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Do Banks Lend Less in Uncertain Times? *

Burkhard Raunig† Johann Scharler‡ Friedrich Sindermann§

Abstract

We study the development of bank lending in the U.S. after four large jumps in uncertainty using an event study approach. We find that more liquid banks reduce lending less than banks with smaller liquidity ratios after a surge in uncertainty. Lending by smaller banks is also less responsive to increases in uncertainty. Banks with a higher capitalization ratio keep up lending to a greater extent, but the effect is only significant for banks which are not part of a multi-bank holding company. This heterogeneity across banks suggests that declines in bank lending following increases in uncertainty are partly the result of a reduced supply of bank loans.

Keywords: uncertainty, bank loan supply, event study

JEL codes: E44, E20, E30

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1 Introduction

A large literature highlights the adverse effects of uncertainty on investment through a real options effect. If decisions are partially irreversible, the value of delaying an investment project increases with rising uncertainty.[1] Bloom (2009), Bloom et al. (2012), and Christiano et al. (2014) emphasize uncertainty shocks as a source of business cycle fluctuations.[2] Along similar lines, Romer (1990) argues that uncertainty about future incomes led to a reduction of the consumption of durable goods during the onset of the Great Depression.

While the existing literature focuses on the adverse consequences of uncertainty for investment and consumption, banks may also adjust their loan supply in times of higher uncertainty. The decision to grant a loan typically involves a longer-term commitment and is therefore not easily reversible, which may induce banks to follow a wait-and-see strategy leading to a restricted supply of loans in times of high uncertainty. A reduced supply of loans may thereby amplify the direct effects of higher uncertainty on households and firms, resulting in further declines in investment and consumption. In fact, it has been argued that uncertainty about their own liquidity (Brunnermeier, 2009) as well as uncertainty about future investment opportunities (Diamond and Rajan, 2009) induced banks to restrict lending during the crisis of 2007-2008, contributing to the downturn.

We extend the existing literature by studying how bank lending in the US reacts to large and sudden jumps in uncertainty. Since uncertainty may influence the amount of outstanding loans through shifts in both, supply and demand, we adopt an approach widely followed by the empirical literature analyzing the bank lending channel (see e.g. Kashyap and Stein, 2000) to disentangle supply and demand effects: we assume that the response of loan supply to an increase in uncertainty is heterogeneous across banks and depends on certain characteristics and balance sheet positions of individual banks, whereas uncertainty-driven fluctuations in the demand for bank loans affect banks largely symmetrically. To implement this approach, we use bank-level data as collected in the Call Reports.

Bloom (2009) identifies uncertainty shocks as large jumps in implied stock market volatility extracted from option prices. We analyze bank lending in the aftermath of four distinct spikes in this uncertainty indicator: the Black Monday of 1987, the Iraq conflict starting in 1990,

[1] See also Bernanke (1983), McDonald and Siegel (1986), Dixit and Pindyck (1994), Bertola and Caballero (1994), Abel and Eberly (1996), and Bloom et al. (2007).

[2] This view is not without controversy. Bachmann and Moscarini (2011) argue that causality runs from the business cycle to uncertainty. Choi (2013) finds that the influence of uncertainty shocks on the business cycle has declined over time.

the Asian Crisis of 1997, and the terrorist attack on September 11, 2001.[3] Since each of these four jumps is closely associated with an exogenous event that did not originate in the US banking sector, we are able to study the role of bank lending in the transmission of exogenous increases in uncertainty. Note that we exclude the financial crisis of 2007, since the US banking sector presumably was a source of the higher uncertainty rather than merely a channel for the transmission of uncertainty.[4] We also exclude certain increases in uncertainty considered in Bloom (2009), such as the accounting scandals in 2001 and 2002, which were not preceded by the prolonged 'calm period' that is required for measuring a bank's general condition at the time of the event.

Interpreting sudden jumps in uncertainty as distinct events and analyzing them in an event study framework has a number of advantages: First, we do not use the uncertainty indicator as a regressor, but only as a means to identify the events for our event study. Thus, we do not have to assume exogeneity of the uncertainty indicator for the full sample period, which would appear quite a strong assumption as causality may generally run in both directions. Second, we study the heterogeneity of loan growth across banks by relating growth developments following surges in uncertainty to the characteristics of a bank measured over a calm period preceding the event. Thereby, we are able to interpret these characteristics in a more structural way and avoid problems related to the potential endogeneity of bank characteristics. Third, measuring bank characteristics over calm periods also resolves potential problems of spurious correlation that might arise if uncertainty drives both, loan growth and balance sheet characteristics. Finally, averaging the banks' characteristics over two years is an effective and straightforward way to deal with issues of seasonality and erroneous reporting, which are quite common in the Call Report data.

We find that abnormal loan growth rates decline on average by 2.5 percentage points over the three quarters following a surge in uncertainty.[5] Bank lending in the aftermath of large jumps in uncertainty varies systematically and significantly across banks: Banks with high liquidity-to-asset ratios at the onset of an uncertainty event have higher loan growth rates in the quarters following the event than less liquid banks, suggesting that real options effects are

[3] On the Black Monday on October 19, 1987, stock markets around the world experienced large drops. The S&P 500 index plummeted by over 20%, which up to the day of writing is the largest single day drop in the history of the index. The Asian crisis started with the devaluation of the Thai baht in July 1997 and quickly spread to a number of other Asian countries.

[4] Bank lending during this period is studied, e.g., in Ivashina and Scharfstein (2010) and Cornett et al. (2011).

