented by computing the magnitude by which banks would decrease CAR's if uncertainty declined to the lowest level measured in the sample, keeping everything else equal.[2] This exercise is performed by computing Eq. (12)

$$\Delta s_i = \hat{\gamma}_1 * [\text{REPP}_i - \text{REPP}_{min}] \tag{14}$$

where Δs_i denotes the change in the capital-to-assets ratio for bank i that would result if uncertainty–measured by REPP–were to decline to the lowest level observed in the sample, REPP_{min}. This is equivalent to say, what if all banks were in the lowest uncertainty bucket? The parameter $\hat{\gamma_1}$ corresponds to the point estimate shown in column 1 of Table 2, which corresponds to year 2006. Fig. 2 plots the histogram corresponding to the reduction in bank capital-to-asset ratios, in percentage points. For convenience, the graph also shows the weighted (by assets) average reduction in bank capital ratios.

The experiment shows that the simulated decrease in uncertainty would, on a weighted average basis, reduce bank capital-to-assets ratios by slightly less than 2 percentage points. The reductions are concentrated in the 0.5–1.5 range, with some banks reducing bank capital ratios in more than 3 percentage points. As before, to see how this experiment performs in other years, I replicate the exercise year by year from 2000 to 2009. The weighted average reduction in CAR's for each year is shown in Fig. 3. As already hinted by the size of coefficients in Table 3, the largest effect is in 2007, but the effect is economically non-trivial in all years.

5. Robustness

5.0.1. Explaining regulatory capital buffers

Banks may hold more capital for regulatory reasons since different exposures receive different risk-weighting of assets. The results shown in Table 2 indeed provide a hint on this issue since exposure to real estate lending, for instance, implies lower capital holdings. To rule out this alternative explanation, that it is regulation what explains the results, I run the same regressions as those in Table 2 but with regulatory capital buffers (excess capital over the minimum required) as dependent variable, instead of the actual capital-to-assets ratios. Table 4 shows the results.

The results with regulatory buffers are even stronger than those with actual CAR's. t-statistics for the uncertainty measures are larger than those shown in Table 2 and the R-squared values more than doubled. To assess quantitative importance, I perform the same exercise from the previous section. I simulate a reduction in uncertainty using the estimates corresponding to our baseline

[2] Shutting down uncertainty completely would not be correct because it would involve a significant regime change, running into a Lucas critique type of problem. For this reason, I simulate a change in uncertainty as measured in sample, in which case the above problem is less of a concern.

Table 3
Regression results by year.

Dep. var.: CAR	Year									
	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009
REPP	1.852***	1.382***	1.225***	1.613***	2.534***	2.438***	2.876***	2.928***	2.270***	2.115***
	(0.370)	(0.346)	(0.348)	(0.351)	(0.358)	(0.354)	(0.372)	(0.387)	(0.353)	(0.357)
VOLCAR	0.936***	0.849***	0.777***	0.835***	0.822***	0.943***	0.946***	0.857***	0.709***	0.534***
	(0.068)	(0.067)	(0.067)	(0.065)	(0.066)	(0.068)	(0.071)	(0.070)	(0.070)	(0.070)
VOLROA	2.232***	1.765***	1.570***	2.270***	2.636***	2.924***	2.592***	2.739***	2.072***	1.998***
	(0.364)	(0.350)	(0.349)	(0.345)	(0.351)	(0.351)	(0.361)	(0.368)	(0.345)	(0.339)
Observations	7250	7116	7070	7035	6860	6697	6526	6336	6176	6034
R^2 (REPP)	0.190	0.202	0.193	0.151	0.137	0.131	0.147	0.160	0.172	0.157
R^2 (VOLCAR)	0.217	0.226	0.213	0.175	0.156	0.158	0.168	0.174	0.183	0.161
R^2 (VOLROA)	0.192	0.204	0.194	0.155	0.138	0.135	0.146	0.159	0.171	0.156

Note: OLS regressions with robust standard errors in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. REPP denotes the relative precautionary premium as defined in Eq. (12), VOLCAR is the volatility of capital-to-asset ratios, while VOLROA is the volatility of ROA.

