WP/13/241

IMF Working Paper

Aggregate Uncertainty and the Supply of Credit

Fabián Valencia

INTERNATIONAL MONETARY FUND

 WP/13/241

IMF Working Paper

Research

Aggregate Uncertainty and the Supply of Credit

Prepared by Fabián Valencia[1]

Authorized for distribution by Giovanni Dell'Ariccia

November 2013

Abstract

Recent studies show that uncertainty shocks have quantitatively important effects on the real economy. This paper examines one particular channel at work: the supply of credit. It presents a model in which a bank, even if managed by risk-neutral shareholders and subject to limited liability, can exhibit self-insurance, and thus loan supply contracts when uncertainty increases. This prediction is tested with the universe of U.S. commercial banks over the period 1984-2010. Identification of credit supply is achieved by looking at the differential response of banks according to their level of capitalization. Consistent with the theoretical predictions, increases in uncertainty reduce the supply of credit, more so for banks with lower levels of capitalization. These results are weaker for large banks, and are robust to controlling for the lending and capital channels of monetary policy, to different measures of uncertainty, and to breaking the dataset in subsamples. Quantitatively, uncertainty shocks are almost as important as monetary policy ones with regards to the effects on the supply of credit.

JEL Classification Numbers:E5, E44, D80

Keywords: Credit Cycles, Credit Crunch, Uncertainty, Self-insurance

Author's E-Mail Address:fvalencia@imf.org

[1] The author thanks Stijn Claessens, Giovanni Dell'Ariccia, Giovanni Ferri, Leonardo Gambacorta, Randall Kroszner, Luc Laeven, and seminar participants at the IMF, the Legatum Institute, the 2013 MoFir workshop, and the 2013 Society for Economic Dynamics conference in Seoul for comments and discussions and Jeanne Verrier for outstanding research assistance.

Contents

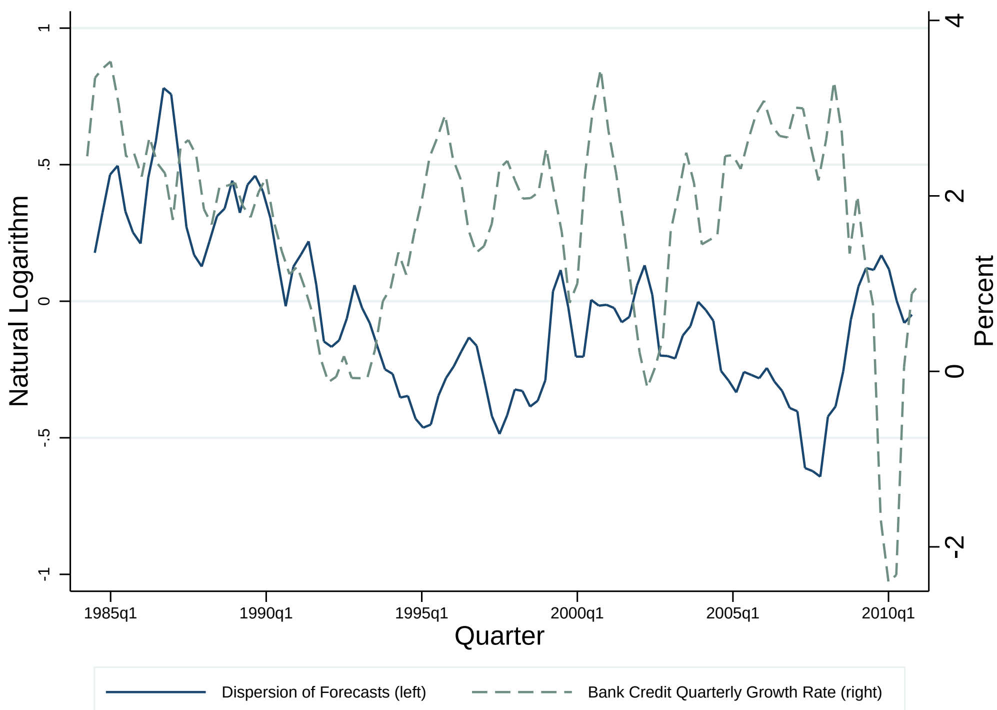
List of Tables

List of Figures

I. INTRODUCTION

Spikes in different measures of uncertainty in late 2008 sparked an interest in studying the quantitative importance of fluctuations in uncertainty for the real economy (Bloom (2009), Bloom, Floetotto, Jaimovich, Saporta-Eksten and Terry (2011), Jurado, Ludvigson and NG (2013), and others). One stylized fact that stands out is that at the same time that uncertainty increased, bank credit growth declined (Figure 1). This paper examines this link with the aim at identifying a particular channel through which uncertainty shocks affect the real economy: the supply of bank credit.

Figure 1. Loan Growth and Uncertainty



Source: Federal Reserve Bank of Chicago and Philadelphia, and author's calculations.

Advancing our knowledge on banks' interaction with the aggregate economy is important because financial intermediaries provide essential services to the economy. Through their role in liquidity creation and diversification of risk they can increase welfare. However, they are also a source of vulnerabilities as often credit booms end in costly financial crashes (Reinhart and Rogoff (2009), Laeven and Valencia (2013), and others) and negative shocks affecting the solvency of financial institutions can have important real effects by curtailing the supply of credit (Peek and Rosengren (1997), Ashcraft (2005), and Peydro, Jiménez, Ongena and Saurina (2012)). Therefore, better understanding the factors affecting credit cycles can help improve the design of ex-ante and ex-post policy intervention.

The work in this paper contributes to several strands of the literature. First, regarding the effects of uncertainty on the real economy, it provides the theoretical foundations and empirical evidence in favor of a particular channel. Second, it contributes to the credit booms literature by looking at a source of amplification of credit cycles. And third, it contributes to the banking literature, where a vast majority of models generate a gambling for resurrection effect when banks are subject to limited liability (Hellmann, Murdock and Stiglitz (2000), Rochet (2009), and others), while in this paper it is shown that even under limited liability, a self-insurance mechanism can arise.

The paper starts with a model in which a bank is subject to frictions in raising external finance. In the model, bank capital mitigates agency costs between creditors and the bank that arise from the presence of risk and asymmetric information. The lower the level of bank capital, the higher the premium creditors demand to be compensated for default risk. The non-linear nature of financial frictions generates a self-insurance mechanism, despite the assumption of risk-neutrality of shareholder-managers and limited liability. This is the case because increases in uncertainty imply that a large negative shock is more likely. Therefore, higher uncertainty makes bank capital more valuable, and thus it pays off to the bank to cut lending to strengthen its balance sheet. These implications are tested empirically by examining the link between changes in uncertainty and the supply of credit.

The empirical investigation is conducted in a large dataset comprising the universe of U.S. commercial banks over the period 1984-2010. By uncertainty, it is meant that the future is unknown, abstracting from distinguishing uncertainty and risk in Knight (1921)'s sense. Therefore, both terms are treated as equivalent. [2] The baseline measure of uncertainty used in this paper corresponds to the dispersion of real GDP growth forecasts from surveys of professional forecasters, maintained by the Federal Reserve Bank of Philadelphia. This measure is chosen as a baseline because it is forward-looking and reflects ex-ante uncertainty. However, because the literature has not settled yet on how to best measure uncertainty, a number of alternative proxies are used in robustness checks. Focusing on aggregate uncertainty, rather than idiosyncratic uncertainty, has also the advantage of mitigating reverse causality concerns since the average bank is unlikely to influence aggregate outcomes. But it is still subject to an important simultaneity problem: uncertainty affects both the demand and supply of credit. Therefore, the key empirical challenge is to show that the response in lending is driven by supply rather than demand.

Identification of supply is achieved by finding a differential response by banks according to their degree of capitalization. One cannot rule out entirely the possibility of demand influencing results, but it is very unlikely that the results are the consequence of demand fluctuations and not supply. The reason for this is that given the large time and cross-section dimensions of the database, it is unlikely that borrowers' capitalization is systematically correlated with those of the banks from whom they borrow. In other words, for demand to explain our results, highly capitalized borrowers would always have to borrow from highly capitalized banks, but banks typically lend to a wide array of borrowers and industries. In addition, if large banks were to be the more capitalized ones, one may think that the above condition would be feasible since large banks have a wider geographical presence in the country. However, smaller banks are the ones with higher capital-to-assets ratios. Finally, if it was demand, the results should hold equally for all types of

[2] Knight (1921) argued that there is a fundamental difference between risk and uncertainty: the latter cannot be casted in a probability framework, while the former can. This argument implies that uncertainty is not measurable. But it may still be the case that agents use subjective probabilities to possible outcomes, with some residual probability assigned to unknown ones.

banks, but the results are substantially weaker for large banks, which is consistent with the idea that larger banks are less affected by frictions in raising external finance than smaller institutions.