[5] We define abnormal loan growth as the deviation of actual loan growth from a bank-specific, average growth rate in our baseline estimation.

less pronounced for more liquid banks. Smaller banks, in terms of assets, also have higher loan growth. This result is consistent with the interpretation that small banks tend to have more idiosyncratic information on the creditworthiness of their customers, have more stable funding, and are more engaged in relationship banking, which entails liquidity insurance. These factors become particularly relevant during times of high uncertainty. The measured effects are also economically relevant: A one standard deviation increase in liquidity (decrease in size) increases the cumulative loan growth rates in the three quarters following a jump in uncertainty by 4 (6.5) percentage points, which corresponds to 16% (25.7%) of the average cross-sectional loan growth dispersion in the three months following an event. We find that capitalization is also a significant factor, but only for banks which are not part of a multi-bank holding company and are consequently not able to tap internal capital markets (Ashcraft, 2006). The effect is comparably small, however, with a one standard deviation increase in capitalization leading to a 0.7 percentage point increase in cumulative loan growth rates (2.7% of the average cross-sectional standard deviation) during periods of higher uncertainty.

Our paper is related to at least three other studies. Baum et al. (2009) show that the cross-sectional dispersion of US banks' loan-to-asset ratios is negatively related to various measures of uncertainty. Furthermore, Baum et al. (2013) find that uncertainty has a significant influence on the transmission of monetary policy. While these papers use either the conditional variance obtained from a GARCH model for industrial production or inflation, or a measure of interest rate uncertainty to proxy uncertainty, we define uncertainty events via the uncertainty shock indicator suggested by Bloom (2009) and apply an event study methodology. Delis et al. (2014) analyze a related, albeit somewhat distinct issue. They study bank lending during anxious periods, which they characterize as periods in which expectations worsen. Although they do not directly analyze the influence of uncertainty, it appears conceivable that anxious periods are also characterized by higher uncertainty to some extent. Using survey measures of consumer and business confidence, they find that bank lending reacts negatively to anxiety.

The remainder of the paper proceeds as follows: Section 2 describes the data and our estimation strategy. Section 3 presents the main results. In Section 4 we check the robustness of the results. Section 5 concludes the paper.

2 Data and Empirical Strategy

2.1 Uncertainty Events

To study the dynamics of bank lending in the aftermath of jumps in uncertainty, we first need to carefully define the dates on which these events took place. Given that bank-level data are available at a quarterly frequency, we define uncertainty events as quarters during which we observe unusually large jumps in volatility according to the indicator of stock market volatility in Bloom (2009). Bloom (2009) identifies these jumps as periods during which the Chicago Board Options Exchange (CBOE) volatility index (VXO)[6] lies at least 1.65 standard deviations above its Hodrick-Prescott trend. The VXO uses the price of a hypothetical 30-day at-the-money option on the S&P100 index to calculate the implied 30-day expected volatility of the index.

The main advantage of this indicator over alternative uncertainty measures is that it appears safe to assume that the identified events are exogenous with respect to the banking sector, as we will argue in greater detail below. Such an assumption would be much more problematic for measures which are directly related to uncertainty in the banking sector, such as measures of interbank market uncertainty or indicators based on the cross-sectional variation of bank micro data.

While Bloom's measure captures uncertainty in a very broad sense, it is still closely related to other measures of uncertainty. Comparisons with uncertainty measures calculated from firm-level data show that periods of high stock-market volatility tend to go along with above-average cross-sectional dispersion in firms' profit growth rates. Moreover, Bloom (2009) reports substantial correlations between stock-market volatility and uncertainty measures calculated from total factor productivity and from the Livingstone survey of professional forecasters.

We define an uncertainty event as an event occurring in the first quarter of each period of elevated implied stock market volatility as identified by Bloom (2009).[7] While Bloom (2009) reports a total of 17 large jumps in uncertainty between October 1962 and October 2008, we consider only jumps which occurred after the first quarter of 1984 as consistent bank-level data are not available prior to 1984. As many of these jumps in uncertainty occur relatively

[6] Since 2003, the CBOE also publishes the VIX, which is based on an updated methodology. However, as this index is only available for a shorter time-span, we follow Bloom (2009) in using the VXO series. The time series as well as methodological information can be retrieved from `http://www.cboe.com/micro/vix/historical.aspx`.

[7] Bloom (2009) uses the month with the maximum deviation from the HP trend. If this definition is applied, the event corresponding to the first Gulf War changes from 1990Q3 to 1990Q4. Using the quarters with the maximum deviation from the HP trend as event quarters does not change our results.

shortly after one another, an interpretation in terms of distinct events is problematic as we require a sufficiently long calm period between individual events to identify changes in lending associated with a specific event. Therefore, we exclude all surges in uncertainty that were preceded by another surge within a period of two years. We also exclude the last jump in uncertainty in 2007/2008 since this uncertainty episode was closely related to the banking sector itself. Although fluctuations in bank lending have probably played a role in the transmission of uncertainty to the real economy during this period, the banking sector itself may also have been a source of uncertainty. As such, this episode is not suitable for studying the role of the banking sector as part of the propagation mechanism and it would complicate the interpretation of the results due to endogeneity issues. This leaves us with four events: 1987Q4, 1990Q3, 1997Q4 and 2001Q3, which are closely connected to the Black Monday (1987Q4), the first Gulf War (1990Q3), the Asian Crisis (1997Q4), and September 11 (2001Q3). Note that although the events are closely associated with either wars, terrorist attacks, or financial events, the exact dates of the events used in our analysis are determined by the corresponding spike in the VXO.