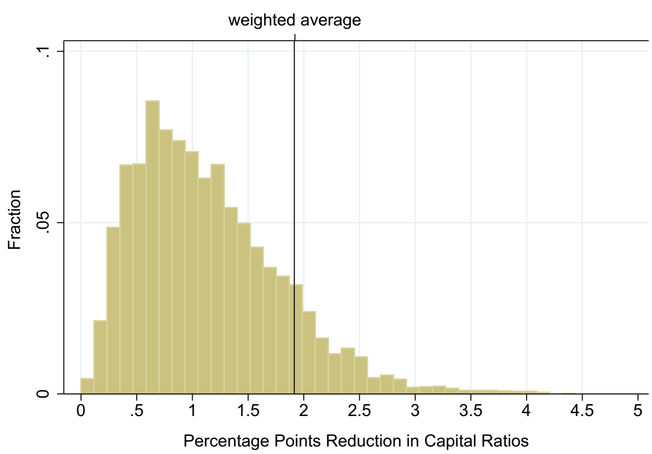

Fig. 2. Distribution of reductions in capital-to-assets ratios. *Note.* Reduction in CAR's as of 2006 after a decrease in REPP to is lowest value for all banks.

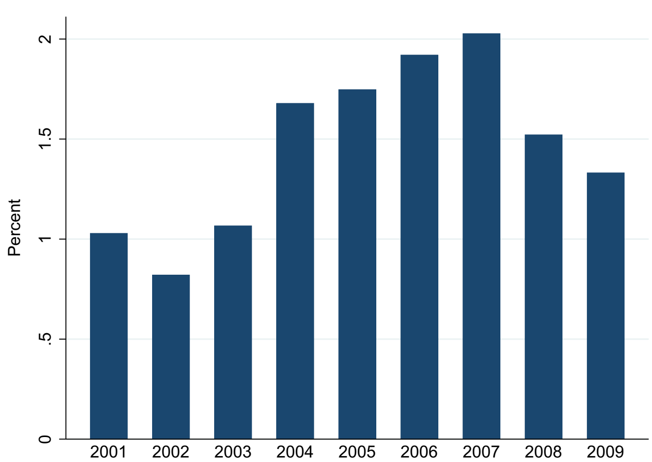

Fig. 3. Weighted average reductions in capital-to-assets ratios. *Note.* Reduction in CAR's after a decrease in REPP to its lowest value for all banks.

measure, REPP, from Table 4. Fig. 4 shows the distribution of the percent reduction in regulatory capital buffers. Unlike Fig. 2, I now express this reduction as a fraction of regulatory capital buffers to have more direct measure of how much of these buffers is explained by the baseline measure of uncertainty used in this paper.

Table 4
Regression results with regulatory capital buffers.

Dep. var.: regulatory capital buffer	Uncertainty measure		
	REPP	VOLCAR	VOLROA
Uncertainty	6.052***	2.129***	6.188***
	(0.630)	(0.123)	(0.597)
Liquidity	0.263***	0.201***	0.249***
	(0.008)	(0.006)	(0.007)
Non-interest income	−0.001	0.024***	−0.005
	(0.009)	(0.008)	(0.009)
Individual loans	0.028*	0.021	0.023
	(0.016)	(0.016)	(0.015)
C&I loans	−0.104***	−0.044***	−0.070***
	(0.014)	(0.013)	(0.013)
Real estate loans	−0.047***	−0.016*	−0.047***
	(0.010)	(0.010)	(0.010)
Total assets	−0.015***	−0.010***	−0.015***
	(0.001)	(0.001)	(0.001)
Largest in BHC	−0.004**	0.0004	−0.006***
	(0.002)	(0.002)	(0.002)
Constant	−5.159***	0.010	0.224***
	(0.567)	(0.036)	(0.033)
Observations	6526	6526	6526
R^2	0.444	0.469	0.445
Time period	2006	2006	2006

Note: OLS regressions with robust standard errors in parenthesis. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$. REPP denotes the relative precautionary premium as defined in Eq. (12), VOLCAR is the volatility of capital-to-asset ratios, while VOLROA is the volatility of ROA.

