

# UNCERTAINTY AND THE LENDING CHANNEL OF MONETARY POLICY

by

Jeanne Verrier

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## ABSTRACT

The dramatic increase in aggregate uncertainty during the Great Recession sparked an interest in the role of uncertainty on the effectiveness of financial sector intervention policies. In particular, banks have been a major source of frictions in the transmission of monetary policy, but the impact of uncertainty on their lending behavior has not received the attention it deserved. This paper empirically investigates the effects of aggregate uncertainty on the supply of credit and tests the hypothesis that the bank lending channel of monetary policy becomes less powerful in times of uncertainty. The data consist in the universe of U.S. commercial banks over the period 1984-2010, and simultaneity concerns are addressed by looking at the differential response of banks by how liquid their balance sheets are. The results suggest that aggregate uncertainty induces banks to curtail lending - all the more as they have less liquidity - and dampens the bank lending channel of monetary policy.

*JEL classification:* E44, E50, E52

*Keywords:* Credit Crunch, Uncertainty, Lending Channel.

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## I. INTRODUCTION

According to the bank lending view of monetary policy, banks react to monetary shocks by contracting lending. The effect is all the more significant as banks are less able to shield against monetary shocks by raising non-reservable liabilities such as uninsured deposits.<sup>1</sup> A number of studies have criticized the importance of this transmission mechanism, arguing that some assumptions are unfounded (see for example Bernanke [2007] and Disyatat [2011]), that the models are subject to misspecification (cf Altunbas et al. [2009] and Gambacorta and Marques-Ibanez [2011]) or that the differential effects between small and large banks have been overestimated (cf Haan et al. [2011] and Black and Rosen [2007]). The debate about the relevance of this channel has been revived with the recent crisis episode, where financial frictions have played a major role in driving business cycles and shifting the stance of monetary policy.

At the same time, the dramatic increase in uncertainty that marked the end of the Great Moderation has renewed the interest for its role in shaping the depth and length of aggregate economic fluctuations. In particular, a number of authors have drawn attention to the strong correlation between uncertainty and bank credit, as is illustrated in Figure 1. While most studies have looked at how higher uncertainty affects the real activity through non-financial firms' decision-making (see for example Bloom et al. [2007], Bloom et al. [2011], Arellano et al. [2011] and Gilchrist et al. [2013]), little attention has been devoted to the supply side of financial frictions, i.e. to the reaction of banks in a context of higher uncertainty.

This paper argues that the lending behavior of banks is affected by changes in uncertainty, and that this has implications for the transmission of monetary policy shocks through the bank lending channel. Theoretical contributions modeling bank's optimal financial structure show the presence of a precautionary motive in banks by which changes in uncertainty lead banks to curtail lending to strengthen balance sheets (e.g. Diamond and Rajan [2000], Van Den Heuvel [2009], Valencia [2008], and Valencia [2011]). Moreover, Valencia [2013] presents a model in which a bank is subject to financial frictions in raising external finance, even under limited liability. There is also theoretical work in general equilibrium framework highlighting the aggregate implications of this mechanism (e.g. Gertler et al. [2011], Brunnermeier and Sannikov [2014]), but empirical work supporting this behavior is scarce. The main value added of this paper is thus to present evidence for such a bank self-insurance behavior, and what this implies for the lending channel of monetary policy.

The data consist in the universe of U.S. commercial banks over the period 1984-2010. Time and cross-sectional variations in U.S. commercial banks balance sheet liquidity are exploited to highlight the differential response in lending to changes in uncertainty. Uncertainty may arise from many sources, including idiosyncratic factors such as the productivity of bank employees, local economic conditions, etc, or aggregate factors such as asset prices, inflation, fiscal policy, or overall growth in the economy. From a theoretical point of view, and in particular in the references cited above, the prescribed behavior arises under any type of uncertainty. Therefore, this paper focuses on aggregate uncertainty because it is less subject to reverse causality concerns

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<sup>1</sup>Seminal studies in the bank lending channel literature include Bernanke and Blinder [1992], Bernanke and Gertler [1995], Peek and Rosengren [1995] and Kashyap and Stein [2000]

than idiosyncratic uncertainty since it is not driven by individual bank conditions. Since most likely idiosyncratic uncertainty is more important for a bank than aggregate uncertainty in making decisions, the choice of aggregate uncertainty implies that the results will likely be underestimated.

As in Valencia [2013], I use as a baseline measure of aggregate uncertainty the dispersion of nominal GDP professional forecasts. This measure is broad enough that in principle should capture many of the aggregate factors that affect a bank's environment. While the use of aggregate uncertainty may rule out reverse causality, it is still subject to an important simultaneity problem because it 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. I argue that by finding a differentiated response driven by the degree of liquidity in banks' balance sheet, I am able to identify supply side effects. Therefore, one of the key variables is the interaction between the measure of aggregate uncertainty and bank-level liquidity. While this strategy cannot put endogeneity concerns entirely at rest, it reduces them substantially. For these results to be driven by demand it would require that the liquidity position of borrowers is correlated with the liquidity position of banks both in the cross-sectional and time dimensions (i.e. liquid borrowers borrow from liquid banks, and their liquidity levels co-move over time).

The results show that increases in uncertainty trigger a reduction in loan growth, but more so at banks with low levels of liquidity. The results are robust to the inclusion of other bank-level and macroeconomic controls. Since aggregate uncertainty tends to be countercyclical, one could argue that lending is reduced because the expected return on loans goes down. This possibility is ruled out by controlling for mean forecasts of nominal GDP growth (to control simultaneously for expected changes in prices and output) and finding that the results survive. This suggests that it is the change in second moments and not just a change in the mean that drives the results. Moreover, the results stay valid when tested with various alternative measures of uncertainty. All are forward-looking, but vary in terms of time horizon and underlying factors.

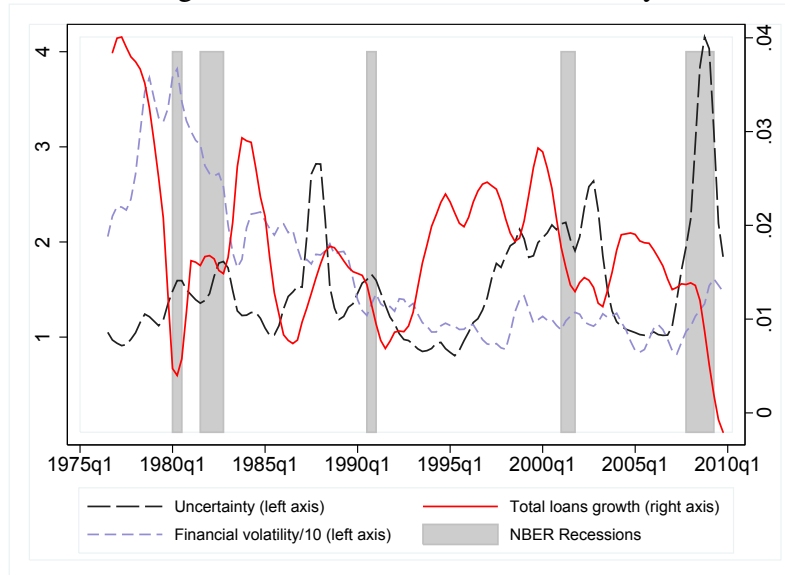
The skeptical reader could argue that if monetary policy responds to uncertainty, it could be that the results are simply capturing the lending channel of monetary policy. The results are robust to explicitly controlling for the lending channel following the same specification as in Kashyap and Stein [2000]. A triple interaction term between liquidity, uncertainty and bank liquidity is added to the regressions to account for the differential response to uncertainty through the stance of monetary policy. The results suggest that uncertainty dampens the power of the bank lending channel. Finally, the sample is partitioned to check if there is a systematic relationship between liquidity positions, borrower characteristics, bank size and type of loans, and see if the effect of uncertainty on the lending channel of monetary policy is stronger in one of these segments.

To date, there is little empirical work that empirically examines the impact of uncertainty on the behavior of banks. Delis et al. [2014] find that, in "anxious periods", consumers and analysts expectations negatively affect the supply of credit but that characteristics such as the liquidity, efficiency and size of banks do not impact lending decisions. Another study by Baum et al. [2013] re-estimates the model of Kashyap and Stein [2000] by including financial uncertainty, using bank holding corporations data. They conclude that, by ignoring uncertainty, Kashyap and Stein [2000]'s equation is misspecified and the results are biased. This study differs from theirs in that I look at individual commercial banks, and use a broader measure of uncertainty. Like them, I find

that uncertainty matters for bank lending but, unlike them, I find that the lending channel is still present and important after controlling for uncertainty.