Although we exclude the recent financial crisis, we include the surges in uncertainty associated with the Black Monday in 1987 and the Asian Crisis in 1997. Both events are closely linked to the financial sector, but neither has originated from the US banking sector. Shiller (1987) shows that the stock market crash in 1987 was not caused by any news except for the news of the drop itself. Thus, it is safe to assume that bank lending was not a source of the high uncertainty surrounding the crash. Similarly, the Asian Crisis had mostly an international dimension and its sources were unrelated to bank lending in the US.

Figure 1 displays the VXO around the four events. The VXO more than tripled within a few days in October 1987 and returned to regular levels rather quickly afterwards. In August 1990, the increase in the VXO was more gradual and volatility remained high for most of the year with another short surge in the VXO in January 1991. During the Asian Crisis in 1997, the VXO experienced an 82% increase within a few days at the end of October. Volatility stayed at a rather high level with occasional ups and downs until the end of January 1998. As a consequence of the terrorist attacks in September 2001, the VXO rose from 33.87 to 49.04 within a few days and returned to pre-attack levels within two weeks. The four events considered in this paper thus display a substantial amount of heterogeneity both with respect to the extent of the increase in the VXO and with respect to the duration of increased VXO levels.

The identification of uncertainty events through jumps in stock-market volatility could be a possible concern. Is it safe to interpret these jumps as manifestations of an increase in the general level of uncertainty caused by another event or could stock market volatility itself be the actual source of uncertainty? While it is conceivable that an increase in stock market volatility causes a rise in uncertainty, it is unlikely that the jumps in volatility we consider as uncertainty events evolved endogenously on the stock market given their rather pronounced size.

2.2 Identification of Loan Supply

Ultimately, we are interested in the response of the loan supply of banks to exceptionally strong increases in uncertainty. The volume of loans observed after an uncertainty shock may, however, also be driven by demand effects. If consumption, investment, and hiring decline after an increase in uncertainty, the demand for bank loans goes down as well. In order to identify the supply effect, we adopt an approach that is widely used in the empirical literature on the bank lending channel. The approach, initially proposed by Kashyap and Stein (1995), is based on the idea that demand-induced variations in loan volumes should be largely symmetric across banks, while the supply reaction of banks is likely to be bank-specific, depending on how easily banks can raise funds and refinance loans after a monetary shock. Specifically, large, well capitalized, and highly liquid banks respond less strongly to monetary policy shocks since they can compensate the policy-induced changes in overall liquidity more easily, and, consequently, do not have to adjust loan volumes (see e.g. Kashyap and Stein, 2000; Kishan and Opiela, 2000; Ehrmann et al., 2003; Gambacorta and Marqués-Ibañez, 2011).

We argue that the response of loan supply to jumps in uncertainty should also vary systematically across banks. This point can be motivated using a real-options framework. Since granting a loan involves future commitment and is not easily reversible, the decision to do so can be interpreted as exercising a call option.[8] The value of such a wait-and-see option increases if uncertainty about funding costs or about the returns associated with a newly granted loan increases. Higher uncertainty may therefore reduce loan supply for at least two reasons: First, banks may prefer to hold larger amounts of liquid reserves, rather than granting loans, as liquidity may become especially scarce during times of high uncertainty. Second, higher uncertainty may translate into less certain future cash flows (e.g. interest payments) associated with loans. The crucial point for our identification is that these two effects not only lead to an adjustment of loan supply, but that the size of the adjustment varies across banks.

Consider first the effect of higher uncertainty about liquidity and refinancing opportunities. As the empirical literature demonstrates, loan supply of larger, well capitalized, and more liquid

[8] See Choi and Smith (2002) for a formal discussion.

banks is less responsive to monetary policy shocks, which is consistent with the idea that these banks have easier access to funding. We argue that this intuition carries over to liquidity, and more generally the access to liquidity, during periods of high uncertainty. Banks are subject to certain minimum capital requirements which are both implicitly demanded by investors as a prerequisite to provide finance to a bank and explicitly stated in the Basel accords. When uncertainty is high, attempts to improve their capital ratio may induce banks to cut lending as the value of the wait–and–see option increases. Large banks should be able to absorb increases in uncertainty relatively easily because they are less likely to be financially constrained. This effect may be amplified if investors and depositors view large banks as too big to fail, giving rise to a flight to perceived quality. A counteracting effect may emerge, however, as small banks tend to rely more on deposit funding than large banks. Smaller banks may therefore experience more stable funding during uncertain times. Thus, we conclude that, with respect to funding uncertainty, the real option effect should be less pronounced for well capitalized and generally more liquid banks. In addition, we expect larger banks to react less to funding uncertainty, although this effect may be dampened or even reversed by more stable deposit funding for small banks.

Next, consider uncertainty about future cash flows. Banks which are more liquid or have easier access to liquidity should be in a better position to absorb future defaults and may therefore be less concerned about higher uncertainty concerning payments associated with loans. In other words, well capitalized, larger, and more liquid banks should also be subject to a smaller real option effect arising from an increase in uncertainty about returns.

There may also be counteracting effects at work. Small banks might have more idiosyncratic information on their customers and may therefore be in a better position to assess the creditworthiness of their customers. Hence, future cash flows may be less uncertain for smaller banks, even during periods of high uncertainty. Thus, although smaller banks may face more uncertainty concerning funding opportunities, their lending could be less affected after a jump in uncertainty, since increases in uncertainty about the cash flows from new loans may be less pronounced. Lending by small banks also frequently falls into the category of relationship banking, which commonly involves implicit insurance elements to keep up lending in economically uncertain times. Small banks may therefore curb loan supply to a lesser extent than large banks.[9]

[9] Ehrmann et al. (2003) make a similar argument in the context of the bank lending channel, pointing out that for small banks maintaining a lending relationship with their customers may dominate other factors (such as a tightening in deposit funding).