The result shows that on average, REPP explains about 50% of banks' regulatory capital buffers. The figure shows that in some cases, the reduction in buffers would exceed 100 percent. This is the outcome of extrapolating a linear estimation, and thus for that reason it is better to focus on the average. Similarly large numbers are obtained if the exercise is performed with the alternative measures of uncertainty and if the base year is changed as it was done in the previous section.

5.0.2. Specification in logs

The distribution of capital-to-asset ratios is highly skewed and so are the distributions of measures of uncertainty. One last check is to examine a log specification, which would get the distributions of the corresponding variables close to a normal distribution. For this purpose, I run the same regressions shown in Table 2 with

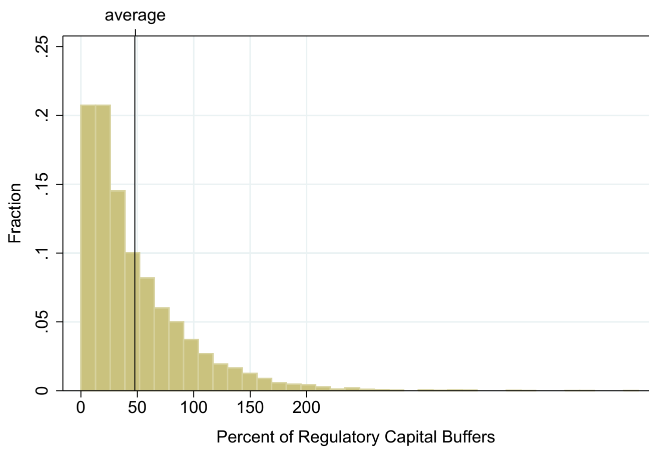

Fig. 4. Distribution of reductions in regulatory capital buffers. *Note.* Percent reduction in regulatory capital buffers as of 2006 after a decrease in REPP to its lowest value for all banks.

the difference that all variables, except for the state dummies and the dummy for largest institution in the BHC, are in natural logarithm. The results are shown in Table 5. The results are quite similar in a statistical sense, yielding comparable *R*-squared values as well as t-statistics.

6. Conclusions

The recent crisis has spurred the interest in better understanding bank behavior and in particular what drives bank leverage. This increased attention follows from the growing consensus in academic and policy thinking of the need to redesign macroeconomic policies to better account for leverage dynamics in the financial sector.

This paper advances our knowledge in this direction by testing for bank self-insurance, and identifies one statistically significant and economically important driver of bank leverage: uncertainty. Banks facing higher uncertainty also keep higher capital-to-assets ratios after controlling for different bank characteristics. The empirical evidence is robust to several measures of uncertainty and other robustness checks. A counterfactual experiment suggests that if uncertainty declined to the minimum level measured in the sample, capital-to-asset ratios would on average decline in slightly less than 2 percentage points. Moreover, I also find that uncertainty explains, on average, about 50 percent of banks regulatory capital buffers.

Appendix A. Endogenous financial frictions

Assume that risk-neutral depositors live for one period and supply funds to the bank infinitely elastically at the interest rate that leaves them indifferent between the expected return from a deposit and the risk free return.

The bank defaults if the realization of α falls below the level at which bank capital, n, equals zero, that is, $n_{t+1} = 0 \rightarrow \underline{\alpha} r^L l_t - i_t d_t = 0,\ \underline{\alpha} = i_t d_t / r^L l_t$. Where i_t is the deposit interest rate, and d_t deposits.

The deposit interest rate is such that the expected return on a deposit equals the risk-free return:

$$\rho_t d_t = i_t d_t (1 - F_\alpha(\underline{\alpha})) + (1 - \mu) l_t E[\alpha | \alpha < \underline{\alpha}] F_\alpha(\underline{\alpha}) \tag{15}$$

where F_α denotes the cumulative distribution function of α, μ denotes the monitoring costs depositors pay to learn the value of the bank's assets (i.e. the loans), as in Townsend (1979). Assuming $\mu = 0.12$, that the distribution of α is log-normal with mean 1 and $\sigma = 0.08$, the spread between i_t and ρ_t as a function of bank leverage $1 - q/l$ is shown in Fig. 5.