The empirical analysis provides evidence consistent with the theoretical predictions. Increases in uncertainty trigger a reduction in loan growth, but more so at banks with low levels of capitalization. The results are robust to alternative definitions of uncertainty, including stock market volatility, loan officer surveys' of lending standards, and volatility of forecast errors. The results are also robust to controlling for changes in the mean of forecasts, to distinguish first from second moments since bad times may also be more volatile times. They are also robust to the inclusion of year fixed effects to control for any other aggregate factor not accounted for and to breaking down the analysis into different loan types. In particular, the results hold for individual and real estate loans. The coefficients are of the expected sign but are not significant for commercial and industrial loans; however, evidence presented in the paper suggests that these loans are made largely under pre-existing commitments, making the actual change in commercial and industrial loan volumes less sensitive to supply conditions. This result can also be interpreted as an additional factor strengthening the case for identification. Draws on credit lines reflect mostly changes in demand, making it plausible to get an insignificant coefficient for C&I loans because it is less sensitive to supply conditions. But then it becomes clearer that the significance of coefficients for the other types of loans cannot be explained by demand fluctuations.

The empirical analysis also explores how bank size dampens the effect of uncertainty. The larger a bank is, the lower the impact of uncertainty on bank lending. Three possible explanations are provided: i) a "too-big-to-fail" effect by which large banks have lower incentives to self-insure against increased uncertainty because of an implicit public guarantee, ii) a "flight-to-quality" effect by which customers at smaller banks switch to large banks when uncertainty increases, and iii) a wider array of hedging strategies available. These reasons imply that the importance of financial frictions for these institutions is lower than for smaller banks.

Finally, the results are also robust to controlling for monetary policy shocks to rule out the possibility of monetary policy responding to uncertainty shocks and hence driving the results. Moreover, in terms of quantitative importance, the results presented in the paper suggest that a 1 standard deviation increase in uncertainty generates an effect in lending that is about 82 percent of what a 1 standard deviation monetary policy shock generates.

The most important contribution of this paper is the empirical evidence in favor of a concrete channel through which uncertainty can affect the real economy. This is the first paper to examine the link between uncertainty and the supply of credit providing both, the theoretical underpinnings and empirical evidence. The only related contribution to our knowledge is Baum, Caglayan and Ozkan (2008) who revisited Kashyap and Stein (2000)'s study of the lending channel of monetary policy to test its robustness to the presence of uncertainty. On the theoretical side, the paper is consistent with several previous contributions in the literature that also generate a self-insurance mechanism (e.g. Diamond and Rajan (2000), Van Den Heuvel (2009), Valencia (forthcoming), Brunnermeier and Sannikov (2011), Gertler, Kiyotaki and Queralto (2011), and others). More generally, the paper also contributes to a growing literature on the effects of uncertainty on the real economy. Some examples include Bloom, Bond and Van Reenen (2007), Bloom (2009), Bloom et al. (2011), Jurado et al. (2013) who show that uncertainty could play an important role in driving business cycles. Arellano, Bai and Kehoe (2011) and Gilchrist, Sim and

Zakrajšek (2011) examine the role of financial frictions as an additional channel through which uncertainty affects aggregate fluctuations. Like these two last studies, financial frictions are what give uncertainty a role in bank lending decisions. But unlike them, the mechanism in this paper operates through the supply of credit.

The next section presents the theoretical framework. Section III presents the empirical analysis, describes the dataset, and discusses the results. Section IV concludes.

II. THEORETICAL FRAMEWORK

The key ingredients of the model are limited liability and asymmetric information (both between the bank and entrepreneurs and between depositors and the bank). These information problems are modeled in the form of costly state verification, a commonly used device in the financial accelerator literature (Bernanke, Gertler and Gilchrist (1999), Carlstrom and Fuerst (1997a), and others).

A. Bank-Borrower Loan Contract

There is a continuum of identical (ex-ante and ex-post), risk-neutral borrowers who live for one period. They receive a fixed endowment at birth of 1 unit of capital, which together with bank loans, l_t, form the total amount of capital used in production $k_t = l_t + 1$. The production technology uses only capital as an input.

$$y_{t+1} = \alpha_{t+1} \mathcal{R} k_t \tag{1}$$

where α_{t+1} is stochastic, unknown at the beginning of the period, and thus constitutes the source of aggregate uncertainty. Furthermore, it is assumed to be i.i.d., mean-one, and continuously distributed over a non-negative support. $\mathcal{R}$ denotes the contribution of other factors of production, assumed to be fixed. Capital depreciates fully at the end of production, after which entrepreneurs consume any surplus. The realization of α_{t+1} is common to all entrepreneurs but known only to them.

Under limited liability, entrepreneurs default whenever α falls below the level at which profits, $\alpha_{t+1}\mathcal{R}k_t - l_t R_t$, are equal to zero, where R_t denotes the interest rate on the loan, including principal repayment. The default threshold is denoted by $\overline{\alpha}_t = \frac{l_t R_t}{\mathcal{R}(1+l_t)}$. The bank pays monitoring costs (or bankruptcy costs) $1 \geq \mu > 0$ to observe α_{t+1} in the case of default, and seizes the residual value of production, as in Townsend (1979). The ex-post return to an entrepreneur can be summarized by

$$\pi(\alpha_{t+1}, l_t, R_t) = \begin{cases} \alpha_{t+1}\mathcal{R}(1+l_t) - l_t R_t & \text{if } \alpha_{t+1} \geq \overline{\alpha}(R_t, l_t) \\ 0 & \text{if } \alpha_{t+1} < \overline{\alpha}(R_t, l_t) \end{cases} \tag{2}$$

The bank is assumed to be a monopoly that makes *take-it-or-leave-it* offers to entrepreneurs including a loan amount and an interest rate R_t that ensures entrepreneurs a return that is at least as good as $\mathcal{R}$. $\mathcal{R}$ is the return they would obtain if they refrain from borrowing and invest only their endowment in the project. Therefore, the interest rate on the loan as a function of the loan amount,$R(l_t)$, is such that the expected return for an entrepreneur equals $\mathcal{R}$, a condition that always holds, otherwise the bank can increase profits by charging a slightly higher interest rate.

Ex-post revenues for the bank are given by

$$g(\alpha_{t+1}, l_t) = \begin{cases} R(l_t)l_t & \text{if } \alpha_{t+1} \geq \overline{\alpha}(R(l_t), l_t) \\ (1-\mu)\alpha_{t+1}\mathcal{R}(1+l_t) & \text{if } \alpha_{t+1} < \overline{\alpha}(R(l_t), l_t) \end{cases} \tag{3}$$

B. Bank-Depositor Contract

Identical and risk-neutral depositors live also 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 earning the risk free return. If the bank defaults, depositors pay monitoring costs to observe the value of bank assets $1 > \omega > \mu$. The latter justifies the existence of the bank by assuming it is more efficient than depositors in monitoring entrepreneur's projects. If the bank does not default, depositors collect the principal plus interest at the end of the period.

As in the case of entrepreneurs, the bank defaults if the realization of α falls below the level at which bank capital, e, equals zero, that is, $e_{t+1} = 0 \rightarrow g(\underline{\alpha}_t, l_t) - i_t d_t = 0$, where i_t is the deposit interest rate, d_t the amount of deposits, and $g(\underline{\alpha}_t, l_t)$ the bank revenue function (Equation (3)).

Notice that for the bank to default, entrepreneurs must have defaulted, given that α is the only source of bankruptcy risk in the model, implying then that $\underline{\alpha}_t < \overline{\alpha}_t$. Therefore, $\underline{\alpha}_t$ is given by

$$\begin{aligned} g(\underline{\alpha}_t, l_t) - i_t d_t &= 0 \\ (1-\mu)\underline{\alpha}_t\mathcal{R}(1+l_t) - i_t d_t &= 0 \\ \frac{i_t d_t}{(1-\mu)\mathcal{R}(1+l_t)} &= \underline{\alpha}(i_t, d_t, l_t) \end{aligned} \tag{4}$$

Under limited liability, the payoff to a depositor is given by

$$h(\alpha_{t+1}, l_t, d_t) = \begin{cases} i_t d_t & \text{if } \alpha_{t+1} \geq \underline{\alpha}(i_t, d_t, l_t) \\ (1-\omega)\alpha_{t+1}\mathcal{R}(1+l_t) & \text{if } \alpha_{t+1} < \underline{\alpha}(i_t, d_t, l_t) \end{cases} \tag{5}$$

The deposit interest rate is such that the expected value of the above expression equals the risk-free return, ρ. Formally, it solves

$$\rho d_t = i_t d_t(1 - F_\alpha(\underline{\alpha}_t)) + (1-\omega)\Re(1+l_t)E\left[\alpha_{t+1}/\alpha_{t+1} < \underline{\alpha}_t\right]F_\alpha(\underline{\alpha}_t) \tag{6}$$

where F_α denotes the cumulative distribution function of α. It is perhaps useful to clarify that the costly state verification framework used here may not necessarily be immune to renegotiation in a multiperiod-contract setting. However, Krasa and Villamil (2000) show that when multi-period contracts are allowed, and liquidation is a choice variable, debt is still optimal and the contract is ex-post efficient. They also show that the costly state verification model used here can be seen as a reduced form of their model.