A relatively high capitalization could indicate that a bank generally behaves in a more precautious way and is less willing to take risks. Thus, even though well capitalized banks should be able to keep up lending due to their easier access to funds, they may not be willing to take on additional risks, especially when the environment is highly uncertain.

Summing up, we identify supply effects of uncertainty on the volume of bank loans by analyzing how the cross-sectional variation in loan growth rates after surges in uncertainty is related to the liquidity, the capitalization, and the size of banks. Increased uncertainty about funding and future returns may give rise to counteracting effects on the value of a wait–and–see option for well capitalized and larger banks. Thus, the influence of size and capitalization is ambiguous and ultimately an empirical question. In any case, we interpret heterogeneity in the evolution of loan volume across banks following jumps in uncertainty as an indication of supply side variation. We maintain the standard assumption from the empirical literature on the bank lending channel that shifts in the demand for loans are not systematically related to bank characteristics.

2.3 Empirical Method

To study the cross-sectional variation in bank lending following the four uncertainty events discussed above, we relate loan growth rates after uncertainty events to balance sheet characteristics. We estimate equations of the type

$$LG_{i\tau} = \beta' X_{i\tau} + \gamma LG_{i\tau}^{prior} + BK_i + EV_\tau + \varepsilon_{i\tau}, \tag{1}$$

where $LG_{i\tau}$ denotes a measure of loan growth for bank i during the event window associated with the event $\tau = 1, ..., 4$, which refers to either the Black Monday of 1987, the Iraq conflict in 1990, the Asian Crisis of 1997, or the terrorist attack of 2001. In our baseline estimation, the event window includes the event quarter and the two subsequent quarters. As a robustness check, we analyze whether the results are sensitive to varying the length of the event window.

$X_{i\tau}$ is a matrix of bank characteristics. In our baseline estimation, it contains the ratio of liquid to total assets, $Liquidity_{i\tau}$, the equity-to-asset ratio, $Capital_{i\tau}$, and the log of total assets, $Size_{i\tau}$. We measure these characteristics as averages over a window of eight quarters preceding event τ. As two-year averages reflect the structural characteristics of the bank, which are predetermined, this approach avoids potential problems of endogeneity, whereas the reaction of loan volumes to uncertainty may influence the banks' balance sheets contemporaneously. For example, deleveraging after a jump in uncertainty is likely to increase banks' liquidity ratios.

Moreover, we avoid spurious correlation which might arise if uncertainty drives both, bank lending and balance sheet positions. This issue is particularly relevant in the case of liquidity and capitalization, as banks facing a surge in uncertainty may shift their portfolios towards more liquid assets and increase their capital buffers. Finally, averages are less sensible to temporary movements and seasonalities in the variables.

Equation (1) includes the average of $LG_{i\tau}$ over the eight quarters prior to the event, denoted by $LG^{prior}_{\tau i}$, to capture persistence in loan growth. $LG^{prior}_{\tau i}$ is normalized by multiplying the average of $LG_{i\tau}$ over the eight pre-event quarters by the length of the event window. This way, the coefficient would be equal to unity if the banks' lending simply continues to grow at the same rate as in the two years preceding the event.

EV_τ are event-specific intercepts. Since many banks in our sample appear in more than one event, we add bank fixed effects denoted as BK_i. The panel structure of our data set offers a number of advantages: First, we are able to allow certain coefficients to vary across the events while restricting others to be the same for all events to save degrees of freedom while at the same time taking heterogeneity across events into account. Second, using event fixed effects we can control for factors which are event-specific and affect all banks equally. Third, we are able to control for unobserved time-invariant heterogeneity at the level of individual banks. Since we are only able to control for a limited number of structural characteristics, this merit is particularly beneficial.

As our sample contains up to four observations of the same bank during different events, we calculate clustered standard errors that allow for within-bank correlation. We report White robust standard errors for all estimations, since pooling different events and banks with different characteristics may introduce heteroskedasticity.

Following the standard event study approach, we take into account that the observed loan growth developments may only be partly due to the event. In our main analysis, we subtract a bank-specific average loan growth rate from the actual loan growth rate during the event window and interpret this deviation as abnormal loan growth dynamics induced by the event. We first regress quarterly loan growth rates for each bank i on a constant,

$$\Delta \log(Loans_t) = \alpha + u_t, \tag{2}$$

using the full sample time span from 1984Q1 to 2007Q3 but excluding quarters during which jumps in uncertainty occurred as well as the three subsequent quarters. Thus, the estimation window excludes the four event windows and all quarters that would in principle be in an event window but are excluded due to a lack of two preceding calm years. Equation (2) can be interpreted analogously to the so-called market equation used to extract abnormal asset returns in event studies in the finance literature (see e.g. MacKinlay, 1997). We use the estimated coefficient from Equation (2) for each bank to predict normal loan growth during the event windows. Then we subtract the predicted loan growth rate from the actual loan growth rate to obtain abnormal loan growth rates, ALG_{it}, for bank i in quarter t. Finally, we cumulate ALG_{it} for each bank over the event window to obtain cumulative, abnormal loan growth rates $CALG_{i\tau}$. We use $CALG_{i\tau}$ as the measure of loan growth, $LG_{i\tau}$, in the main analysis.