The next section presents the empirical strategy. Section III describes the dataset used in the study. Section IV shows the baseline results, Section V analyzes the specific effects of uncertainty on the transmission of monetary policy shocks through the bank lending channel and presents several robustness exercises. Section VI concludes.

Figure 1. Loan Growth and Uncertainty



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



## II. EMPIRICAL STRATEGY

This paper suggests that the bank lending behavior of banks changes under uncertainty, and that this has implications for the bank lending channel of monetary policy. The analysis is clearly subject to a simultaneity problem because both the supply and demand for loans react to uncertainty. I address this concern by appealing to bank-level data and exploiting the cross-sectional variation in U.S. banks balance sheets. I look at the differential response of banks to changes in uncertainty depending on how liquid their balance sheets are. This identification strategy is similar to the approach followed by Kashyap and Stein [2000] in studying the lending channel of monetary policy. It ameliorates simultaneity concerns substantially since for any other factor to be the driver of the results, this factor would have to be correlated with the liquidity positions of the individual banks. Concretely, for demand to be driving my results, it would have to be the case that borrowers with (less) more liquid balance sheets systematically demand loans from (less) more liquid banks. Given the large number of banks in the data and their widespread location throughout the United States, this condition is quite unlikely.

Concretely, I estimate regressions of the following type

$$\begin{aligned} \Delta \log(L_{it}) = & \sum_{j=1}^4 \alpha_j \Delta \log(L_{it-j}) + \sum_{j=1}^4 \delta_j UNC_{t-j} + \sum_{j=1}^4 \beta_j \Delta CPI_{t-j} + \sum_{j=1}^4 \gamma_j \Delta GDP_{t-j} \\ & + LIQ_{it-1} \left( \zeta + \sum_{j=1}^4 \lambda_j UNC_{t-j} + \sum_{j=1}^4 \eta_j \Delta CPI_{t-j} + \sum_{j=1}^4 \tau_j \Delta GDP_{t-j} + \mu TIME \right) \\ & + \nu TIME + \sum_{k=1}^3 \xi_k QUARTER_{kt} + \sum_{k=1}^{12} \rho_k FRB_{ki} + v + \epsilon_{it} \end{aligned} \quad (1)$$

where  $L$  represents total loans,  $UNC$  is aggregate uncertainty,  $\Delta CPI$  is inflation,  $GDP$  is the natural logarithm of real GDP,  $LIQ$  is the ratio of securities holdings to total assets, and  $TIME$ ,  $QUARTER$  and  $FRB$  are respectively time, seasonal, and geographical dummies.

The direct effect of uncertainty on loan growth, the coefficient on  $UNC_{t-j}$ , is expected to be negative. The theoretical model presented in Valencia [2013] tells us that banks wish to increase liquidity when uncertainty increases. Therefore, the effect of uncertainty should be smaller for more liquid banks, i.e. one would expect:  $\frac{\partial^2 \log(L_{it-1})}{\partial LIQ_{it-1} \partial UNC_{t-j}} > 0$ .

It should be noted that liquidity is endogenous and responds to uncertainty. However, to follow Valencia [2013] where liquidity is a state variable, I treat it initially as a weakly exogenous or predetermined variable. Notice however that the endogeneity of liquidity works against finding a significant positive  $\sum_{j=1}^4 \lambda_j$ . If a bank responded to an increase in uncertainty by raising liquidity before t-1, then effectively in t-1 the bank will be closer to its desired liquidity ratio and thus the need to reduce lending to build up liquidity would be less pressing. However, since liquidity may vary endogenously for other reasons, I checked that the coefficients remain of the same sign and

statistically significant when liquidity is treated as a fully endogenous variable. Under this specification, the magnitude of the coefficients  $\delta_j$  and  $\lambda_j$  decrease, which highlights the presence of a bias when liquidity is not treated as endogenous. Notice that increasing the number of variable would reduce this bias, but at the cost of increasing the variance.

Equation (1) is estimated using dynamic panel data techniques. I use a GMM estimator developed by Blundell and Bond [1998]. The difference between this estimator and the standard Arellano and Bond [1991] estimator is that in addition to using lagged levels of the regressors as instruments for the equation in first differences, it uses lagged first differences of the regressors for the equation in levels. By exploiting these two sets of moment conditions, Blundell and Bond [1998], building on Arellano and Bover [1995], proposes a system estimator that improves the properties of the standard first-differenced GMM estimator. Implementation requires also to specify the lag structure of the regression and the instruments to be used. As a default, the estimator uses all available lags, but that is not feasible to implement with my data and may introduce a possible loss of efficiency given the large number of cross-sections. Instead, I chose 4 lags as baseline and checked how results change if a different lag structure is chosen. It turns out that the results changed only marginally when I increased the maximum number of lags from 4 to 20, and decreased it from 4 to 1. For computational speed, however, I preferred to stick to 4.

Arellano and Bond [1991] recommend against using the non-robust two-step estimator for inference on the coefficients from estimations in dynamic panels because the standard errors tend to be biased downwards. Therefore, I report the results under the robust two-step estimator. I do not report the Sargan test for overidentifying restrictions because its asymptotic distribution is known only under homoskedasticity.<sup>2</sup> The test for no serial correlation of second order in the error term is also reported in the tables. Under the null hypothesis of no serial correlation of second order, a rejection would imply that the moment conditions are not valid. Because the first difference of independently and identically distributed idiosyncratic errors will be serially correlated, this implies that the model is not misspecified. Finally, I report a goodness of fit measure recommended by Windmeijer [1995], which corresponds to the correlation between actual and fitted values of the dependent variable.

### III. DATA

The bank-level data includes 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. I exclude the first part of the sample (1978q4-1983q4) because the Call Reports were collected and cleaned less systematically prior to 1984. In particular, banks were in general required to provide more detail concerning assets and liabilities starting in 1984, resulting in discontinuities in many series. I use consolidated financial statements (RCFD series) because in general the largest banks only provide financial data on a consolidated foreign and domestic basis.

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<sup>2</sup>I also ran the regressions with the one-step GMM estimator and obtained the Sargan test and concluded that the overidentifying restrictions were valid. However, I prefer to report results that are robust to heteroskedasticity.

Liquidity is defined here like in Kashyap and Stein [2000] as the ratio of securities holdings to total assets. As in their study, I 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. The capital-to-assets ratio used in the regressions corresponds to tangible equity to tangible assets, computed as total equity minus intangible assets divided by total tangible assets. Tangible assets are measured as total assets minus intangible assets. I opted for this measure because it is closer to the economic capital of a bank than the pure accounting capital ratio.

My 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 nominal GDP growth four quarters ahead, to capture both uncertainty about prices and real output. 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. Four quarters is the longest horizon available for nominal GDP in the surveys.

The macro variables used as controls include real GDP growth, seasonally adjusted, CPI inflation rate seasonally adjusted. In the regression where the lending channel is controlled for, I use the change in the effective federal funds rate as the monetary policy instrument.

The data is filtered to be in line with what other authors working with Call Reports have done (e.g. Kashyap and Stein [2000] and Den Haan et al. [2002]), as follows:

- Only federally insured institutions chartered as commercial banks and located in the 50 contiguous U.S. states plus the District of Columbia are included. This implies that I drop 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. I lose close to 10 percent of the sample with this step (118,323 observations).
- Mergers are corrected for 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.
- The possibility of other jumps in the series or outliers is controlled for by setting to missing the quarter in which loan growth is more than five standard deviations away from the cross-sectional mean. Reducing this threshold to 3 standard deviations has no material impact on the results. I also include observations of loan series if at least four consecutive quarterly growth rates are available.
- Reporting errors such as negative assets and negative loans are removed. After applying these filters I am left with a total of bank-quarter observations of 1,060,335 from an original of 1,178,658 for total loans. Missing observations throughout the sample further reduce the actual observations used in the baseline regression to 946,257.
- In the regressions with C&I lending as dependent variable, only banks with at least 5% of their total lending in C&I loans are included.

- 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. I solve the first two by focusing on data starting in 1984. I follow Kashyap and Stein [2000] to construct a consistent time series to avoid a jump in 1994.