C. Bank Optimization Problem

The bank is an infinitely-lived entity, managed by its risk-neutral shareholders. The problem they solved is given below

$$\underset{\{d_t, c_t, l_t\}}{Max}\, E_s\left(\sum_{t=s}^{t=\infty}\beta^{t-s}c_t/\alpha_{t+1} \geq \underline{\alpha}_t\right)\left[1 - F_\alpha(\underline{\alpha}_t)\right] \tag{7}$$

or in Bellman's equation form

$$V(e_t) = \underset{\{d_t, c_t, l_t\}}{Max}\left\{c_t + \beta E_t\left[V(e_{t+1})/\alpha_{t+1} \geq \underline{\alpha}\right]\left[1 - F_\alpha(\underline{\alpha}_t)\right]\right\} \tag{8}$$

subject to

$$l_t \leq d_t + e_t - c_t \tag{9}$$

$$c_t \geq 0 \tag{10}$$

$$e_{t+1} = \begin{cases} g(\alpha_{t+1}, l_t) - i(l_t, d_t)d_t & \text{if } \alpha_{t+1} \geq \underline{\alpha}_t \\ 0 & \text{if } \alpha_{t+1} < \underline{\alpha}_t \end{cases} \tag{11}$$

where the objective is to maximize the expected present discounted value of dividends, conditional on the bank not having defaulted, with c_t denoting dividends and β the discount factor. Equation (9) is a resource constraint limiting the amount of loans to be at most the amount of available resources. These resources stem from deposits and bank capital net of dividends. Equation (10) rules out equity financing. Equation (11) denotes the transition equation of bank capital, where limited liability implies it cannot go below zero.

Imagine that at some hypothetical last period of life, T, the bank is liquidated and distributes its existing capital in dividends. Define also bank capital net of dividends as $q_t = e_t - c_t$. The first order conditions as of period $T-1$ are given by

$$q \;: (i_{T-1} - (l_{T-1} - q_{T-1})i^q_{T-1}) \left[1 - F(\underline{\alpha}_{T-1})\right] = \tfrac{1}{\beta} \tag{12}$$

$$\begin{aligned} l \;: &(1 - F(\overline{\alpha}_{T-1}))(R_{T-1} + l_{T-1}R^l_{T-1}) \\ &+ (1-\mu)\mathfrak{R}\int_{\underline{\alpha}_{T-1}}^{\overline{\alpha}_{T-1}} \alpha_T dF(\alpha) - (1 - F(\underline{\alpha}_{T-1}))(i_{T-1} + (l_{T-1} - q_{T-1})i^l_{T-1}) = 0 \end{aligned} \tag{13}$$

In the first order condition with respect to end-of-period capital, Equation (12), the left-hand side corresponds to the marginal value of bank capital, and because of limited liability, only the upside enters the equation. The right hand side is the marginal value of dividends, determined by the time preference rate. In the second first order condition, the optimal amount of lending is such that marginal profits are zero, with marginal revenues determined by the first two terms. The first one is what the bank expects to get if borrowers remain solvent, whereas the second term is what it expects to get if they default. The last term is the expected marginal cost of lending, multiplied by the probability of remaining solvent because of limited liability. Changes in uncertainty, that is changes in the standard deviation of α, σ, *ceteris paribus* has the effect of changing expected profits through two channels in the above equation: 1) changes in the probability of default of both, borrowers and the bank, and 2) changes in the loan and deposit interest rates since they price the risk of default.

From the perspective of period $T-2$ and earlier, or simply t because the problem is now identical in every period, there is an additional channel through which uncertainty affects the bank's decisions, future marginal profits, captured by the marginal value function, $V'(e)$, that appears in the first order conditions,

$$\begin{aligned} q \;: &(i_t - (l_t - q_t)i^q_t)V'(e_{t+1}/\alpha \geq \overline{\alpha}_t)\left[1 - F(\overline{\alpha}_t)\right] \\ &+ (i_t - (l_t - q_t)i^q_t)\int_{\underline{\alpha}_t}^{\overline{\alpha}_t} V'(e_{t+1}/\overline{\alpha}_t \geq \alpha_{t+1} > \underline{\alpha}_t)dF(\alpha) = \tfrac{1}{\beta} \end{aligned} \tag{14}$$

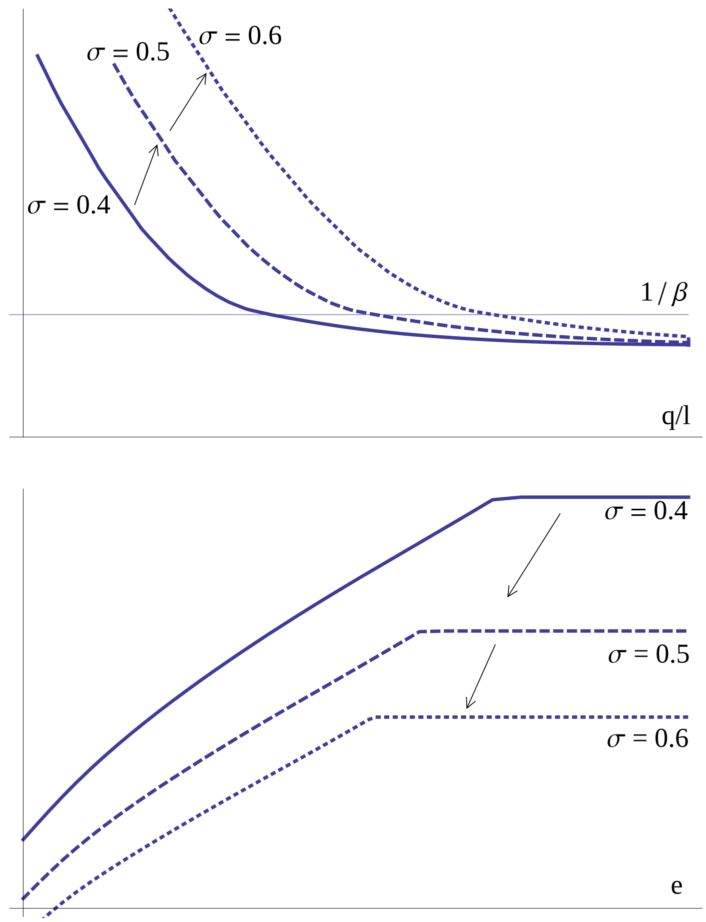
$$\begin{aligned} l \;: &(1 - F(\overline{\alpha}_t))V'(e_{t+1}/\alpha \geq \overline{\alpha}_t)(R_t + l_tR^l_t - i_t - (l_t - q_t)i^l_t) \\ &+ \int_{\underline{\alpha}_t}^{\overline{\alpha}_t} V'(e_{t+1}/\overline{\alpha}_t \geq \alpha_{t+1} > \underline{\alpha}_t)(\alpha_{t+1}(1-\mu)\mathfrak{R} - i_t - (l_t - q_t)i^l_t))dF(\alpha) = 0 \end{aligned} \tag{15}$$

The above problem is solved numerically following the procedure shown in the appendix. Since the interest in this theoretical section is just to generate qualitative implications, calibration is discussed only in the appendix and not elaborated here. The effect of uncertainty can be seen graphically in Figure 2.

The top chart shows equation (14). The graph is depicting the marginal value of bank capital as a function of the capital-to-assets ratio, which is the same as the capital-to-loans ratio because the bank holds only loans on the asset side.[3] Because of financial frictions, the marginal value of bank capital is decreasing in

[3] In constructing this graph, lending is set to the value that solves equation (15).

Figure 2. Marginal Value of Bank Capital and Optimal Lending Function



Marginal value of bank capital (top) and optimal lending function (bottom) for different levels of risk (σ)

the capital-to-assets ratio. When the latter is low, financial frictions intensify because the risk of default is high, and thus it is very costly for the bank to raise deposits. The shareholders optimally reduce dividends, but because they cannot issue equity, they can only reduce them to zero. For large amounts of bank capital, its marginal value is below the time preference rate (the horizontal line in the graph), inducing shareholders to distribute dividends. The point where these two forces are exactly balanced determines the equilibrium or target level of capital in the model.

When uncertainty increases, the marginal value of bank capital shifts upwards because bankruptcy becomes more likely at all levels of capital and hence future profits become more volatile. In response to this, the bank increases its optimal level of capital to reduce bankruptcy risk and shield the business from a more volatile environment. Capital in this model thus works as a buffer against shocks that affect the profitability of lending. To adjust to the new target, the bank reduces lending, as suggested by the bottom chart. Some of the decrease in lending is permanent as suggested by the inward shift of the optimal lending function shown in the bottom of Figure 2. This is the case because with permanently higher uncertainty, funding costs rise permanently as well because of a higher risk of bankruptcy. But there can be a temporary overshooting in the contraction in lending. Looking at the top chart, the increase in the marginal value of bank capital follows in part from higher costs to fund new loans. The bank reduces dividends to build capital but it can only do so gradually, and thus funding costs may remain higher than what they will be at the new target for some time. As a result, lending contracts are initially more than what is needed to reach the new target. The drag in lending generated by an uncertainty shock naturally depends on the initial conditions as suggested by the optimal lending policy function. If the shock hits when bank capital is below the target, a larger and longer contraction in lending ensues.