The bank fixed effects, which we include in our main specification, already incorporate (a multiple of) the bank-specific normal loan growth rate. Thus, the only difference between estimations based on time-invariant normal loan growth rates and the actual, observed loan growth rates lies in the estimated constant term. Nevertheless, we use abnormal loan growth rates throughout this paper, since we also estimate specifications without bank fixed effects and consider abnormal loan growth rates based on extended versions of Equation (2) in a robustness analysis. Using abnormal loan growth rates rather than observed, actual loan growth rates, ensures comparability of results from different specifications. In addition, we are able to interpret the event fixed effects in terms of average abnormal loan growth rates.

A concern with respect to our empirical strategy could be that it is unclear whether causality only runs from uncertainty jumps to bank lending or also the other way around. It is conceivable that developments in the banking sector cause uncertainty. As mentioned above, we exclude the recent financial crisis from our study for precisely this reason. However, we argue that this is unlikely for the events we consider in our analysis, as these events are closely related to developments which are plausibly exogenous with respect to bank lending.

Co-founding events could be another concern, as increases in uncertainty generally do not occur in isolation, but are accompanied by other developments which also potentially influenced bank lending. In particular, jumps in stock market volatility may coincide with large declines in stock prices. In this case, our empirical analysis would also capture the influence of strongly declining stock market prices. Addressing this concern, Bloom (2009) shows that stock market volatility is largely independent from stock market levels and returns, since the correlation between detrended stock market levels and detrended stock market volatility is low.

Stock market dynamics are rather heterogeneous across the four events we consider. Figure 2 shows that the largest drop in stock market levels occurred in 1987, when stock prices plummeted by more than 22%. The drop was smaller during the other events. The decline in stock prices during the Asian crisis in 1997, for example, was below 10%. While the time span between the first major drop in stock prices and the recovery was between 6 and 12 months in the case of the first two events, stock market recovery took less than a month in the case of the Asian crisis and the 9/11 terrorist attacks. This demonstrates that there is a strong variation across the four events in both the magnitude of the drop in stock prices and the time to recovery. We control for these developments through the inclusion of event fixed effects.

The overall macroeconomic environment may also play a role as high levels of volatility may be associated with declines in economic activity. The two events in 1990 and 2001 were accompanied by recessions. As lower economic activity may result in lower demand for loans, loan growth dynamics in the aftermath of these two events may mirror demand effects to a larger extent. Again, we control for business cycle dynamics at the time of the events, and induced loan demand developments, through the inclusion of event fixed effects.

Note, however, that event fixed effects only alleviate the issue of co-founding events to the extent that these developments affect all banks alike. In other words, we control for the demand-side effects induced by potentially co-founding events according to our identifying assumptions. Nonetheless, there may also be supply related effects.[10] To address this issue, we will evaluate supply effects separately for each of the events. If co-founding events are important, the effects of the balance sheet characteristics should differ systematically across events depending on concurrent, event-specific developments, such as macroeconomic conditions.

2.4 Bank Lending Data

We use quarterly US bank balance sheet data from the Consolidated Reports of Condition and Income (Call Reports).[11] Our population of banks includes all insured commercial banks between the first quarter of 1984 and the third quarter of 2007. The sample selection largely follows Kashyap and Stein (2000) and Den Haan et al. (2002). Periods before 1984 are excluded because of major discontinuities in the time series and the data set is cut off after the third quarter of 2007 to exclude the financial crisis from the analysis. We include only banks which are located in DC or in one of the 50 US states and assigned to one of the twelve Federal Reserve districts. As mergers create major discontinuities in the banks' balance sheets, we use the merger

[10] In fact, Peek and Rosengren (1997) use price changes on Japanese stock markets to identify loan supply of Japanese banks in the US. However, it is difficult to generalize these results, as Japanese banks traditionally held unusually large amounts of corporate stocks (sometimes referred to as 'hidden reserves').

[11] While we focus on the developments of loan growth rates, a similar analysis could use interest rates. However, our data does not offer a clean way to calculate interest rates at a bank-specific level. In particular, it is not possible to trace the category of interest income and to distinguish between interest from outstanding and new loans. In contrast, calculating loan growth rates from the Call Reports is well established in the literature.

file provided by the Federal Reserve Bank of Chicago to exclude both the bank-quarter in which a bank acquired another bank as well as the bank-quarter thereafter. In order to clean the data set from reporting errors and outliers, we apply a number of additional data cleansing filters. First, all bank-quarters with non-positive assets are eliminated from the sample. Second, any bank with a liquidity ratio of zero or lower is dropped for the whole timespan. Third, any bank with a deposit ratio in excess of 100 percent is dropped from the sample. Forth, for each quarter we delete banks with a loan growth rate outside of the 5 standard deviation band around the mean loan growth. Finally, as we concentrate on commercial & industrial (C&I) loans in our baseline analysis, we include only banks with at least 5% C&I-loans in their loan portfolio.

We focus on C&I loans for several reasons: Demand should be more homogeneous within this particular loan category, which is why we expect event fixed effects to work better as a control for demand factors, and the remaining heterogeneity is more likely to reflect loan supply.[12] Similarly, as we filter out banks with a small share of C&I loans, our sample gets more homogeneous with respect to the type of banks we observe. It would be problematic to mix banks that are purely engaged in mortgage lending with banks that primarily lend to businesses. Finally, as C&I loans tend to be of short maturity, an eventual effect of uncertainty events on loan supply may be particularly pronounced within this loan category (Kishan and Opiela, 2000).