As the figure shows, the spread is increasing and convex in bank leverage. It is important to note that as shown in Bernanke et al.

Table 5
Regression results with variables in logs.

Dep. var.	ln(Regulatory Buffer)			ln(CAR)		
	REPP	VOLCAR	VOLROA	REPP	VOLCAR	VOLROA
Uncertainty	15.319***	1.438***	0.156***	16.629***	0.624***	0.092***
	(3.445)	(0.058)	(0.026)	(2.865)	(0.052)	(0.022)
Liquidity	0.140***	0.114***	0.136***	0.038***	0.016***	0.027***
	(0.008)	(0.005)	(0.006)	(0.004)	(0.003)	(0.004)
Non-interest income	−0.026***	0.016**	−0.028***	−0.033***	−0.007	−0.028***
	(0.007)	(0.006)	(0.007)	(0.006)	(0.006)	(0.006)
Individual loans	0.021***	0.032***	0.022***	0.001	0.001	−0.002
	(0.005)	(0.004)	(0.005)	(0.004)	(0.004)	(0.004)
C&I loans	−0.085***	−0.018***	−0.069***	−0.047***	−0.013**	−0.034***
	(0.006)	(0.007)	(0.007)	(0.006)	(0.006)	(0.006)
Real estate loans	−0.158***	0.021	−0.151***	−0.127***	−0.058***	−0.130***
	(0.017)	(0.019)	(0.018)	(0.015)	(0.016)	(0.015)
Total assets	−0.087***	−0.050***	−0.086***	−0.033***	−0.017***	−0.032***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Largest in BHC	−0.027***	0.037***	−0.029***	−0.057***	−0.043***	−0.069***
	(0.009)	(0.008)	(0.009)	(0.009)	(0.008)	(0.008)
Constant	3.530***	5.301***	2.658***	−0.016	−0.363	−1.349***
	(0.418)	(0.177)	(0.232)	(0.334)	(0.270)	(0.175)
Observations	6455	6455	6455	6455	6455	6455
R^2	0.376	0.447	0.377	0.135	0.153	0.132
Time period	2006	2006	2006	2006	2006	2006

Note: OLS regressions with robust standard errors in parenthesis. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. REPP denotes the relative precautionary premium as defined in Eq. (12), VOLCAR is the volatilityof capital-to-asset ratios, while VOLROA is the volatility of returns over assets.

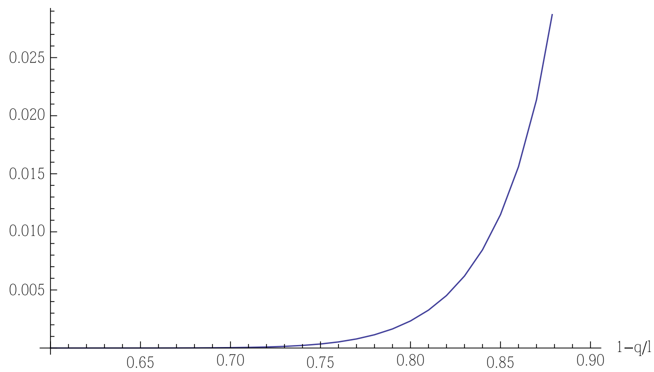

Fig. 5. Endogenous spread under costly state verification. *Note.* Spread between deposit rate and risk-free rate under a costly state verification contract.

(1999), a sufficient condition for the contract to yield an interior solution and for the spread to have the shape above is that the expression $\underline{\alpha}h(\underline{\alpha})$ is increasing in $\underline{\alpha}$ where $h(\underline{\alpha}) = \frac{\underline{\alpha}f(\underline{\alpha})}{1-F(\underline{\alpha})}$ denotes de hazard rate. They show that any monotonic transformation of the normal distribution satisfies this property, including the lognormal, which is what I assume above. In the paper, the properties of the exogenous function f take a similar shape, but it is assumed to be only twice continuously differentiable, which is the minimum condition that is needed to generate the properties of the spread shown in the above figure.

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