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
Aggregate Uncertainty (nominal), 4 quarters ahead	Log of percentage points	0.2	0.4	0.0	0.2	0.5	-0.5	1.1
Aggregate Uncertainty (real), 4 quarters ahead	Log of percentage points	-0.1	0.4	-0.3	-0.1	0.2	-0.9	0.9
Aggregate Uncertainty (inflation), 4 quarters ahead	Log of percentage points	-0.2	0.3	-0.5	-0.3	0.0	-0.9	0.4
Aggregate Uncertainty (nominal), 2 quarters ahead	Log of percentage points	0.3	0.4	0.0	0.3	0.5	-0.5	1.1
Jurado et al. measure, 2 quarters ahead		0.1	0.9	-0.6	-0.1	0.3	-1.0	4.0
Consumers sentiment, 4 quarters ahead		108.1	27.2	92.0	113.0	126.0	38.0	157.0
Financial volatility	Log of annualized std dev	2.7	0.4	2.4	2.6	2.9	1.9	4.2
Inflation	Percent	0.7	0.5	0.5	0.8	0.9	-2.4	1.7
Real GDP growth	Percent	2.9	2.0	2.2	3.1	4.2	-4.1	8.5
Expected nominal GDP growth	Percent	5.5	1.2	4.9	5.5	6.2	2.0	9.3
Monetary policy indicator	Percent	-0.1	0.5	-0.3	0.0	0.2	-2.1	1.0
Liquidity	Percent	32.6	16.2	20.9	30.7	42.6	0.0	100.0
Total assets	Log of th. USD	11.1	1.3	10.3	11.0	11.8	0.0	21.3
Tangible Equity / Tangible Assets	Percent	1.3	2.0	0.3	0.8	1.6	-4.3	15.3

#### IV. BASELINE RESULTS

The estimation results of Equation (1) are reported in the first column of Table 2. For compactness, I do not report the coefficients on dummy variables, and report only the joint significance for all lags of each continuous variable and their interactions. Of the macroeconomic variables, real GDP growth and inflation have a significant impact on lending: higher growth induces more lending, whereas higher inflation, which implies also higher nominal rates on loans, is associated with lower lending. However in both cases, the sign of the coefficients on the interactions between GDP growth and inflation with liquidity, are of the opposite sign than the coefficients on the uninteracted variables. This implies that more liquid banks can smooth the effects of macroeconomic fluctuations on lending better.

Aggregate uncertainty comes up with the expected negative sign, implying that higher uncertainty is associated with lower lending in the economy. Also as expected, the interaction between uncertainty and liquidity comes up with a positive sign, suggesting that more liquid banks curtail lending by less than less liquid banks. The precautionary motive predicted by in the theoretical model in Valencia [2013] is supported by this evidence. As can be seen in the regressions, the interaction between uncertainty and liquidity is in all cases significant at the 1 percent level.

I also ran a number of additional regressions not reported in the paper. In particular, the results were robust to using only the RCON series (balance sheets consolidated domestically only) instead of the RCFD series (consolidated foreign and domestic balance sheets), as well as to the exclusion of a time trend, or to the inclusion of cash in my definition of liquid assets.

### **A. Additional Bank Controls**

In the baseline specification, the only bank-level variable is the level of liquidity. If liquidity is correlated with other bank characteristics, one may be concerned with an omitted variable problem. In the second column of Table 2, the baseline regression is augmented with additional bank controls, including total assets (in logs) and the tangible equity ratio. These two are the most direct controls that may be systematically correlated with liquidity. For instance, as documented in Kashyap and Stein [2000], large banks hold systematically lower liquidity. Similarly, there may be a systematic relationship between capitalization and liquidity. I include the tangible equity ratio rather than total equity because I am interested in a measure of capital that is as close as possible to economic capital. Both bank indicators are highly statistically significant.

The results suggest that the more capital a bank has, the more it lends, but the larger the bank, the lower the growth rate in loans. The latter is not surprising, since the larger a bank gets, the lower the space to grow even further. Importantly, the results on uncertainty remain unaltered, with the coefficient on the interaction between uncertainty and liquidity even increasing somewhat.

### **B. First versus Second Moments**

Jurado et al. [2013] finds that uncertainty is clearly countercyclical, which is exemplified by Figure 1. This logic implies that changes in the mean forecasts of future economic activity are correlated with changes in uncertainty. Fortunately, the surveys of professional forecasters give a direct measure of expectations about future macroeconomic performance that can be used as a control in the regressions to rule out this possibility. In column 3 of Table 2, the regressions are augmented with the mean 4-quarter-ahead forecast of nominal GDP growth as well as the interaction between this variable and liquidity.

Expected GDP growth has a positive sign as one would expect. Notice also that the coefficient is larger than that for past GDP, which is consistent with the idea that banks are forward-looking. Better times ahead spur lending, but less so for more liquid banks, implying that the logic that more liquid banks are in a better position to smooth the impact of cyclical variations in economic activity on lending persists. Importantly, the results on uncertainty and the interaction of uncertainty and liquidity remain highly statistically significant and with the magnitudes of the coefficients broadly unchanged.

Table 3 shows the individual coefficients for uncertainty and the interaction for uncertainty and liquidity for all the regressions in Table 2. The coefficients are predominantly of the expected sign.

Table 2. Baseline Results

	(1)	(2)	(3)
Dep. var.: Total Loans growth	Baseline	Bank controls	Expected GDP
<u>Macroeconomic controls</u>			
Aggr. Uncertainty, $\sum_{j=1}^4 \delta_j$	-2.155*** (0.295)	-2.846*** (0.318)	-2.025*** (0.333)
Inflation, $\sum_{j=1}^4 \beta_j$	-1.709*** (0.160)	-2.511*** (0.176)	-3.380*** (0.187)
GDP growth, $\sum_{j=1}^4 \gamma_j$	0.452*** (0.044)	0.928*** (0.055)	0.486*** (0.067)
Exp. GDP growth, $\sum_{j=1}^4 \sigma_j$			2.144*** (0.181)
<u>Bank-level controls</u>			
Loans, $\sum_{j=1}^4 \alpha_j$	0.467*** (0.010)	-0.110*** (0.015)	-0.112*** (0.015)
Assets, $\sum_{j=1}^4 \phi_j$		-20.923*** (0.762)	-20.985*** (0.771)
Tangible equity, $\sum_{j=1}^4 \chi_j$		1.152*** (0.129)	1.111*** (0.129)
Liquidity <sub>it-1</sub> , $\zeta$	0.207*** (0.028)	0.358*** (0.035)	0.899*** (0.060)
<u>Macroeconomic*Bank-level controls</u>			
Liquidity <sub>it-1</sub> *Aggr. Uncertainty, $\sum_{j=1}^4 \lambda_j$	0.087*** (0.009)	0.108*** (0.009)	0.087*** (0.010)
Liquidity <sub>it-1</sub> *Inflation, $\sum_{j=1}^4 \eta_j$	0.051*** (0.005)	0.079*** (0.005)	0.102*** (0.005)
Liquidity <sub>it-1</sub> *GDP growth, $\sum_{j=1}^4 \tau_j$	-0.007*** (0.001)	-0.017*** (0.001)	-0.004** (0.002)
Liquidity <sub>it-1</sub> *Exp. GDP growth, $\sum_{j=1}^4 \theta_j$			-0.054*** (0.005)
Constant	-4.775* (2.859)	192.228*** (9.503)	173.171*** (10.305)
Number of obs.	946,257	933,930	933,930
2nd order zero AC test			
in 1st-diff. errors (p-value)	0.004	0.419	0.449
Goodness-of-fit <sup>1</sup>	0.105	0.037	0.036

Note: Blundell-Bond (1998). Robust standard errors reported in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

The instruments include 4 lags of the first difference of all exogenous regressors, 4 lags of the dependent variable, and 4 lags of the predetermined variable (liquidity) for the difference equation. For the level equation, the instruments include the lagged first difference of the dependent variable and the predetermined variable (liquidity).

<sup>1</sup> Following Windmeijer [1995], the goodness-of-fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

Table 3. Individual Coefficients

Dep. var.: Total Loans growth	(1) Baseline	(2) Bank controls	(3) Expected GDP
Uncertainty <sub>t-1</sub> , $\delta_1$	-0.208* (0.107)	-0.309*** (0.108)	0.042 (0.110)
Uncertainty <sub>t-2</sub> , $\delta_2$	-0.566*** (0.102)	-0.596*** (0.106)	-0.169 (0.116)
Uncertainty <sub>t-3</sub> , $\delta_3$	-0.631*** (0.104)	-0.915*** (0.110)	-0.817*** (0.113)
Uncertainty <sub>t-4</sub> , $\delta_4$	-0.751*** (0.108)	-1.027*** (0.110)	-1.080*** (0.119)
Liquidity <sub>it-1</sub> *Uncertainty <sub>t-1</sub> , $\lambda_1$	0.012*** (0.003)	0.018*** (0.003)	0.007** (0.003)
Liquidity <sub>it-1</sub> *Uncertainty <sub>t-2</sub> , $\lambda_2$	0.016*** (0.003)	0.019*** (0.003)	-0.010*** (0.003)
Liquidity <sub>it-1</sub> *Uncertainty <sub>t-3</sub> , $\lambda_3$	0.026*** (0.003)	0.031*** (0.003)	0.024*** (0.003)
Liquidity <sub>it-1</sub> *Uncertainty <sub>t-4</sub> , $\lambda_4$	0.033*** (0.003)	0.040*** (0.003)	0.046*** (0.003)

Note: Blundell-Bond (1998). Robust standard errors reported in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

### C. Alternative Measures of Uncertainty

Because there is no definite measure of aggregate uncertainty, robustness checks are presented with alternative measures of uncertainty. I show that the effect of uncertainty on the lending channel of monetary policy is robust to the choice of this measure. The results are in Table 4.