Following Kashyap and Stein (2000) and Black et al. (2010), we measure liquidity as the sum of securities held to maturity, securities available for sale, federal funds sold, and securities purchased under agreements to resell, relative to total assets. Again following Kashyap and Stein (2000), we proxy the size of a bank with the logarithm of total bank assets. We define bank capitalization as the ratio of total equity capital to total assets. Following Den Haan et al. (2002), we define total equity capital as the sum of common stock, surplus, and retained earnings. We identify a bank as being part of a multi-bank holding company following Ashcraft (2006). Finally, we use the method described in Loutskina (2011), to calculate a bank-specific securitization possibility index.[13] Table 1 provides the exact specification of our bank balance sheet variables.

Table 2 reports pre- and post-event average loan growth rates (averaged across banks) as well as the corresponding standard deviations. While the pre-event period covers the eight quarters preceding an event, the post-event period encompasses the event quarter and the two subsequent quarters. On average, loan growth slowed down substantially after the surges in

[12] Kashyap and Stein (2000) make a similar argument in the context of the bank lending channel.

[13] This index weighs market-wide securitization averages in different loan categories by the importance of these categories in banks' loan portfolios to measure the ability to securitize loans at the bank level.

uncertainty in 1990 and 2001. In 1997, there was a small increase in the growth rate during and after the event, whereas loan growth increased strongly in 1987. Thus, loan growth rates appear to behave rather heterogeneously after the four events.

Figure 3 shows the cumulative, abnormal loan growth rates averaged across banks around each of the four events. We observe strong declines in average $CALG$s in the event quarters in 1990 and in 2001, which mirrors the developments of the actual loan growth rates reported in Table 2. While $CALG$s also declined, on average, in 1987, the downward trend started already well before the event quarter. In 1997, despite a short-lived decline in the quarter preceding the event, $CALG$s on average continued an upward trend. Overall, we see that $CALG$s declined after two out of the four events, and continued prior trends, on average, after the remaining two events. The only event after which we observe increasing average $CALG$s is the event associated with the Asian Crisis in 1997. This is also the only event in the sample which was neither accompanied by a recession nor by strongly declining stock market prices.

These observations suggest that even large increases in uncertainty are unlikely to lead to a reduction in the volume of bank loans. It may, however, slow down an expansion or reinforce a decline of the loan volume. We now move on to analyze loan growth developments at bank level and especially the heterogeneity across banks.

3 Results

Table 3 shows the estimation results from the baseline specification. In Column (I) we pool the four events into a single sample. The constant term indicates that cumulative, abnormal loan growth rates declined by about 2.5%, on average, during the three post-event quarters. Banks which held more liquidity in the two calm years preceding an uncertainty event had, on average, significantly higher abnormal loan growth rates in the three quarters following the event. *Capital* and *Size* turn out to be insignificant. The positive and significant coefficient of $CALG^{prior}$ successfully captures bank-specific trends.

In Column (II) we add event fixed effects. The average $CALG$s were negative in the aftermath of three of the four events. We also see that including event fixed effects leaves the coefficients for the bank characteristics virtually unchanged. Once we control for time-invariant, unobserved heterogeneity at the bank level by including bank fixed effects in Column (III), the results change in two important aspects. First, the coefficient for *Liquidity* substantially increases in magnitude. This observation underlines the result that banks with more liquid balance sheets are more likely to keep up lending in uncertain times. Second, the coefficient for *Size* turns significantly negative. Loan growth associated with small banks is significantly higher after strong increases in uncertainty. This could be an indicator of the importance of relationship banking, or of small banks having more information on their customers. Smaller banks could also face less volatility in their funding opportunities due to their stronger reliance on deposit funding.

Taken together, these results suggest that loan growth rates evolve heterogeneously depending on how liquid a bank was prior to the increase in uncertainty and also on the size of a bank. The heterogeneities indicate that the dynamics of loan volumes following increases in uncertainty originate from shifts in loan supply given that demand side variations are not systematically linked to either *Liquidity* or *Size*.

While this assumption appears safe for *Liqudity*, variation over *Size* may also be due to demand fluctuations as Kashyap and Stein (2000) and Ashcraft (2006) argue that larger banks typically have larger firms as customers. If the demand for bank loans varies systematically with the size of the borrowing firms, our estimation may pick up demand effects rather than variations in supply. Bloom et al. (2007) find that the effect of uncertainty does not differ significantly between small and large firms, and, if anything, is less pronounced for larger firms. Consequently, if the effect of *Size* is driven by demand rather than supply, we would expect *Size* to enter with a positive sign. However, we obtain a negative effect.

The estimated effects are also economically significant: Based on the results from our preferred specification reported in Column (III) of Table 3, a one standard deviation increase in *Liquidity* would increase a bank's CALG rate by about four percentage points. Compared to the average CALG rate of -2.5% over the four events, this effect is not only statistically but also economically significant. Another way of demonstrating this is to relate the size of the effect to the cross-sectional dispersion of CALG, as measured by the standard deviation:[14] A one standard deviation change in *Liquidity* accounts for 16% of the average cross-sectional dispersion in CALG rates. Similarly, a one standard deviation decrease in *Size* would increase a bank's CALG rate by 6.5 percentage points. This corresponds to 25.7% of the average cross-sectional dispersion in CALG rates.