Note that a more realistic modeling approach would have involved introducing, in addition to aggregate uncertainty, idiosyncratic uncertainty, with the latter being the source of asymmetric information. Although more realistic, this alternative approach would not change the implications of the model. What drives the above behavior is the non-linearity of financial frictions and some form of uncertainty, regardless of its source. Introducing idiosyncratic uncertainty would however introduce the complication that the default threshold for the borrower would not be a simple analytical expression as the one obtained with only one source of risk.

III. Empirical Analysis

The empirical section exploits the implications derived from the model above for identification purposes. In particular, it will examine whether reductions in lending follow increases in uncertainty and if they are larger for banks with lower capital-to-asset ratios.

A. Data

The data comprise 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 1984q1-2010q2, which includes all federally insured banks. The first part of the sample (1978q4-1983q4) is excluded because prior to 1984, the call reports were collected and cleaned less systematically. In particular, starting in 1984, banks were in general required to provide more detail concerning assets and liabilities, resulting in discontinuities in many series. Concerning the level of consolidation, the dataset includes the consolidated financial statements (RCFD series) because in general the largest banks only provide financial data on a consolidated foreign and domestic basis.

The capital-to-assets ratio is defined as total equity capital divided by total assets. The alternative definition of capitalization used in the regressions involve the tangible equity ratio, computed as total equity minus intangible assets divided by total tangible assets, where the latter is computed by substracting intangible assets from total assets. This measure is often used as a more conservative metric of solvency since it excludes assets whose value in case of bankruptcy is likely to be zero. Liquidity is defined as in Kashyap and Stein (2000), as the ratio of securities holdings to total assets. As in their study, cash is not included in the numerator because for most of the sample, it may largely reflect required reserves, which cannot be freely drawn down.

Our baseline measure of uncertainty comes from the Survey of Professional Forecasters, conducted by the Federal Reserve Bank of Philadelphia. It corresponds to the cross-sectional dispersion in the surveys, looking in particular at forecasts of real GDP growth four quarters ahead. The dispersion index is computed as the difference between the 75th and the 25th percentile of the projections for Q/Q growth, expressed in annualized percentage points. The horizon of 4 quarters corresponds to the longest available, but in robustness checks forecasts at a 2-quarter horizon is also used.

The alternative measures of uncertainty include, in addition to the one described above, stock market volatility, senior loan officer surveys of lending standards, and the volatility of 4-quarter ahead forecasts errors as reported in Jurado et al. (2013).

With regards to stock market volatility, the VIX would have been an obvious choice since it is a direct measure of market expectations of near-term volatility of S&P500 stock index options. Unfortunately, the VIX is computed starting only in 1990. However, the annualized standard deviation of daily returns of the S&P500, which can be computed for the whole sample period, approximates the VIX very well. The correlation between this measure and the VIX for the overlapping period is 76 %.

The measure from surveys of lending standards comes directly from the Senior Loan Officer Opinion Survey on Bank Lending Practices maintained by the Board of Governors of the Federal Reserve System. The survey asks loan officers whether they have tightened lending standards during the quarter preceding the date the survey is conducted. In addition, the loan officers are asked the reasons for tightening lending standards. They are provided with eight reasons for tightening, one of which is *less favorable or more uncertain economic outlook*. The answers are reported in terms of the difference between the fraction of banks responding that they have tightened and those responding that they have loosened lending standards due to this reason. An increase in this measure reflects that this reason for tightening has become more important. In the tables this variable is denoted as SLOOS outlook.

The last measure comes from Jurado et al. (2013). They use a macrodataset with 279 monthly series of financial and macroeconomic variables. They construct forecasts for individual series conditional on information available at time t and compute squared forecast error series for each variable at different horizons. The one used in this paper corresponds to 1-year ahead forecasts. Macroeconomic uncertainty is interpreted as the common (latent) factor among the 279 series of squared forecasts errors. In the tables this variable is denoted as volatility of forecast error.

Macro variables used as controls include seasonally adjusted real GDP growth and seasonally adjusted CPI inflation rate. The regressions with monetary policy shocks use the change in the effective federal funds rate as a proxy for the latter.

Data filtering is in line with what other authors working with Call Reports have done (e.g. Kashyap and Stein (2000) and Den Haan, Sumner and Yamashiro (2002)) as follows:

- The final dataset includes only federally insured institutions chartered as commercial banks, and located in the 50 contiguous U.S. states plus the District of Columbia. This implies dropping from the sample non-deposit trust companies, saving banks, credit unions, cooperative banks, industrial banks, brokers, etc. because these institutions do not report on a quarterly basis. This step involves losing close to 10 percent of the sample (118,323 observations).
- Mergers can lead to discontinuities in the data and thus to deal with them the quarters when they took place are set to missing for the loan series. The dates for mergers come from SNL Financial Database.
- It is possible that other jumps in the series or outliers remain and thus the quarter in which loan growth is more than five standard deviations away from the cross-sectional mean is set to missing. Reducing this threshold to 3 standard deviations has no material impact on the results. In addition, observations corresponding to loan series i is included only if at least four consecutive quarterly growth rates are available.

- Reporting errors such as negative assets and loans are removed. After applying these filters the final number of bank-quarter observations is 1,060,335 from an original of 1,178,658 for total loans. Missing observations throughout the sample further reduce the actual number used in the baseline regression to 988,123.
- In the regressions with C&I lending as dependent variable, that sample excludes banks with less than 5% of their total lending in C&I 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 not a problem because the sample used in this paper starts in 1984. To address the jump in 1994 the same adjustments made in Kashyap and Stein (2000) to construct a consistent time series are done here.

Table 1 shows summary statistics for all variables used in the regressions.

Table 1. Summary Statistics

Variable	Units	Mean	Std. Dev.	p25	p50	p75	Min	Max
Total loans growth	Percent	2.3	8.0	-1.2	1.7	4.9	-98.0	111.5
C&I loans growth	Percent	1.7	18.7	-5.7	1.1	8.5	-166.9	187.9
Individual loans growth	Percent	1.0	14.3	-4.2	0.4	5.1	-191.0	188.1
Real Estate loans growth	Percent	3.1	10.2	-1.2	1.9	5.7	-106.7	117.6
Total assets	Log of th. USD	11.1	1.3	10.3	11.0	11.8	0.0	21.3
Liquidity	Percent	32.6	16.2	20.9	30.7	42.6	0.0	100.0
Total equity / Total assets	Percent	9.7	3.4	7.6	8.9	11.0	4.0	31.1
Tangible Equity / Tangible Assets	Percent	1.3	2.0	0.3	0.8	1.6	-4.3	15.3
Real GDP growth	Percent	3.1	1.9	2.4	3.1	4.2	-4.1	8.5
Expected GDP growth	Percent	5.7	1.3	5.0	5.6	6.3	2.0	9.3
Inflation	Percent	0.8	0.5	0.6	0.8	1.0	-2.4	1.7
Monetary policy indicator	Percent	-0.1	0.6	-0.4	0.0	0.2	-2.1	1.0
Disperson of professional forecasts (4 quarters ahead)	Logs	0	0.4	-0.3	0	0.2	-0.9	0.9
Disperson of professional forecasts (2 quarters ahead)	Logs	0	0.4	-0.3	0.1	0.3	-1.0	0.8
Stock market volatility	Log of annualized std dev	2.7	0.4	2.4	2.6	2.9	1.9	4.2
SLOOS outlook	percent	30.0	45.2	-4.5	18.6	72.2	-51.3	100
Common factor of forecast errors (6-months)		0	0.8	-0.6	-0.1	0.2	-1.0	4.0
Common factor of forecast errors (12-months)		0	0.7	-0.5	0	0.3	-0.9	3.3

B. Empirical Strategy

To identify the response of the supply of credit, the implications from the model presented in the previous section come in handy. In particular, because of the convexity of the marginal value of bank capital, the lower the initial level of capitalization when the uncertainty shock hits, the larger its effect on lending. Empirically, the strategy focuses then on the response of bank lending to changes in uncertainty depending on how capitalized banks are. This identification strategy is similar to the one used by Kashyap and Stein (2000) to study the lending channel of monetary policy in which the degree of liquidity determines the response of banks to monetary policy shocks because insured and non-insured deposits are not perfect substitutes.