The first test, presented in the second column, consists in breaking down nominal uncertainty in its real and inflation components. The two measures also come from the Survey of Professional Forecasters and are computed in a similar manner as uncertainty related to nominal GDP. The results hold and, while uncertainty related to real GDP and inflation are highly correlated (65.2 percent), only expectations about real GDP matter for bank lending decisions, which can be explained by a context of low inflation over the sample period in the U.S.

Secondly, I use as an alternative measure of uncertainty the same dispersion of professional forecasts but instead of looking at 4-quarter ahead forecasts, I use a shorter horizon corresponding to a 2-quarter ahead forecast. The indirect effect of uncertainty through its interaction with liquidity remains significant. However, the magnitude is somewhat smaller and the direct effect of uncertainty on bank lending is no longer significant. This finding may be driven by the fact that uncertainty over shorter horizons is less important because the average maturity of loans is larger than 2 quarters.

As a third robustness check, I resort to an econometric measure of uncertainty proposed by Jurado et al. [2013]. It is constructed as the common variation in uncertainty across many series (132 macroeconomic and 147 financial indicators) in order to eliminate the dependence on any particular series and offers a much more persistent measure than most other proxies. Results for the 1-year ahead forecasts are presented here, but similar results are obtained with the other measures proposed by Jurado et al. [2013]. As above, uncertainty is found to have no direct effect but a significant indirect effect through liquidity.

Another popular measure comes from the University of Michigan Surveys of Consumers. This measure is forward looking and focuses on consumers' uncertainty. Like my baseline measure, it is forward looking with a 4 quarter horizon. The results presented here correspond to the consumers' expectations regarding business conditions (series T28). Similar results are obtained with the Index of Consumers' Expectations (ICE)

Finally, an alternative measure of uncertainty is obtained from financial markets, in particular stock market volatility. In principle, the VIX would have been my default choice since it is a direct measure of market expectation of near-term volatility of S&P500 stock index options. Unfortunately, the VIX is computed starting only in 1990. Instead, I use the annualized standard deviation of daily returns of the S&P500, which allows to go back in time as long as needed. The correlation between this measure and the VIX for the overlapping period is 76 %, but is only weakly correlated with the baseline measure (6.25 percent over the sample period). As discussed earlier in the paper, uncertainty may stem from different factors and the low correlation in part reflects these measures capturing different sources of uncertainty. In particular, this new measure captures directly financial uncertainty and thus is narrower than my baseline measure. In terms of signs and statistical significance, the results are quite similar to the specification shown in the first column.

An alternative way to account for financial volatility, which is not pursued here, is to use GARCH models. However, I prefer to avoid using a generated regressor and rely entirely on market or expectation surveys data.



Table 4. Alternative Measures of Uncertainty

Dep. var.: Total Loans growth	(3) Forecasts T+4	(4) Breakdown	(5) Forecasts T+2	(6) Jurado et al.	(7) Consumer sentiment	(8) Financial Vol.
<u>Macroeconomic controls</u>						
Aggr. Uncertainty (nominal), $\sum_{j=1}^4 \delta_j$	-2.025*** (0.333)		-0.255 (0.309)	0.241 (0.147)	-0.072*** (0.005)	-0.991*** (0.233)
Aggr. Uncertainty (real), $\sum_{j=1}^4 \delta_j$		-1.075*** (0.327)				
Aggr. Uncertainty (inflation), $\sum_{j=1}^4 \delta_j$		0.039 (0.340)				
Inflation, $\sum_{j=1}^4 \beta_j$	-3.380*** (0.187)	-2.578*** (0.202)	-2.833*** (0.179)	-2.889*** (0.188)	-3.968*** (0.210)	-2.901*** (0.180)
GDP growth, $\sum_{j=1}^4 \gamma_j$	0.486*** (0.067)	0.471*** (0.059)	0.475*** (0.064)	0.662*** (0.070)	1.089*** (0.071)	0.508*** (0.066)
Exp. GDP growth (nominal), $\sum_{j=1}^4 \sigma_j$	2.144*** (0.181)		2.168*** (0.190)	2.347*** (0.176)	2.222*** (0.167)	2.250*** (0.185)
Exp. GDP growth (real), $\sum_{j=1}^4 \sigma'_j$		2.891*** (0.182)				
Exp. inflation, $\sum_{j=1}^4 \sigma''_j$		1.478*** (0.225)				
<u>Bank-level controls</u>						
Loans, $\sum_{j=1}^4 \alpha_j$	-0.112*** (0.015)	-0.131*** (0.015)	-0.107*** (0.015)	-0.137*** (0.015)	-0.113*** (0.015)	-0.117*** (0.014)
Assets, $\sum_{j=1}^4 \phi_j$	-20.985*** (0.771)	-20.952*** (0.768)	-20.875*** (0.763)	-21.297*** (0.789)	-20.911*** (0.767)	-21.295*** (0.773)
Tangible equity, $\sum_{j=1}^4 \chi_j$	1.111*** (0.129)	1.103*** (0.128)	1.104*** (0.128)	1.035*** (0.131)	1.147*** (0.129)	1.098*** (0.128)
Liquidity <sub>it-1</sub> , $\zeta$	0.899*** (0.060)	0.042*** (0.006)	0.890*** (0.063)	1.106*** (0.055)	0.773*** (0.054)	0.851*** (0.066)
<u>Macroeconomic*Bank-level controls</u>						
Liquidity <sub>it-1</sub> *Aggr. Uncertainty (nominal), $\sum_{j=1}^4 \lambda_j$	0.087*** (0.010)		0.054*** (0.009)	0.027*** (0.005)	0.002*** (0.000)	0.022*** (0.007)
Liquidity <sub>it-1</sub> *Aggr. Uncertainty (real), $\sum_{j=1}^4 \lambda'_j$		0.080*** (0.005)				
Liquidity <sub>it-1</sub> *Aggr. Uncertainty (inflation), $\sum_{j=1}^4 \lambda''_j$		-0.005 (0.006)				
Liquidity <sub>it-1</sub> *Inflation, $\sum_{j=1}^4 \eta_j$	0.102*** (0.005)	0.042*** (0.006)	0.080*** (0.005)	0.091*** (0.005)	0.119*** (0.006)	0.079*** (0.005)
Liquidity <sub>it-1</sub> *GDP growth, $\sum_{j=1}^4 \tau_j$	-0.004** (0.002)	-0.003** (0.002)	-0.003* (0.002)	-0.004*** (0.002)	-0.024*** (0.002)	-0.004*** (0.002)
Liquidity <sub>it-1</sub> *Exp. GDP growth (nominal), $\sum_{j=1}^4 \theta_j$	-0.054*** (0.005)		-0.050*** (0.005)	-0.067*** (0.005)	-0.054*** (0.004)	-0.045*** (0.005)
Liquidity <sub>it-1</sub> *Exp. GDP growth (real), $\sum_{j=1}^4 \theta_j$		0.061*** (0.009)				
Liquidity <sub>it-1</sub> *Exp. inflation, $\sum_{j=1}^4 \theta_j$		-0.011 (0.010)				
Constant	173.171 (10.305)	173.356 (10.150)	170.011*** (10.128)	170.118*** (10.241)	176.406*** (10.029)	178.587*** (10.734)
Number of obs.	933,930	933,930	933,930	879,809	933,930	933,930
2nd order zero AC test						
in 1st-diff. errors (p-value)	0.449	0.825	0.400	0.604	0.316	0.597
Goodness-of-fit <sup>1</sup>	0.036	0.036	0.036	0.034	0.036	0.036

Note: Blundell-Bond (1998). Robust standard errors reported in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

The instruments include 4 lags of the first difference of all exogenous regressors, 4 lags of the dependent variable, and 4 lags of the predetermined variable (liquidity) for the difference equation. For the level equation, the instruments include the lagged first difference of the dependent variable and the predetermined variable (liquidity).

<sup>1</sup> Following Windmeijer [1995], the goodness-of-fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

Table 5. Pairwise Correlations Between Alternative Measures of Uncertainty

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1)	1						
(2)	0.69	1					
(3)	0.57	0.65	1				
(4)	0.48	0.44	0.51	1			
(5)	0.17	0.18	0.07	0.48	1		
(6)	0.03	0.06	-0.03	-0.23	-0.50	1	
(7)	0.06	0.17	-0.01	0.41	0.60	-0.22	1

(1) Aggr. Uncertainty (nominal), 4 quarters ahead

(2) Aggr. Uncertainty (real), 4 quarters ahead

(3) Aggr. Uncertainty (inflation), 4 quarters ahead

(4) Aggr. Uncertainty (nominal), 2 quarters ahead

(5) Jurado et al.