Summing up, we find that liquid banks and also smaller banks tend to have higher loan growth rates after large jumps in uncertainty. Capitalization does not influence the dynamics

[14]The standard deviations of *Liquidity*, *Size*, and *CALG* in the regression sample equal 14.23, 1.103, and 25.24, respectively.

of loan growth after surges in uncertainty, although well capitalized banks are less responsive to monetary policy shocks (see e.g. Kishan and Opiela, 2000) and are generally viewed as healthier and in a better position to absorb shocks (see e.g. Merrouche et al., 2013). Well capitalized banks, despite their ability to raise funds when needed, may be less willing to take risks. In this case, banks may not be willing to grant additional loans when uncertainty is high. Our results are also consistent with the interpretation that a high capitalization, as a way to ensure access to liquidity, plays a less important role once we directly include liquidity in the regression, an aspect to which we will return below.

To assess the importance of co-founding events, we interact the three bank characteristics with event dummies, thereby allowing all parameters, except for the coefficient of $CALG^{prior}$, to vary across the four events. If our results are driven by co-founding events, we expect the coefficients to vary strongly across the four events. In addition, measuring the effects of the bank characteristics on the event level is an appropriate way to control for other remaining heterogeneities between the events, such as variations in the duration of the increase in uncertainty.

Column (I) of Table 4 shows the results for the specification without bank fixed effects. The results reported in Column (II) are obtained from regressions including bank fixed effects. The coefficient of *Liquidity* is significantly positive for all events and increases in magnitude once we add bank fixed effects. The quantitative effect of *Liquidity* is again quite robust across the events. Column (I) shows that *Capital* is insignificant across all four events, which is in line with our previous results. When we add bank fixed effects, capitalization has a positive and significant effect during the two earlier uncertainty periods, while the effect gets smaller over time and turns insignificant in the case of the two more recent events. A possible interpretation is that capitalization has become less relevant as a way to ensure access to liquidity in uncertain times.

Table 4 also shows that controlling for unobserved heterogeneity at the bank level eliminates most of the heterogeneity in the *Size* coefficient. Although for the event associated with the Black Monday of 1987 the measured effect is smaller in absolute terms than for the three more recent events, the effect is significantly negative across all events in Column (II).

To sum up, our results show that although the effects of *Liquidity* and *Size* are remarkably robust across the four events, once we control for unobserved heterogeneity at the bank level, the effect of *Capital* decreases steadily and eventually loses its statistical significance in the two most recent events.[15] Since the effects are relatively similar across events, we conclude that the

[15] In unreported results we estimate separate regressions for each of the four events. Although we are not able

specific circumstances surrounding individual events do not seem to influence our results and are well captured by the event fixed effects. Although the influence of *Capital* declines steadily, this variation does not appear to be systematically related to e.g. the macroeconomic conditions, and thus loan demand, prevalent at specific events.

Table 5 sheds more light on the role of capitalization. Column (I) shows that once we drop *Liquidity* from Equation (1), *Capital* becomes significant at the 5 percent level. Thus, high capitalization loses its relevance as a way to ensure access to liquidity when we explicitly condition on *Liquidity*. Hence, *Liquidity* and *Capital* are to a certain extent substitutes. Column (II) reports the results taking into account membership in a bank holding company. A prominent strand in the bank lending channel literature (see e.g. Ashcraft, 2006) argues that banks that are part of a bank holding company are less likely to face liquidity constraints as they are able to use internal funding channels. Since this reasoning may also influence the access to liquidity after a surge in uncertainty, we augment our regression equation with an indicator variable, $MBHC$, that is equal to one if a bank was part of a multi-bank holding company in the quarter preceding the uncertainty event and zero otherwise. The estimated coefficient on $MBHC$ is positive, as expected, but not significant.

In Column (III) we interact $MBHC$ with *Liquidity*, *Capital*, and *Size* to see whether the effect of these variables changes if an internal capital market exists. The interaction terms are small and statistically insignificant, with the exception of *Size* $\times$ $MBHC$. The negative coefficient for this interaction term suggests that loan growth rates of small banks tend to be relatively high (in comparison to the average) in times of uncertainty, if these banks are part of a multi-bank holding company. Thus, access to internal funding channels reduces the effect of size, while other factors, such as closer relationships with the banks' customers, dominate.

Capital becomes significant at the 10 percent level, suggesting that although capitalization improves the access to financing during times of uncertainty, this effect becomes insignificant for banks in a bank holding company with access to an internal capital market. However, the effect is relatively small: The estimated coefficient implies that a one standard deviation increase in *Capital* leads to an increase in $CALG$ rates by about 0.7 percentage points if a bank is not part of a holding company. This corresponds to 2.8% of the average cross-sectional dispersion in $CALG$ rates. Finally, in Column (IV) we interact *Size* and *Capital* to see if *Capital* exerts different effects depending on the size of a bank (see Kishan and Opiela, 2000; Merrouche et al., 2013). The interaction term is insignificant, while our other findings remain unchanged.

to control for unobserved heterogeneity in this case, the qualitative results remain largely unchanged.

Overall, these additional estimations show that although *Capital* may be relevant in some cases, e.g. in the absence of internal capital markets, it does not appear to play a dominant role in banks' loan supply in the months following an event, especially when we control for *Liquidity*.