Concretely, the strategy is implemented by estimating regressions of the following type

$$
\begin{aligned}
\Delta \log(L_{i,t}) =& \alpha \Delta CPI_{t-1} + \beta \Delta GDP_{t-1} + \gamma UNC_{t-1} + \kappa LIQ_{i,t} + \chi \log Assets_{i,t-1} \\
&+ CAP_{i,t-1} \left(\zeta + \eta \Delta CPI_{t-1} + \tau \Delta GDP_{t-1} + \lambda UNC_{t-1} + \mu TIME \right) \\
&+ \nu TIME + \sum_{k=1}^{3} \xi_k QUARTER_k + \sum_{k=1}^{11} \rho_k FRB_k + \upsilon_i + \epsilon_{i,t}
\end{aligned} \tag{16}
$$

where $L_{i,t}$ denotes total loans, CPI denotes the natural logarithm of the CPI, GDP denotes the natural logarithm of real GDP, UNC denotes aggregate uncertainty, CAP denotes the capital-to-assets ratio, LIQ denotes the ratio of liquid assets to total assets, $\log$ Assets denotes the natural logarithm of total assets and $TIME$, $QUARTER$ and FRB are respectively a time trend, and seasonal and geographical dummies. The geographical dummies are based on the federal reserve district where the bank has its headquarters. Δ is a first differences operator and υ_i denotes bank fixed effects. The key term in the regression is the interaction between aggregate uncertainty and the banks' capital-to-asset ratio. A fixed effect estimator is used in the regressions.

C. Results

The first column of Table 2 reports the estimation results. For brevity, the coefficients on the seasonal and locational dummies are not reported. Uncertainty is measured as the dispersion of four-quarter-ahead professional forecasts of real GDP growth. Standard errors are clustered at the bank level.

As predicted by the theoretical model, an increase in uncertainty is associated with a reduction in loan growth as suggested by the negative coefficient on uncertainty. Importantly, the coefficient on the interaction between uncertainty and bank capitalization is positive, implying that banks with lower levels of capitalization curtail lending more than those better capitalized. While the results from the uninteracted term can arguably be consistent with a decline in both credit demand and supply, the differential response to uncertainty that is captured through the interactions is however clearer evidence of a supply effect. For demand to be driving these results, the balance sheet position of borrowers need to be systematically correlated with that of the bank from whom they borrow. Given the large sample of banks in the dataset covering over 100 quarters of data and the wide array of borrowers to whom they lend, this would seem unlikely. This would be somewhat more likely if the largest banks were the ones with higher capital-to-asset ratios. This would follow because largest banks have a wider geographical presence. However, small banks are the ones with higher capital-to-assets ratios (Figure 3).

These results are robust to the inclusion of a number of other variables, including real GDP growth and inflation, which may signal a change in the mean that could be correlated with uncertainty. Jurado et al. (2013) document that measures of uncertainty tend to be countercyclical, therefore, periods of weak economic activity may also be periods of increased uncertainty. And weak economic activity induces banks to lend less as they expect lower profitability. A more explicit attempt to isolate first from second moments is performed in column (5) of Table 2. In this column, the regression includes the mean forecast of real GDP growth from the same surveys used to compute the baseline measure of uncertainty. The results on uncertainty are robust to the inclusion of past and forecasts of real GDP growth.

The results are also robust to the inclusion of other bank controls. In particular, they are robust to the inclusion of the fraction of liquid assets in banks' balance sheets as well as an indicator of bank size, the natural logarithm of total assets. As shown in column (4), the main results are unchanged whether the

Table 2. Regression Results

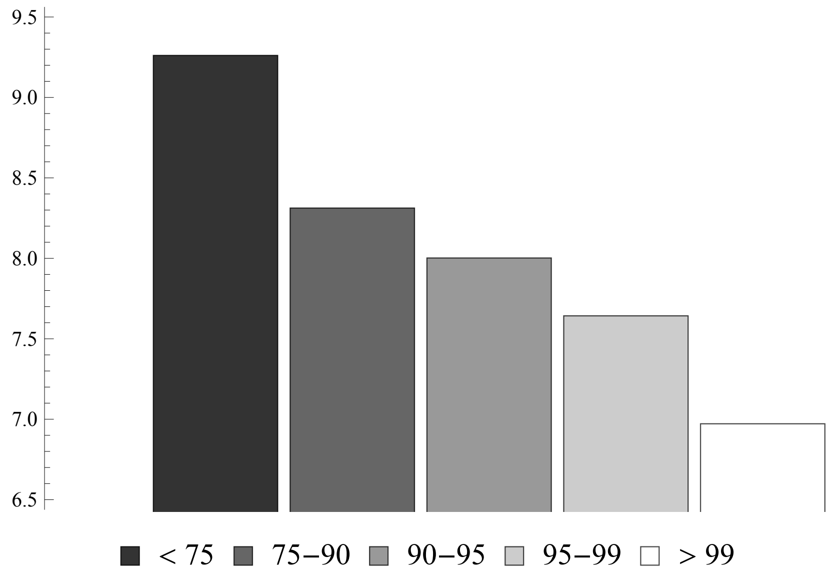
	(1) Baseline	(2) Tangible equity	(3) No time trend	(4) Δ ln assets	(5) E[GDP growth]
Δ Real GDP	0.368	0.264	0.237	0.396	0.369
	(0.023)***	(0.007)***	(0.022)***	(0.022)***	(0.025)***
E[Δ Real GDP]					-0.009
					(0.058)
Uncertainty	-0.647	-0.478	-1.832	-0.712	-0.673
	(0.123)***	(0.038)***	(0.128)***	(0.113)***	(0.123)***
Inflation	0.078	0.118	-0.211	0.164	0.037
	(0.063)	(0.018)***	(0.065)***	(0.059)***	(0.064)
Liquidity	0.074	0.087	0.063	0.068	0.074
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.002)***
ln assets	-2.073	-1.815	-1.111		-2.070
	(0.066)***	(0.073)***	(0.038)***		(0.066)***
Δ ln assets				13.423	
				(0.346)***	
Bank capitalization (CAR)	0.881		0.565	0.724	0.884
	(0.046)***		(0.013)***	(0.043)***	(0.047)***
Time	0.058	0.053		0.007	0.057
	(0.003)***	(0.001)***		(0.002)***	(0.003)***
CAR*Time	-0.002			-0.001	-0.002
	(0.000)***			(0.000)***	(0.000)***
CAR*inflation	0.013		0.029	0.009	0.016
	(0.007)**		(0.007)***	(0.006)	(0.007)**
CAR*Δ Real GDP	-0.008		-0.002	-0.011	-0.007
	(0.002)***		(0.002)	(0.002)***	(0.003)**
CAR*Uncertainty	0.073		0.139	0.065	0.077
	(0.013)***		(0.014)***	(0.012)***	(0.013)***
CAR*E[Δ Real GDP]					-0.009
					(0.006)
Tangible CAR (TCAR)		1.098			
		(0.092)***			
TCAR*time		-0.004			
		(0.001)***			
TCAR*inflation		-0.021			
		(0.013)*			
TCAR*Δ Real GDP		0.069			
		(0.005)***			
TCAR*uncertainty		0.226			
		(0.026)***			
Constant	4.818	5.814	2.853	-9.435	4.904
	(1.766)***	(1.559)***	(1.597)*	(1.541)***	(1.767)***
R^2	0.09	0.08	0.08	0.09	0.09
N	988,123	989,818	988,123	973,118	988,123

Note: Fixed effects regressions with standard errors clustered at the bank level. All regressors except the time, seasonal, and locational dummies are lagged one period. For brevity, the coefficients on the seasonal and locational dummies are not reported in the table. Uncertainty is measured as the dispersion of 4-quarters ahead professional forecasts of real GDP growth. Expected GDP growth is measured as the mean among 4-quarters ahead professional forecasts of real GDP growth. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

natural logarithm of assets or its first difference is in the regression. Changing the definition of capitalization to a more conservative measure, one that excludes intangible assets such as goodwill, has no qualitative impact on our main results (column (2)), but the magnitude of the coefficient on the interaction between bank capitalization and uncertainty increases. Note also that the main results are robust to excluding the time trend as demonstrated in column (3). In fact, the coefficient of interest almost doubles when the time trend is excluded.

Notice also that the interaction of bank capitalization with the macroeconomic variables come up significant, offering additional support for the existence of frictions in the supply side of credit. These results overall imply that changes in aggregate conditions affect bank lending differently depending on how capitalized banks are.

Figure 3. Bank Capitalization and Bank Size



Median capital-to-asset ratio in percent for banks in each percentile group according to total assets.

One potential concern with the results shown above is of course that changes in regulation or the expected changes in regulation drive the results. It is typically the case that regulation is tightened after a financial crisis. Basel I was the response to the banking problems in the 80's, and Basel III is the response to the recent crisis. To comply with tighter regulation banks may curtail credit at the same time that uncertainty is high. To rule this concern out, the regressions in Table 3 check the robustness of the results excluding particular subsamples.

In the first column, the regressions exclude the period before 1993Q1 when Basel I was introduced. In the second column, the regressions exclude the period before the Interstate Banking and Branching Act of 1994, which allowed interstate mergers and acquisitions. In the third column the regressions exclude the period after the collapse of Lehman brothers and the beginning of discussions about Basel III. A final and more stringent test is reported in column 5 where the regressions include year fixed effects in the baseline specification, which would take care of all other events not accounted for above. The main message provided by this experiment is that the main results are not affected.