(6) Consumers sentiment

(7) Financial volatility

## V. IMPLICATIONS FOR THE BANK LENDING CHANNEL OF MONETARY POLICY

### A. Controlling for the Lending Channel

Given that both monetary policy and uncertainty respond countercyclically to economic developments, the results could be driven by the existence of a lending channel of monetary policy. Since I am using a specification very similar to Kashyap and Stein [2000], the lending channel of monetary policy can directly be controlled for.

I do so by augmenting my regression equation with the change in the effective Federal Funds rate, as an indicator of monetary policy, following Bernanke and Blinder [1992] and Kashyap and Stein [2000]. The results are reported in Table 6, column (2). The conclusions are qualitatively similar to those in Kashyap and Stein [2000]: the positive  $\sum_{j=1}^4 \lambda_j$  implies that banks curtail lending after a monetary tightening, but less liquid banks do so more strongly than banks with more liquid balance sheets. Importantly, the result on uncertainty remain unchanged.

In the third column of Table 6, I augment the regression with a triple interaction between monetary policy, uncertainty, and liquidity. The coefficient is negative and significant, indicating that the higher the uncertainty in the economy, the less powerful the lending channel becomes. Therefore, uncertainty dampens the lending channel of monetary policy. Unlike Baum et al. [2013] who pursued a similar research question and found the lending channel was no longer significant when controlling for uncertainty, I find the opposite. The difference in conclusion may be the consequence of using a different sample: mine uses the universe of U.S. commercial banks, whereas theirs uses only bank holding corporations. More importantly, they measure uncertainty using stock market volatility, while I use a broader measure of uncertainty. Moreover, stock market volatility may be capturing market movements that are not necessarily reflecting a much higher uncertain environment from a bank's perspective. For instance, Figure 1 shows three important spikes in this indicator, one around 1987 (black Tuesday), one around 2003 (Invasion of Iraq), and the recent crisis. The spikes were pronounced but except for the most recent one there is no clear direct impact on banks' perception of risks.

The dampening of the lending channel can also arise from the perspective of liquidity injections in the banking sector as those introduced during the crisis. If those injections take place while uncertainty is rising, their total impact on lending will be dampened by uncertainty.

Table 6. Uncertainty and the Lending Channel

Dep. var.: Total Loans growth	(9) Kashyap & Stein specification	(10) + Uncertainty	(11) + Uncertainty *M. Policy
<u>Macroeconomic controls</u>			
Aggr. Uncertainty, $\sum_{j=1}^4 \delta_j$		-2.347*** (0.332)	-2.363*** (0.339)
Inflation, $\sum_{j=1}^4 \beta_j$	-1.783*** (0.166)	-3.070*** (0.183)	-3.190*** (0.185)
GDP growth, $\sum_{j=1}^4 \gamma_j$	1.237*** (0.049)	0.824*** (0.068)	0.794*** (0.069)
Expected GDP growth, $\sum_{j=1}^4 \sigma_j$		2.447*** (0.180)	2.595*** (0.190)
Mon. pol., $\sum_{j=1}^4 \omega_j$	-2.215*** (0.147)	-2.543*** (0.149)	-2.915*** (0.200)
<u>Bank-level controls</u>			
Loans, $\sum_{j=1}^4 \alpha_j$	-0.112*** (0.015)	-0.121*** (0.015)	-0.120*** (0.015)
Assets, $\sum_{j=1}^4 \phi_j$	-20.816*** (0.771)	-20.859*** (0.779)	-20.808*** (0.779)
Tangible equity, $\sum_{j=1}^4 \chi_j$	1.190*** (0.129)	1.118*** (0.129)	1.127*** (0.129)
Liquidity, $\zeta$	0.659*** (0.034)	1.088*** (0.061)	1.093*** (0.064)
<u>Macroeconomic*Bank-level controls</u>			
Liquidity <sub>it-1</sub> *Aggr. Uncertainty, $\sum_{j=1}^4 \lambda_j$	0.009 (0.005)	0.093*** (0.010)	0.095*** (0.010)
Liquidity <sub>it-1</sub> *Inflation, $\sum_{j=1}^4 \eta_j$	0.051*** (0.005)	0.092*** (0.005)	0.093*** (0.005)
Liquidity <sub>it-1</sub> *GDP growth, $\sum_{j=1}^4 \tau_j$	-0.024*** (0.002)	-0.013*** (0.002)	-0.012*** (0.002)
Liquidity <sub>it-1</sub> *Expected GDP growth, $\sum_{j=1}^4 \theta_j$		-0.062*** (0.005)	-0.064*** (0.005)
Liquidity <sub>it-1</sub> *Mon. pol., $\sum_{j=1}^4 \mu_j$	0.063*** (0.004)	0.071*** (0.004)	0.072*** (0.006)
Uncertainty <sub>t-1</sub> *Mon. pol.			0.092*** (0.292)
Liquidity <sub>it-1</sub> *Uncertainty <sub>t-1</sub> *Mon. pol.			-0.011*** (0.008)
Constant	-14.637*** (2.897)	-10.417*** (2.922)	162.995*** (10.836)
Number of obs.	933,930	933,930	933,930
2nd order zero AC test in 1st-diff. errors (p-value)	0.516	0.603	0.670
Goodness-of-fit <sup>1</sup>	0.037	0.036	0.036

Note: Blundell-Bond (1998). Robust standard errors reported in parenthesis. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

The instruments include 4 lags of the first difference of all exogenous regressors, 4 lags of the dependent variable, and 4 lags of the predetermined variable (liquidity) for the difference equation. For the level equation, the instruments include the lagged first difference of the dependent variable and the predetermined variable (liquidity).

<sup>1</sup> Following Windmeijer [1995], the goodness-of-fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

## **B. Excluding the Crisis Period**

During the recent crisis, a number of intervention policies and changes in regime (i.e. interest payments on bank reserves, new emergency liquidity facilities, TARP, etc.) may have altered bank behavior. Therefore, I check if the results are driven by the most recent observations by running the regression only up to 2008Q3.

For comparison purposes, I also include in Table 7 the regression results reported in column 3 of Table 6. The effect of uncertainty remains significant. While the magnitude of the direct effect on loan growth is unchanged, the results show that its indirect effect became more important during the crisis. Indeed, the coefficients on the interaction between uncertainty and liquidity as well as the triple interaction term increase respectively by 20 percent and 90 percent in absolute value when the crisis is included in the sample. Another difference to highlight is an increased importance of GDP growth (past and expected) on influencing lending.

Table 7. Results With and Without Crisis Period

	(11)	(12)
Dep. var.: Total Loans growth	Incl. crisis	Excl. crisis
<u>Macroeconomic controls</u>		
Aggr. Uncertainty, $\sum_{j=1}^4 \delta_j$	-2.363*** (0.339)	-2.383*** (0.386)
Inflation, $\sum_{j=1}^4 \beta_j$	-3.190*** (0.185)	-3.920*** (0.262)
GDP growth, $\sum_{j=1}^4 \gamma_j$	0.794*** (0.069)	0.733*** (0.078)
Expected GDP growth, $\sum_{j=1}^4 \sigma_j$	2.595*** (0.190)	2.424*** (0.190)
Mon. pol., $\sum_{j=1}^4 \omega_j$	-2.915*** (0.200)	-1.946*** (0.233)
<u>Bank-level controls</u>		
Loans, $\sum_{j=1}^4 \alpha_j$	-0.120*** (0.015)	-0.146*** (0.015)
Assets, $\sum_{j=1}^4 \phi_j$	-20.808 (0.779)	-21.091*** (0.808)
Tangible equity, $\sum_{j=1}^4 \chi_j$	1.127*** (0.129)	1.152*** (0.136)
Liquidity, $\zeta$	1.093*** (0.064)	0.886*** (0.066)
<u>Macroeconomic*Bank-level controls</u>		
Liquidity <sub>it-1</sub> *Aggr. Uncertainty, $\sum_{j=1}^4 \lambda_j$	0.095*** (0.010)	0.078*** (0.011)
Liquidity <sub>it-1</sub> *Inflation, $\sum_{j=1}^4 \eta_j$	0.093*** (0.005)	0.119*** (0.007)
Liquidity <sub>it-1</sub> *GDP growth, $\sum_{j=1}^4 \tau_j$	-0.012*** (0.002)	-0.008*** (0.002)
Liquidity <sub>it-1</sub> *Expected GDP growth, $\sum_{j=1}^4 \theta_j$	-0.064*** (0.005)	-0.058*** (0.005)
Liquidity <sub>it-1</sub> *Mon. pol., $\sum_{j=1}^4 \mu_j$	0.072*** (0.006)	0.045*** (0.007)
Uncertainty <sub>t-1</sub> *Mon. pol.	0.092*** (0.292)	0.438 (0.298)
Liquidity <sub>it-1</sub> *Uncertainty <sub>t-1</sub> *Mon. pol.	-0.011*** (0.008)	-0.001*** (0.008)
Constant	162.995*** (10.836)	171.866*** (10.523)
Number of obs.	933,930	
2nd order zero AC test in 1st-diff. errors (p-value)	0.670	0.629
Goodness-of-fit <sup>1</sup>	0.036	0.035

Note: Blundell-Bond (1998). Robust standard errors reported in parenthesis.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1. The instruments include 4 lags of the first difference of all exogenous regressors, 4 lags of the dependent variable, and 4 lags of the predetermined variable (liquidity) for the difference equation. For the level equation, the instruments include the lagged first difference of the dependent variable and the predetermined variable (liquidity).