1. Alternative Measures of Uncertainty

There is no consensus in the literature regarding what the best way to measure uncertainty is. Jurado et al. (2013) provide a nice discussion of the most popular measures. Some examples include the crossectional volatility of firm profitability, stock market volatility or the VIX, surveys of professional forecasts, and volatility of forecasts errors. Ultimately all of these measures can be criticized in some way. For instance, measures relying on crossectional volatility of profitability arguably may reflect also heterogeneity and not uncertainty and lack a forward-looking feature. The dispersion of forecasts among professional forecasters may be the outcome of disagreements, not uncertainty. Stock market volatility is affected by liquidity of the underlying stocks. And volatility of forecasts errors is not necessarily reflecting the uncertainty that agents faced ex-ante since it is measured ex-post. However, despite these shortcomings, all of these

Table 3. Subsamples and Year Fixed Effects

	(1) Post Basel I	(2) Post Interstate Banking	(3) Before Lehman	(4) Year Fixed Effects
Δ Real GDP	0.232	0.169	0.336	0.088
	(0.037)***	(0.039)***	(0.028)***	(0.028)***
E[Δ Real GDP]	0.218	0.317	0.033	0.124
	(0.087)**	(0.090)***	(0.066)	(0.059)**
Uncertainty	-0.909	-0.873	-0.550	-0.533
	(0.210)***	(0.215)***	(0.130)***	(0.126)***
Inflation	-0.258	-0.137	0.330	-0.205
	(0.076)***	(0.077)*	(0.095)***	(0.066)***
Liquidity	0.099	0.107	0.076	0.076
	(0.003)***	(0.003)***	(0.002)***	(0.002)***
ln assets	-2.524	-3.111	-2.003	-2.091
	(0.107)***	(0.127)***	(0.069)***	(0.066)***
CAR	0.469	0.527	1.031	0.869
	(0.078)***	(0.093)***	(0.049)***	(0.048)***
Time	0.036	0.038	0.067	0.018
	(0.005)***	(0.006)***	(0.003)***	(0.003)***
CAR*time	0.001	0.001	-0.003	-0.002
	(0.000)	(0.001)	(0.000)***	(0.000)***
CAR*inflation	0.029	0.027	-0.012	0.022
	(0.007)***	(0.007)***	(0.010)	(0.007)***
CAR*Δ Real GDP	0.007	0.008	-0.004	-0.006
	(0.004)*	(0.004)**	(0.003)	(0.003)**
CAR*E[Δ Real GDP]	-0.026	-0.031	-0.013	-0.011
	(0.009)***	(0.009)***	(0.007)*	(0.006)*
CAR*Uncertainty	0.106	0.103	0.082	0.076
	(0.021)***	(0.022)***	(0.014)***	(0.013)***
Constant	11.239	16.662	4.089	11.140
	(1.863)***	(2.121)***	(2.268)*	(1.810)***
R^2	0.11	0.13	0.08	0.09
N	552,347	472,603	935,116	988,123

Note: Fixed effects regressions with standard errors clustered at the bank level. All regressors except the time, seasonal, and locational dummies are lagged one period. For brevity, the coefficients on the seasonal, locational dummies, and year fixed effects (column (4)) are not reported in the table. Uncertainty is measured as the dispersion of 4-quarters-ahead professional forecasts of real GDP growth. Expected GDP growth is measured as the mean among 4-quarters-ahead professional forecasts of real GDP growth. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

variables contain information about uncertainty and for the purpose of this paper it suffices to show that the results presented here are not particularly sensitive to the chosen baseline measure.

Table 4 shows the estimation outcomes using alternative measures of uncertainty. Column (1) shows the results under the baseline measure, the dispersion of forecasts among professional forecasters at a horizon of 4 quarters. Column (2) is a similar measure to the baseline but at a shorter horizon (2 quarters). Columns

(3) and (4) are borrowed from Jurado et al. (2013) and how they construct these measures is explained in Section A. The measure in column (5) comes from the survey of Senior Loan Officer's Opinions on Lending Standards and corresponds to the net fraction of banks tightening standards due to a more uncertain outlook (see Section A for details). The final measure shown in column (6) corresponds to the volatility of daily returns of the S&P500. The table shows that the main results hold across the different measures of uncertainty employed in this exercise.

Table 4. Alternative Measures of Uncertainty

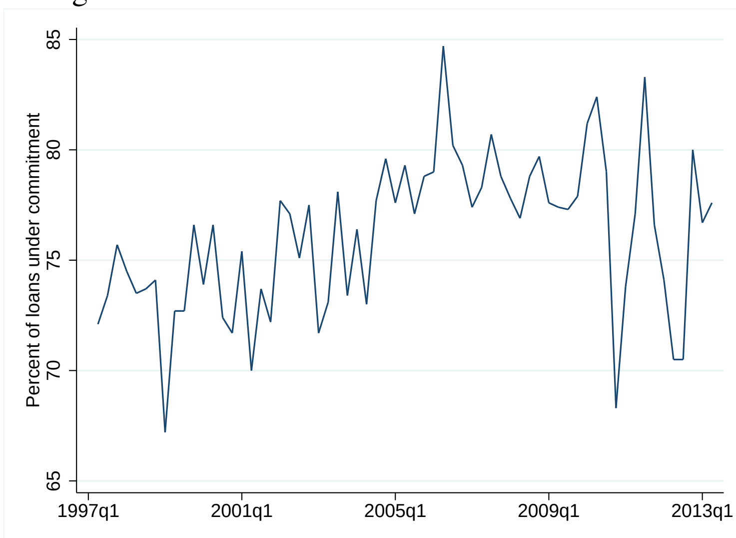
	(1) Dispersion Forecasts (4q)	(2) Dispersion Forecasts (2q)	(3) Forecast error Volatility (2q)	(4) Forecast error Volatility (4q)	(5) SLOOS outlook	(6) S&P volatility
Δ Real GDP	0.369	0.372	0.350	0.352	0.161	0.375
	(0.025)***	(0.025)***	(0.026)***	(0.026)***	(0.039)***	(0.025)***
E[Δ Real GDP]	-0.009	-0.119	-0.064	-0.062	0.168	-0.016
	(0.058)	(0.062)*	(0.060)	(0.060)	(0.093)*	(0.063)
Inflation	0.037	0.045	0.072	0.078	0.001	0.081
	(0.064)	(0.064)	(0.064)	(0.063)	(0.074)	(0.064)
Liquidity	0.074	0.073	0.075	0.075	0.108	0.075
	(0.002)***	(0.002)***	(0.002)***	(0.002)***	(0.004)***	(0.002)***
ln assets	-2.070	-2.067	-2.080	-2.081	-3.284	-2.080
	(0.066)***	(0.066)***	(0.066)***	(0.066)***	(0.133)***	(0.066)***
CAR	0.884	0.880	0.973	0.967	0.532	0.865
	(0.047)***	(0.048)***	(0.045)***	(0.045)***	(0.099)***	(0.056)***
Time	0.057	0.059	0.065	0.064	0.043	0.064
	(0.003)***	(0.003)***	(0.003)***	(0.003)***	(0.007)***	(0.003)***
CAR*time	-0.002	-0.002	-0.003	-0.003	0.000	-0.003
	(0.000)***	(0.000)***	(0.000)***	(0.000)***	(0.001)	(0.000)***
CAR*inflation	0.016	0.015	0.013	0.012	0.011	0.015
	(0.007)**	(0.007)**	(0.007)**	(0.007)*	(0.007)	(0.007)**
CAR*Δ Real GDP	-0.007	-0.007	-0.004	-0.004	0.009	-0.007
	(0.003)**	(0.003)***	(0.003)	(0.003)	(0.004)**	(0.003)***
CAR*E[Δ Real GDP]	-0.009	0.002	-0.001	-0.001	-0.016	-0.001
	(0.006)	(0.007)	(0.007)	(0.006)	(0.009)*	(0.007)
Uncertainty	-0.673	-0.642	-0.204	-0.233	-0.005	-0.037
	(0.123)***	(0.113)***	(0.061)***	(0.069)***	(0.001)***	(0.101)
CAR*Uncertainty	0.077	0.065	0.032	0.037	0.001	0.038
	(0.013)***	(0.012)***	(0.006)***	(0.007)***	(0.000)***	(0.011)***
Constant	4.904	5.024	4.145	4.184	18.218	4.220
	(1.767)***	(1.774)***	(1.756)**	(1.756)**	(2.302)***	(1.810)**
R^2	0.09	0.09	0.09	0.09	0.13	0.09
N	988,123	988,123	988,123	988,123	437,263	988,123

Note: Fixed effects regressions with standard errors clustered at the bank level. All regressors except the time, seasonal, and locational dummies are lagged one period. For brevity, the coefficients on the seasonal and locational dummies are not reported in the table. Uncertainty is measured as: (1) the dispersion of 4-quarters-ahead professional forecasts of real GDP growth; (2) same as (1) at a horizon of 2 quarters; (3) Common factor in volatility of forecast errors of 279 macroeconomic and financial variables at a horizon of 2 quarters taken from Jurado et al. (2013); (4) same as (3) at a horizon of 4 quarters; (5) is the net fraction of banks responding that they have tightened lending standards due to an uncertain outlook, taken from the Survey of Senior Loan officer's opinions on lending standards; (6) average (quarterly) volatility of S&P daily returns. Expected GDP growth is measured as the mean among 4-quarters-ahead professional forecasts of real GDP growth. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

2. Different Types of Loans and Bank Size

Because different types of loans may have different sensitivity to the business cycle, it is useful to look at how the results change when Equation 16 in run for specific types of loans instead of total loans. Table 5 shows that the main results hold for individual and real estate loans. The coefficients are of the expected sign for commercial and industrial loans, but the interaction between capital and uncertainty is not significant. One likely explanation is that C&I loans may reflect to a large extent drawings on pre-existing loan commitments and thus the actual increase in C&I loans is less sensitive to shifts in the supply. Indeed, the survey of terms of business lending (STBL) conducted by the Board of Governors of the Federal Reserve System suggests that a large fraction of C&I loans is made under commitment (Figure 4).[4] Nevertheless, the channel described in this paper holds for the first two types of loans, which together constitute on average 75 percent of the total loans portfolio of banks as of 2008q2. Nonetheless, this is actually good news for identification. If changes in C&I loan volumes are driven mostly by changes in demand as the chart seems to suggest, then getting an insignificant coefficient is perfectly consistent with our approach. But the fact that the coefficients on the other types of loans are significant cannot then be explained by demand.

Figure 4. Fraction of C&I loans under commitment



Fraction of loans in the sample that are drawn under pre-existing commitments.
Source: Survey of Terms of Business Lending (Federal Reserve Board of Governors).

The regression in the last column of Table 5 includes a triple interaction between bank capitalization, bank size, and uncertainty. The interaction between assets and uncertainty is significant and positive, suggesting that large banks are in a better position to shield their business against increases in uncertainty. However, the triple interaction is negative and statistically significant, suggesting that self-insurance through bank capital becomes weaker for large banks. This is not a surprise. Large banks have other means to hedge against uncertainty, including diversification by operating in multiple countries. At the same time, for the very large institutions, there are too-big-to-fail considerations which reduce banks' incentives to self-insure. And ultimately, these institutions may benefit from fly-to-quality effects during times of turmoil.

There is an additional aspect to highlight in the above result. If demand was the driver of results, they would not necessarily be much weaker for large banks as the above regression shows. In contrast, the reasons provided as possible explanations for this result make perfect sense under the mechanism this paper identifies because the reasons provided above imply that large banks face less intense frictions in raising external finance than smaller banks.

[4]It is important to clarify that the actual number is not known because there is no comprehensive dataset on new loans that shows their characteristics. However, the STBL is conducted quarterly in a representative sample of over 300 banks, and the survey reports the fraction of C&I loans that are granted under pre-existing commitments.

Table 5. Loan type and bank size

	(1) C&I loans	(2) Individual	(3) R.E. loans	(4) Size
Δ Real GDP	0.664	0.550	0.166	0.402
	(0.044)***	(0.039)***	(0.032)***	(0.025)***
E[Δ Real GDP]	0.271	-0.237	0.143	-0.007
	(0.110)**	(0.093)**	(0.069)**	(0.056)
Uncertainty	-0.701	-1.539	-0.435	-4.924
	(0.238)***	(0.190)***	(0.156)***	(1.144)***
Inflation	0.541	-0.064	0.015	0.032
	(0.141)***	(0.124)	(0.080)	(0.063)
Liquidity	0.088	0.042	0.042	0.073
	(0.003)***	(0.002)***	(0.002)***	(0.002)***
ln assets	-2.425	-2.578	-1.965	-0.391
	(0.081)***	(0.075)***	(0.070)***	(0.104)***
CAR	1.347	1.160	0.786	2.195
	(0.073)***	(0.063)***	(0.054)***	(0.097)***
Time	0.094	0.065	0.029	0.031
	(0.005)***	(0.004)***	(0.003)***	(0.003)***
CAR*time	-0.004	-0.004	-0.002	0.000
	(0.000)***	(0.000)***	(0.000)***	(0.000)
CAR*inflation	-0.012	0.024	0.007	0.017
	(0.014)	(0.012)**	(0.008)	(0.007)***
CAR*Δ Real GDP	-0.016	-0.007	0.002	-0.010
	(0.005)***	(0.004)*	(0.003)	(0.003)***
CAR*E[Δ Real GDP]	-0.026	-0.022	-0.006	-0.010
	(0.011)**	(0.010)**	(0.007)	(0.006)*
CAR*Uncertainty	0.027	0.112	0.057	0.386
	(0.025)	(0.020)***	(0.017)***	(0.131)***
CAR*ln assets				-0.154
				(0.009)***
Uncertainty*ln assets				0.386
				(0.104)***
CAR*ln assets*Uncertainty				-0.029
				(0.012)**
Constant	-0.510	11.935	8.643	-9.784
	(2.159)	(2.853)***	(1.579)***	(2.243)***
R^2	0.02	0.03	0.04	0.09
N	908,759	981,635	982,232	988,123

Note: Fixed effects regressions with standard errors clustered at the bank level. All regressors except the time, seasonal, and locational dummies are lagged one period. For brevity, the coefficients on the seasonal and locational dummies are not reported in the table. Uncertainty is measured as the dispersion of 4-quarters-ahead professional forecasts of real GDP growth. The regressions with C&I loans include only banks with at least 5 percent of their portfolios in C&I loans. Expected GDP growth is measured as the mean among 4-quarters-ahead professional forecasts of real GDP growth. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

3. Monetary Policy

This last exercise has two purposes: The first is to address the possibility of an omitted variable problem, monetary policy. The second is to use monetary policy shocks as a benchmark to measure the quantitative importance of uncertainty shocks. The regression specification used so far is now augmented to control for monetary policy shocks. The motivation to include this variable arises from the fact that if monetary policy responds to uncertainty, then monetary policy may be the actual driver of the results presented so far, especially given that Jurado et al. (2013) document that measures of uncertainty tend to be countercyclical. Moreover, since bank lending has been documented to respond with a lag to monetary policy shocks (Bernanke and Blinder (1992)), the regression now includes 4 lags of the change in the effective feds funds rate as a measure of monetary policy shocks. To contrast this effect with those of uncertainty in a similar way, also 4 lags of uncertainty are included. The results are presented in Table 6.

Table 6. Bank Capital and Lending Channels of Monetary Policy

	(1) Bank Capital Channel	(2) Bank Capital and Lending Channel
Δ Real GDP	0.525	0.524
	(0.027)***	(0.027)***
E[Δ Real GDP]	0.028	0.039
	(0.053)	(0.053)
Inflation	-0.080	-0.058
	(0.059)	(0.059)
$\sum_{j=1}^{4} \Delta FFrate_{t-j}$	-.193	-.588
	(0.099)*	(0.100)***
$\sum_{j=1}^{4} Uncertainty_{t-j}$	-0.708	-0.743
	(0.174)***	(0.175)***
Liquidity	0.064	0.066
	(0.002)***	(0.002)***
ln assets	-1.622	-1.614
	(0.058)***	(0.058)***
CAR	0.485	0.472
	(0.043)***	(0.043)***
Time	0.036	0.035
	(0.003)***	(0.003)***
CAR*time	-0.001	-0.001
	(0.000)***	(0.000)**
CAR*inflation	0.021	0.021
	(0.006)***	(0.006)***
CAR*Δ Real GDP	-0.025	-0.025
	(0.003)***	(0.003)***
CAR*E[Δ Real GDP]	-0.015	-0.014
	(0.005)***	(0.006)**
CAR*$\sum_{j=1}^{4} \Delta FFrate_{t-j}$	0.041	0.023
	(0.010)***	(0.011)**
CAR*$\sum_{j=1}^{4} Uncertainty_{t-j}$	0.051	0.052
	(0.018)***	(0.018)***
Liquidity*$\sum_{j=1}^{4} \Delta FFrate_{t-j}$		0.018
		(0.001)***
Constant	5.050	5.028
	(1.546)***	(1.552)***
R^2	0.06	0.06
N	940,037	940,037

Note: Fixed effects regressions with standard errors clustered at the bank level. All regressors except the time, seasonal, and locational dummies are lagged one period. For brevity, the coefficients on the seasonal and locational dummies are not reported in the table. Uncertainty is measured as the dispersion of 4-quarters ahead professional forecasts of real GDP growth. Expected GDP growth is measured as the mean among 4-quarters-ahead professional forecasts of real GDP growth. Monetary policy is measured as the change in the effective federal funds rate. * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

For compactness, the table reports only the sum of coefficients wherever multiple lags are used and their significance. In the first column, the regressions include the bank capital channel of monetary policy. As argued in Van Den Heuvel (2009), the transmission of monetary policy shocks through the supply of credit is affected by the capital position of banks. Less-capitalized banks are more affected by a monetary policy contraction than better-capitalized ones. The table shows that indeed, the data offers support to the existence of a bank capital channel of monetary policy, but the results on uncertainty still hold. In the second column, the regression is augmented with the bank lending channel of monetary policy, which operates through the differential liquidity position of banks as in Kashyap and Stein (2000), and thus the key variable is the interaction between liquidity and monetary policy shocks. Again, this channel is statistically significant, but as in the previous case, its presence in the regressions do not affect the results on uncertainty.