<sup>1</sup> Following Windmeijer [1995], the goodness-of-fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

### **C. Differentiating Among Types of Loans**

The next exercise is to examine the behavior of uncertainty across different types of loans. This step aims at ruling out the possibility that banks operating predominantly in one type of loan are systematically more liquid than banks concentrated in other market segments. Concretely, suppose for instance that the demand for C&I loans is highly procyclical, and the demand for other type of loans is acyclical. Suppose also that banks that happen to be more active in the C&I loans segment are also banks that have more liquidity. These banks will lend more in expansions than banks concentrated in other types of loans, total loans for these banks will grow more than for other banks. Because uncertainty is countercyclical, the regressions on total loans would capture the correlation between the cyclicalities of the bank's business model and its liquidity position. This may be a stretch, but I nevertheless address concerns of this type by partitioning the sample according to loan type and examine if the results continue to hold for individual loan types. If the results hold for a given loan type, this potential explanation can be ruled out.

Table 8 shows the results of estimating specification (11) for C&I, real estate, and individual loans. The results continue to hold for the three types of loans considered. The direct and indirect effects of uncertainty on lending particularly are stronger for C&I and real estate loans, which is logical given that the banks' risk exposure in terms of volume and maturities is much higher with C&I and real estate loans than individual loans.

### **D. Result by Bank Size**

As it was the case for loan types discussed above, a similar concern may arise if systematically small banks hold more liquidity, which in fact is the case as discussed in Kashyap and Stein [2000]. If these banks also lend to less cyclical borrowers, then in a downturn, when uncertainty goes up, lending by these banks shrinks relatively less but because they also hold more liquid assets, the result is partly attributed to changes in uncertainty. While I control for size in my regressions already, I conduct a more stringent test and partition the sample according to three groups, small, medium, and large banks. These groups correspond to banks below the 95th, between 95th and 99th, and above the 99th percentile of assets, respectively.

The results presented in Table 9 show that the effects of uncertainty documented in previous regressions still hold within the classes of small- and medium-sized banks, which rules out the possibility of a correlation between cyclicalities of demand and bank size. Notice, however, that the results do not hold for large banks. The model presented in Valencia [2013] offers some intuition to what other channels monopolistic banks can use to shield their business from future unexpected shocks. In reality, large banks have many more alternatives than the simple one captured in this model. They may be relatively less affected by financial frictions, they benefit from implicit insurance schemes such as too big to fail, better diversification of risks, and the benefit from flight to quality during downturns when depositors of small banks may perceive these large institutions as safer. Also note that the direct and indirect effects of uncertainty are stronger for medium banks than for small banks. This is not surprising given the results of the previous section and the fact that the portfolio of medium banks have a higher share of C&I and real estate loans than small banks.

Table 8. Results by Loan Type

Dep. var.: Total Loans growth	(13) C&I	(14) Individual	(15) Real Estate
<u>Macroeconomic controls</u>			
Aggr. Uncertainty, $\sum_{j=1}^4 \delta_j$	-3.807*** (0.671)	-1.050** (0.492)	-3.051*** (0.362)
Inflation, $\sum_{j=1}^4 \beta_j$	-3.781*** (0.372)	-2.267*** (0.299)	-1.052*** (0.191)
GDP growth, $\sum_{j=1}^4 \gamma_j$	0.970*** (0.129)	0.757*** (0.094)	0.666*** (0.071)
Expected GDP growth, $\sum_{j=1}^4 \sigma_j$	2.736*** (0.342)	1.226*** (0.235)	1.337*** (0.193)
Mon. pol., $\sum_{j=1}^4 \omega_j$	-3.720*** (0.435)	-1.099*** (0.308)	-2.522*** (0.225)
<u>Bank-level controls</u>			
Loans, $\sum_{j=1}^4 \alpha_j$	-0.126*** (0.010)	-0.000 (0.010)	0.021** (0.010)
Assets, $\sum_{j=1}^4 \phi_j$	-29.518*** (0.979)	-19.778*** (0.855)	-18.768*** (0.638)
Tangible equity, $\sum_{j=1}^4 \chi_j$	0.444** (0.186)	0.079 (0.163)	0.490*** (0.129)
Liquidity, $\zeta$	1.297*** (0.113)	0.529*** (0.075)	0.624*** (0.061)
<u>Macroeconomic*Bank-level controls</u>			
Liquidity <sub>it-1</sub> *Aggr. Uncertainty, $\sum_{j=1}^4 \lambda_j$	0.104*** (0.020)	0.046*** (0.014)	0.099*** (0.010)
Liquidity <sub>it-1</sub> *Inflation, $\sum_{j=1}^4 \eta_j$	0.200*** (0.011)	0.070*** (0.008)	0.029*** (0.005)
Liquidity <sub>it-1</sub> *GDP growth, $\sum_{j=1}^4 \tau_j$	-0.012*** (0.004)	-0.010*** (0.003)	-0.012*** (0.002)
Liquidity <sub>it-1</sub> *Expected GDP growth, $\sum_{j=1}^4 \theta_j$	-0.058*** (0.009)	-0.030*** (0.006)	-0.038*** (0.005)
Liquidity <sub>it-1</sub> *Mon. pol., $\sum_{j=1}^4 \mu_j$	1.103*** (0.013)	0.042*** (0.008)	0.054*** (0.006)
Uncertainty <sub>t-1</sub> *Mon. pol.	1.906*** (0.715)	0.422 (0.493)	0.215 (0.368)
Liquidity <sub>it-1</sub> *Uncertainty <sub>t-1</sub> *Mon. pol.	-0.057*** (0.021)	0.010 (0.013)	-0.018* (0.010)
Constant	242.328*** (13.861)	172.467*** (10.781)	172.858*** (9.032)
Number of obs.	915,082	920,403	923,140
2nd order zero AC test in 1st-diff. errors (p-value)	0.958	0.190	0.658
Goodness-of-fit <sup>1</sup>	0.023	0.019	0.019

Note: Blundell-Bond (1998). Robust standard errors reported in parenthesis.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

The instruments include 4 lags of the first difference of all exogenous regressors, 4 lags of the dependent variable, and 4 lags of the predetermined variable (liquidity) for the difference equation. For the level equation, the instruments include the lagged first difference of the dependent variable and the predetermined variable (liquidity).

<sup>1</sup> Following Windmeijer [1995], the goodness-of-fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.