The battery of tests presented so far offer strong support for a robust statistical relationship between uncertainty and lending. The paper has shown evidence of how there is a supply component in this relationship by looking at the differential response of banks according to the level of bank capitalization. Taking the results presented in Table 6, the differential response of lending between a bank at the 75th percentile of the distribution of capital-to-asset ratios and one at the 25th percentile, to a 1 standard deviation increase in uncertainty is 82 percent of the effect on lending generated by a 1 standard deviation monetary policy shock. In other words, the effect of uncertainty through the supply of bank credit is almost as strong as the effect of the bank capital and lending channels of monetary policy.

IV. Conclusions

Since the crisis, there is a growing interest in studying the importance of uncertainty shocks for business cycle fluctuations. There is also increased interest in better understanding the drivers of credit cycles, and the importance of financial intermediaries capital for lending. This paper makes contributions in all these directions. First, it presents theoretical foundations and empirical evidence for a particular channel through which uncertainty shocks can affect the real economy. Second, this channel relies on the existence of financial frictions affecting financial intermediaries and it is shown that, through a self-insurance mechanism, uncertainty shocks can exacerbate credit cycles. Third, it shows how even under limited liability, this self-insurance mechanism can arise. The empirical evidence provided in the paper robustly supports a response of the supply of credit to changes in macroeconomic uncertainty, more so for banks that have low levels of capital. Contrasting the effects of uncertainty to those of the lending and capital channels of monetary policy, the results suggest that 1 standard deviation uncertainty shocks is almost (82 percent) as large as a 1 standard deviation monetary policy shock.

References

Arellano, Cristina, Yan Bai, and Patrick Kehoe, 2011, "Financial Markets and Fluctuations in Uncertainty," *Federal Reserve Bank of Minneapolis, Research Department Staff Report.*

Ashcraft, Adam, 2005, "Are Banks Really Special? New Evidence from the FDIC-Induced Failure of Healthy Banks," *American Economic Review*, Vol. 95, No. 5 (December), pp. 1712-1730.

Baum, Christopher, Mustafa Caglayan, and Neslihan Ozkan, 2008, "The Role of Uncertainty in the Transmission of Monetary Policy Effects on Bank Lending," Working Paper 561, Boston College,).

Bernanke, B., M. Gertler, and S. Gilchrist, 1999, "The Financial Accelerator in a Quantitative Business Cycle Framework," *Handbook of Macroeconomics*, Vol. 1c, pp. 1341-1393.

Bernanke, Ben S., and Alan S. Blinder, 1992, "The Federal Funds Rate and the Channels of Monetary Policy," *The American Economic Review*, Vol. 82, No. 4 (September), pp. 901-921.

Bloom, Nicholas, 2009, "The Impact of Uncertainty Shocks," *Econometrica*, Vol. 77, pp. 623-685.

______, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen Terry, 2011, "Really Uncertain Business Cycles," *Stanford University mimeo.*

______, Stephen Bond, and John Van Reenen, 2007, "Uncertainty and Investment Dynamics," *Review of Economic Studies*, Vol. 74, pp. 391-415.

Brunnermeier, Markus K., and Yuliy Sannikov, 2011, "A Macroeconomic Model with a Financial Sector," *Princeton University mimeo.*

Carlstrom, C., and T. Fuerst, 1997, "Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis," *American Economic Review*, Vol. 87, No. 5, pp. 893-910.

Carlstrom, Charles T., and Timothy S. Fuerst, 1997, "Agency Costs, Net Worth, and Business Fluctuations: A Computable General Equilibrium Analysis," *The American Economic Review*, Vol. 87, No. 5, pp. 893-910.

Carroll, Christopher, 2006, "The Method of Endogenous Gridpoints for Solving Dynamic Stochastic Optimization Problems," *Economics Letters*, Vol. 91, No. 3, pp. 312-20.

Diamond, Douglas W., and Raghuram G. Rajan, 2000, "A Theory of Bank Capital," *The Journal of Finance*, Vol. 55, No. 6 (December), pp. 2431-2465.

Gertler, Mark, Nobuhiro Kiyotaki, and Albert Queralto, 2011, "Financial Crises, Bank Risk Exposure and Government Financial Policy," *New York University working paper.*

Gilchrist, Simon, Jae W. Sim, and Egon Zakrajšek, 2011, "Uncertainty, Financial Frictions, and Irreversible Investment."

Haan, Wouter J. Den, Steven W. Sumner, and Guy Yamashiro, 2002, "Construction of Aggregate and Regional Bank Data Using the Call Reports," Technical Report,). University of Amsterdam unpublished manuscript.

Hellmann, Thomas F., Kevin C. Murdock, and Joseph E. Stiglitz, 2000, "Liberalization, Moral Hazard in Banking, and Prudential Regulation: Are Capital Requirements Enough?," *American Economic Review*, Vol. 90, No. 1 (August), pp. 147-165.

Jurado, Kyle, Sydney Ludvigson, and Serena NG, 2013, "Measuring Uncertainty," *New York University and Columbia University mimeo.*

Kashyap, A., and J. Stein, 2000, "What Do a Million Observations on Banks Say About the Transmission of Monetary Policy?," *American Economic Review*, Vol. 90, No. 3, pp. 407-428.

Knight, Frank, 1921, *Risk, Uncertainty, and Profit* (Hart, Schaffner & Marx; Houghton Mifflin Co.).

Krasa, Stefan, and Anne Villamil, 2000, "Optimal Contracts When Enforcement is a Decision Variable," *Econometrica*, Vol. 68, pp. 119-134.

Laeven, Luc, and Fabián Valencia, 2013, "Systemic Banking Crises Database," *IMF Economic Review*, Vol. 61, pp. 225-270.

Peek, Joe, and Eric S Rosengren, 1997, "The International Transmission of Financial Shocks: The Case of Japan," *American Economic Review*, Vol. 87, No. 4 (September), pp. 495-505.

Peydro, José Luis, Gabriel Jiménez, Steven Ongena, and Jesús Saurina, 2012, "Credit Supply Monetary Policy: Identifying the Bank Balance-Sheet Channel with Loan Applications," *American Economic Review*, Vol. 102, No. 5 (August), pp. 2301-26.

Reinhart, Carmen M., and Kenneth S. Rogoff, 2009, *This Time Is Different: Eight Centuries of Financial Folly* (Princeton University Press).

Rochet, Jean-Charles, 2009, *Why Are There So Many Banking Crises?: The Politics and Policy of Bank Regulation* (Princeton University Press).

Townsend, R., 1979, "Optimal Contracts and Competitive Markets with Costly State Verification," *Journal of Economic Theory*, Vol. 21, No. 2, pp. 265-935.

Valencia, Fabián, forthcoming, "Banks' Precautionary Capital and Credit Crunches," *Macroeconomic Dynamics.*

Van Den Heuvel, Skander, 2009, "The Bank Capital Channel of Monetary Policy," unpublished manuscript, University of Pennsilvania,).

APPENDIX I. NUMERICAL SOLUTION METHOD

As argued in the paper, the purpose of the model is to illustrate how the mechanism of self-insurance arises in a qualitative form without aiming at generating quantitative implications. For this reason, the parameters are not chosen as to match particular patterns in the data and are simply chosen within the range of values seen in the literature. Bankruptcy costs are chosen so that the bank is more efficient than depositors in liquidating projects ($\omega > \mu$) and both are within the range of values used in the literature (Bernanke et al. (1999), Carlstrom and Fuerst (1997b), and others). The level of the risk-free rate is inconsequential in this model, so it is normalized to 0. The values are shown below.

Table 7. Parameter Values

Parameter	Value
β	0.995
$\mathcal{R}$	1.01
μ	0.13
ω	0.20
ρ	1.00

The model is solved by backwards induction using Carroll (2006)'s endogenous gridpoints method. The method involves first finding the values of $\overline{q}$ and $\overline{l}$ that satisfy equations (12) and (13). The next step requires choosing a grid of values for capital net of dividends, q. For each of these values of q larger than $\overline{q}$, the constraint on no-equity finance is not binding and the optimal solution for dividends is given by $q - \overline{q}$ and the solution for lending is $\overline{l}$. For each value of q below $\overline{q}$, the constraint on dividends is binding and thus the optimal solution for dividends is 0 and the one for lending is found using a root-finding procedure on equation (13). The values of bank capital as of the beginning of the period, e_t, are recovered by using the definition of $q = e - c$, using the pre-determined grid of values for q and the optimal solution for dividends for each q. The step yields pairs e, c and e, l which are used, through piecewise linear interpolation, to construct continuous functions $c(e)$ and $l(e)$. With these functions on hand, the next step involves constructing a numerical approximation for the marginal value function. Using the marginal value function on hand, the above steps are repeated on equations (14) and (15), which reflect the problem from the perspective of one period earlier, to generate new optimal dividends, lending, and marginal value functions. This last step is repeated until the maximum absolute difference between the dividends and lending functions and their previous period counterparts is below 0.001.