Table 9. Results by Bank Size

Dep. var.: Total Loans growth	(16) Small	(17) Medium	(18) Large
<u>Macroeconomic controls</u>			
Aggr. Uncertainty, $\sum_{j=1}^4 \delta_j$	-1.478*** (0.354)	-6.007*** (1.782)	-0.109 (5.921)
Inflation, $\sum_{j=1}^4 \beta_j$	-2.719*** (0.192)	-0.820 (0.864)	0.097 (3.650)
GDP growth, $\sum_{j=1}^4 \gamma_j$	0.726*** (0.074)	0.888** (0.368)	0.858 (1.178)
Expected GDP growth, $\sum_{j=1}^4 \sigma_j$	2.281*** (0.202)	0.022 (1.013)	-1.670 (3.403)
Mon. pol., $\sum_{j=1}^4 \omega_j$	-2.866*** (0.213)	-0.409 (1.080)	-0.052 (5.185)
<u>Bank-level controls</u>			
Loans, $\sum_{j=1}^4 \alpha_j$	-0.166*** (0.015)	-0.324*** (0.067)	-0.368 (0.484)
Assets, $\sum_{j=1}^4 \phi_j$	-23.897*** (0.778)	-25.409*** (1.649)	-8.433*** (1.383)
Tangible equity, $\sum_{j=1}^4 \chi_j$	0.810*** (0.810)	0.337 (0.337)	0.333 (0.333)
Liquidity, $\zeta$	1.133*** (0.069)	0.599 (0.443)	0.047* (1.487)
<u>Macroeconomic*Bank-level controls</u>			
Liquidity <sub>it-1</sub> *Aggr. Uncertainty, $\sum_{j=1}^4 \lambda_j$	0.063*** (0.010)	0.181*** (0.061)	-0.145 (0.245)
Liquidity <sub>it-1</sub> *Inflation, $\sum_{j=1}^4 \eta_j$	0.079*** (0.006)	0.054* (0.031)	-0.079 (0.157)
Liquidity <sub>it-1</sub> *GDP growth, $\sum_{j=1}^4 \tau_j$	-0.009*** (0.002)	-0.016 (0.012)	0.037 (0.060)
Liquidity <sub>it-1</sub> *Expected GDP growth, $\sum_{j=1}^4 \theta_j$	-0.056*** (0.005)	-0.006 (0.035)	0.007 (0.140)
Liquidity <sub>it-1</sub> *Mon. pol., $\sum_{j=1}^4 \mu_j$	0.072*** (0.006)	0.046 (0.037)	0.034 (0.034)
Uncertainty <sub>t-1</sub> *Mon. pol.	0.999*** (0.306)	-1.519 (1.519)	-0.428 (7.699)
Liquidity <sub>it-1</sub> *Uncertainty <sub>t-1</sub> *Mon. pol.	-0.016* (0.009)	-0.007 (0.051)	-0.021 (0.314)
Constant	192.293*** (10.536)	289.681*** (24.075)	129.289*** (37.211)
Number of obs.	829,598	27,516	5,860
2nd order zero AC test in 1st-diff. errors (p-value)	0.882	0.725	0.825
Goodness-of-fit <sup>1</sup>	0.032	-0.027	-0.008

Note: Blundell-Bond (1998). Robust standard errors reported in parenthesis.\*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

The instruments include 4 lags of the first difference of all exogenous regressors, 4 lags of the dependent variable, and 4 lags of the predetermined variable (liquidity) for the difference equation. For the level equation, the instruments include the lagged first difference of the dependent variable and the predetermined variable (liquidity).

<sup>1</sup> Following Windmeijer [1995], the goodness-of-fit measure is the squared correlation coefficient between actual and predicted levels of the dependent variable.



## E. Aggregate effect

This study addresses simultaneity concerns by resorting to micro data. This highlights the qualitative importance of uncertainty in shaping the lending behavior of banks, but comes with the cost that the results do not hold in the aggregate. However, I resort to differential marginal effects to compare the quantitative importance of the indirect effect of uncertainty on lending, through its interaction with balance sheet strength and through the stance of monetary policy. My key variables are the estimated coefficients on the interaction between uncertainty and liquidity (the  $\lambda_j$ ) and on the triple interaction term, and I look at the differential marginal effect between a bank at the 25th percentile of liquidity and a bank at the 75th percentile of liquidity using the data provided in Table 1. Notice that this is only the impact effect, the total effect will be larger once the dynamic effects of loan growth are factored in.

Figures 2 and 3 plot the differential marginal effects by time period, loan type and bank size. The magnitudes of the effect for each segment (in light grey) are compared to the baseline results (in dark grey). Non-significant results are shown as bars with no fill. Figure 2 shows the differential marginal effects of uncertainty through its interaction with the strength of the bank's balance sheet, while Figure 3 shows the differential marginal effects of uncertainty through the stance of monetary policy. The purpose of the graphs is to visually compare the relative magnitude of the differential effects. In Figure 2, a one percent increase in uncertainty triggers a differential response of 0.095 percent on average in a quarter between a bank at the 25th percentile and the 75th percentile of liquidity, but this magnitude does not vary much across time period, loan type and bank size. Figure 2 suggests that the differential response is much more marked through the bank lending channel: it increases by a factor 10 when the Great Recession is included in the sample, and by a factor 5 for C&I loans compared to total loans.

Figure 2. Differential Marginal Effect of Uncertainty on Bank Lending Through the Bank's Liquidity Position

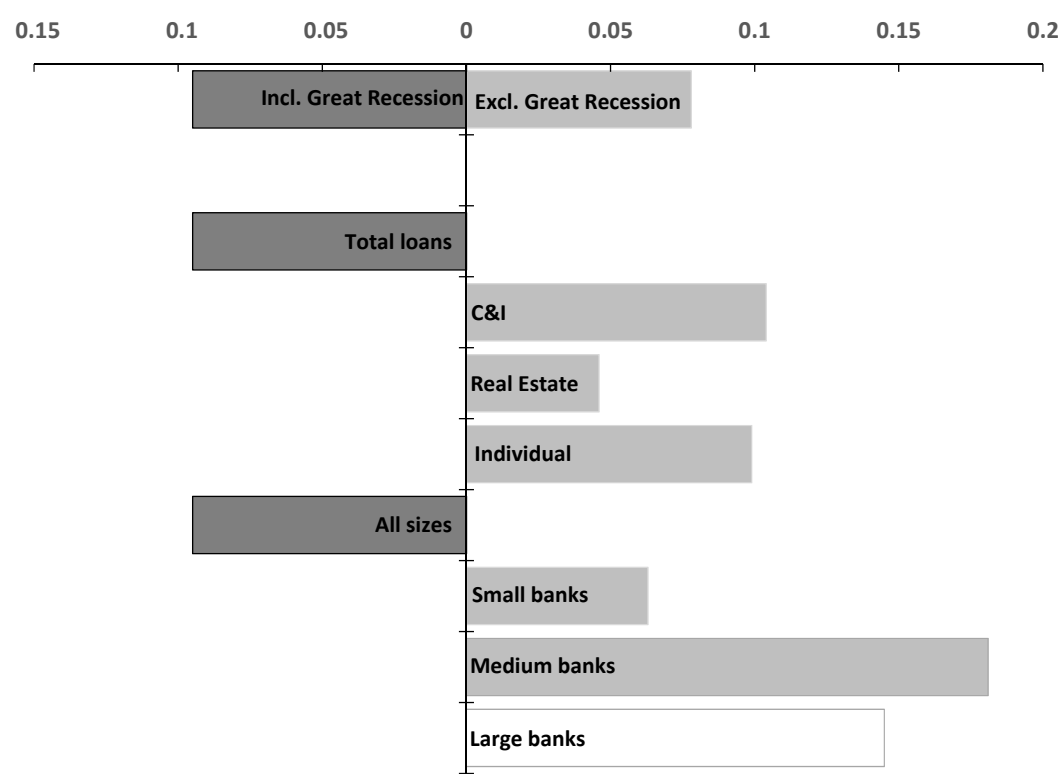
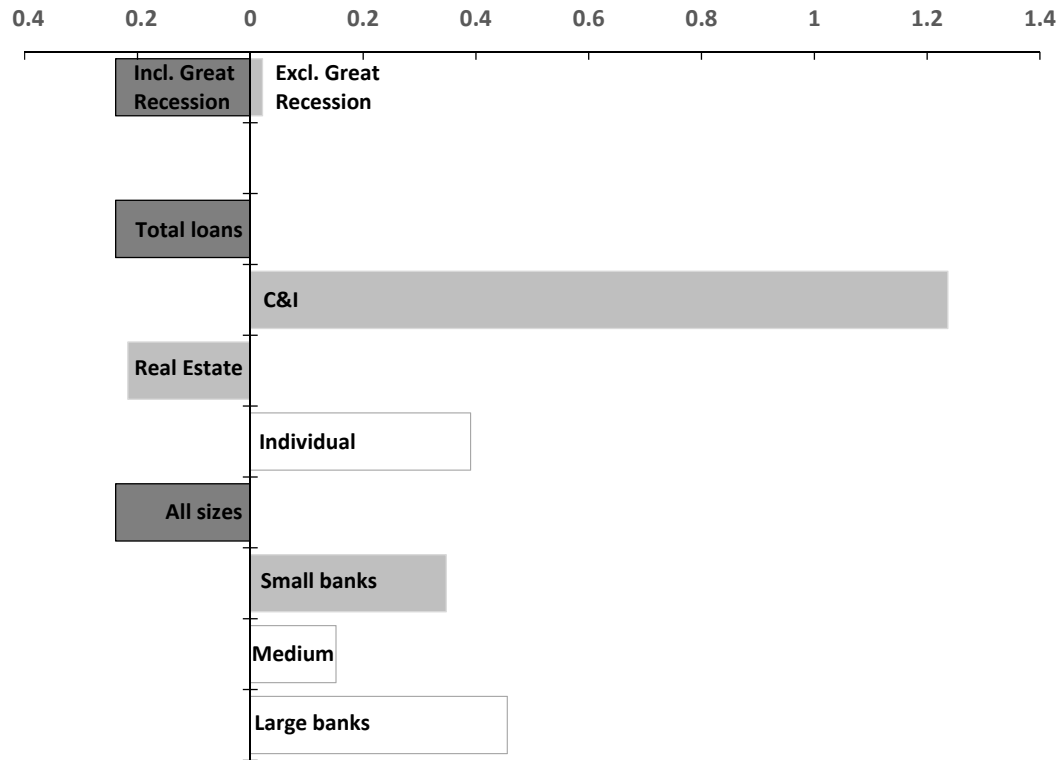


Figure 3. Differential Marginal Effect of Uncertainty on Bank Lending Through the Bank Lending Channel



## VI. CONCLUSIONS

This paper exploits the cross-sectional variation in U.S. commercial banks balance sheet strength, in particular in the degree of liquidity, to examine how aggregate uncertainty influences the supply of credit. It finds evidence that increases in uncertainty are associated with a reduction in the supply of credit, more so at less liquid banks. This direct and indirect effect of uncertainty on bank lending are robust to the inclusion of bank controls and changes in the mean forecasts, and hold with different measures of uncertainty. This paper also highlights the indirect effect of uncertainty through the stance of monetary policy by controlling for the lending channel of monetary policy and including a triple interaction term between uncertainty, liquidity and monetary policy. The results hold when controlling for the bank lending channel of monetary policy, suggesting that uncertainty negatively affects loan growth through the stance of monetary policy. This indirect effect is all the stronger as the bank's precautionary motive is high, i.e. when the proportion of C&I and real estate loans is high, and when the bank is small. If one had data on aggregate uncertainty at the regional level, an interesting extension of this paper would consist in looking at the differential response of banks according to their location, an idea that has been undertaken by Chodorow-Reich [2014] in a different context.

## REFERENCES

- Yener Altunbas, Leonardo Gambacorta, and David Marques. The bank lending channel: Lessons from the crisis. *European Economic Review*, 53:996–1009, 2009.
- Cristina Arellano, Yan Bai, and Patrick Kehoe. Financial markets and fluctuations in uncertainty. *Federal Reserve Bank of Minneapolis, Research Department Staff Report*, 2011.
- Manuel Arellano and Stephen R. Bond. Some tests of specification for panel data: Monte carlo evidence and an application to employment equations. *Review of Economic Studies*, 58: 277–297, 1991.
- Manuel Arellano and Olympia Bover. Another look at the instrumental-variable estimation of errorcomponents models. *Journal of Econometrics*, 68:29–51, 1995.
- Christopher Baum, Mustafa Caglayan, and Neslihan Ozkan. The role of uncertainty in the transmission of monetary policy effects on bank lending. *The Manchester School*, 81(2): 202–225, March 2013.
- Ben S. Bernanke. The financial accelerator and the credit channel. Speech at the conference on the credit channel of monetary policy in the twenty-first century conference, 2007.
- Ben S. Bernanke and Alan S. Blinder. The federal funds rate and the channels of monetary policy. *The American Economic Review*, 82(4):901–921, September 1992.
- Ben S. Bernanke and Mark Gertler. Inside the black box: The credit channel of monetary policy transmission. *Journal of Economic Perspectives*, 9(4):27–48, 1995.
- Lamont Black and Richard J. Rosen. The effect of monetary policy on the availability of credit: How the credit channel works. *FRB of Chicago Working Papers Series*, 13, 2007.
- Nicholas Bloom, Max Floetotto, Nir Jaimovich, Itay Saporta-Eksten, and Stephen Terry. Really uncertain business cycles. *Stanford University mimeo*, 2011.
- Nick Bloom, Stephen Bond, and John Van Reenen. Uncertainty and investment dynamics. *Review of Economic Studies*, 74:391–415, 2007.
- Richard W. Blundell and Stephen R. Bond. Initial conditions and moment restrictions in dynamic panel data models. *Journal of Econometrics*, 87:115–143, 1998.
- Markus K. Brunnermeier and Yuliy Sannikov. A macroeconomic model with a financial sector. 2014.
- Gabriel Chodorow-Reich. The employment effects of credit market disruptions: Firm-level evidence from the 2008-2009 financial crisis. *Quarterly Journal of Economics*, 129(1):1–59, 2014.
- Manthos D. Delis, Georgios P. Kouretas, and Chris Tsoumas. Anxious periods and bank lending. *Journal of Banking and Finance*, 38:1–13, 2014.

- Wouter J. Den Haan, Steven W. Sumner, and Guy Yamashiro. Construction of aggregate and regional bank data using the call reports. Technical report, 2002. University of Amsterdam unpublished manuscript.
- Douglas W. Diamond and Raghuram G. Rajan. A theory of bank capital. *The Journal of Finance*, 55(6):2431–2465, December 2000.
- Piti Disyatat. The bank lending channel revisited. *Journal of Money, Credit and Banking*, 43: 711–734, 2011.
- Leonardo Gambacorta and David Marques-Ibanez. The bank lending channel: Lessons from the crisis. *Economic Policy*, 26(66):135–182, 2011.
- Mark Gertler, Nobuhiro Kiyotaki, and Albert Queralto. Financial crises, bank risk exposure and government financial policy. *New York University working paper*, 2011.
- Simon Gilchrist, Jae W. Sim, and Egon Zakrajšek. Uncertainty, financial frictions, and irreversible investment. 2013.
- Wouter Den Haan, Steven Sumner, and Guy Yamashiro. Bank loan components and the time-varying effects of monetary policy shocks. *Economica*, 78:593–617, 2011.
- Kyle Jurado, Sydney C. Ludvigson, and Serena Ng. Measuring uncertainty. *New York University and Columbia University mimeo*, 2013.
- A. Kashyap and J. Stein. What do a million observations on banks say about the transmission of monetary policy? *American Economic Review*, 90(3):407–428, 2000.
- Joe Peek and Eric S. Rosengren. Is bank lending important for the transmission of monetary policy? *Federal Reserve Bank of Boston*, 39:1–14, 1995.
- Fabián Valencia. Banks’ precautionary capital and credit crunches. Working Paper 08/248, International Monetary Fund, October 2008.
- Fabián Valencia. Monetary policy, bank leverage, and financial stability. Working Paper 11/244, International Monetary Fund, October 2011.
- Fabián Valencia. Aggregate uncertainty and the supply of credit. Working Paper 13/241, International Monetary Fund, November 2013.
- Skander Van Den Heuvel. The bank capital channel of monetary policy. unpublished manuscript, University of Pennsylvania, 2009.
- Frank Windmeijer. A note on  $r^2$  in the instrumental variables model. *Journal of Quantitative Economics*, 11:257–261, 1995.

# JEANNE VERRIER

jeanne.verrier@gmail.com ■ (202) 386-8483 ■ 336 U Street NW, Washington DC, 20001  
Citizenship: French (US work authorization)

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## » EDUCATION

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**Johns Hopkins University**, Economics Department, Baltimore  
*M.A. in Economics, 2012-2014*

**ESCP Europe**, Paris  
*Master in Management, 2005-2009*

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## » ACADEMIC DISTINCTIONS

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**George Owen Fellowship** for outstanding PhD students, Johns Hopkins University, *2012-2014*

**Economics Department Fellowship** (tuition & stipend), Johns Hopkins University, *2012-2014*

**First Prize** for Masters' Thesis in Economics (650 candidates), ESCP Foundation, *2009*

**Academic Distinction** for Undergraduate Thesis in Social Sciences (Top 30 over 545 candidates), *2006*

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## » RESEARCH

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"Do Macroeconomic Indicators Explain India's Sovereign Ratings?" (with Amaresh Samantaraya), *Journal of Applied Economic Research*, Jul.-Sep. 2009, No. 3, pp. 193-221

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## » WORK EXPERIENCE

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**Johns Hopkins University**, Economics Department, Baltimore  
*Teaching Assistant & Instructor, 2013-2014 (9 months)*

**International Monetary Fund**, Research Department, Washington DC  
*Research Assistant Program, 2009-2012 (3 years)*

**Reserve Bank of India**, Monetary Policy Department, Mumbai  
*Summer Trainee, 2008 (2 months)*

**BNP Paribas**, Energy and Commodities Department, Singapore branch  
*Junior Credit Analyst, 2007 (6 months)*

**French Ministry of Economy**, Trade Commission in Bangkok  
*Summer Intern, 2006 (2 months)*

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## » OTHER

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**Languages:** French (native), English (fluent), Italian (intermediate), German (beginner)

**IT skills:** Stata, MATLAB, Mathematica, LaTeX, R, EViews