4 Additional Analysis

A number of additional estimations support our results. First, we vary the length of the period over which abnormal loan growth rates are accumulated between one and three periods. Using a shorter time period makes it less likely that we pick up other effects that may have occurred after an event.[16] Table 6 shows the results. Two observations emerge: First, there is substantial variation across the events with respect to the timing of average abnormal bank lending. Comparing the event fixed effects across the columns, for example, shows that during the event associated with the uncertainty surrounding Gulf War I in 1990, the largest drop in average bank lending appeared in the third event quarter.[17] For the event associated with the September 11 terrorist attacks in 2001 on the other hand, substantial declines in average (abnormal) loan growth rates occurred in the second and third quarter.[18] Second, despite the heterogeneity in the evolution of average $CALG$s, the increases in the effects of *Liquidity* and *Size* are remarkably stable when we add additional quarters.

Table 7 presents the results from three-dimensional panel regressions, where (non-cumulative) abnormal loan growth rates are regressed on both quarter and event fixed effects. Using this modified estimation approach allows us to isolate the development of average $CALG$s on a quarterly basis. While Table 6 shows that average $CALG$s develop rather heterogeneously during the quarters following an event, the quarter fixed effects reported in Column (I) of Table 7 indicate that average lending recovers at least partly in the second and third quarter after the event.

Adding bank fixed effects in Column (II) and $CALG^{prior}$ in Column (III) does not change this conclusion. In Column (IV), we add interaction terms between the quarter fixed effects and the three bank characteristics. The effects of *Liquidity* and *Size* increase in absolute terms over the three quarters, which points towards an important role of small and liquid banks in the

[16]Two events are associated with recessions. While these recessions started either simultaneously with the event or even slightly before the event, the trough occurred substantially later: According to the NBER's business cycle dating committee, the 1990 recession started in the beginning of the third quarter of 1990 but the trough was not reached until March 1991. In 2001, the recession began in March, with the trough occurring in November of the same year. Hence, by focusing on the time shortly after the event, we are less likely to pick up the effects of recessions in addition to the increase in uncertainty.

[17]This corresponds to the first quarter of 1991, the quarter of 'Operation Desert Storm', which saw another surge in the VXO in January.

[18]Part of the explanation might be that the terrorist attacks happened during the last month of the first event quarter.

amelioration of lending conditions following the tightening in the first quarter.

Loutskina (2011) uses a bank-specific index of securitization possibility to show that the possibility of securitization makes banks less sensitive to funding shocks such as monetary policy shocks. A similar mechanism could be at work in the case of uncertainty events: Banks with better securitization possibilities may lend more than other banks after surges in uncertainty, as they can tap an additional source of liquidity. To explore this issue, we construct this index, which we denote by *Securitization*, for our sample. Table 8 shows that the coefficient of securitization possibility is small and insignificant in Column (I), where we do not control for *Liquidity*. Securitization possibility does not appear to be a substitute for liquidity in times of uncertainty. Once we control for *Liquidity*, however, the coefficient strongly increases in size and turns highly significant. Thus, if we compare banks with similar liquidity levels, those banks that can securitize their loan portfolio more easily, appear to curb their loan supply to a smaller extent during event periods.

To check whether our results are sensitive to the way in which we eliminate outliers, we apply the filter suggested by Loutskina (2011) and re-estimate our baseline regressions. In particular, we drop all bank-quarters with loan growth rates exceeding 100% or asset growth rates above 50% (both growth rates are measured in absolute values), and also exclude bank-quarters with loan-to-asset ratios below 10%. Table 9 reports the results obtained by employing the alternative outlier filter. While *Size* is now positively significant at the 10% level in the regressions without bank fixed effects, the results are remarkably similar to our baseline estimates, once we include bank fixed effects. We conclude that our earlier results were not driven by outliers.

While the focus of this paper is on C&I-loans, it is also of interest to analyze whether our results hold for bank lending in general. Table 10 shows the results from re-estimating our baseline regressions for total loans. What is perhaps most remarkable is that the effect of *Liquidity* remains almost unchanged compared to Table 3. In times of high uncertainty, liquidity appears to be as pivotal to banks' total lending behavior as it is for C&I lending. The effect of *Size* loses some of its strength but is still highly significant. While *Capital* enters significantly negative in Columns (I) and (II), the effect virtually disappears, once we add bank fixed effects, which again is consistent with our previous results for C&I-loans. Thus, our results carry over, at least qualitatively, to bank lending in general.

Finally, we consider an extended version of Equation (2) to estimate abnormal loan growth rates:

$$\Delta \log(Loans_t) = \alpha_0 + SEASON_\kappa + \alpha_1 \Delta \overline{\log(Loans_t)} + \alpha_2 \Delta \log(Loans_{t-1}) + u_t, \qquad (3)$$

where $SEASON_\kappa$ refers to three seasonal dummies, leaving out the first season. For this specification, we also include aggregate C&I loan growth, $\overline{\log(Loans_t)}$, which allows us to filter general demand-related fluctuations in loan growth, captured by aggregate loan growth, already at this stage. The coefficient on the average loan growth rate can be interpreted as the degree to which a bank reacts to general developments in the banking sector, and therefore reflects the interconnectedness of the banking sector. To capture the bank-specific loan growth dynamics we add a first-order autoregressive term to the equation.

Table 11 shows the results for $CALG$s based on different versions of equation 3. The coefficients for *Liquidity* and *Size* are robust over all specifications. Compared to the baseline specifications they decrease slightly in magnitude. Both coefficients remain highly significant over all specifications.

5 Concluding Remarks

We present robust evidence indicating that after jumps in uncertainty, liquid and smaller banks keep up lending to a greater extent than larger and less liquid banks. We also find that well capitalized banks are less influenced by uncertainty, although the effect of capitalization quantitatively small and only significant for banks which are not part of a multi-bank holding company.

This heterogeneity of loan growth across banks is consistent with the interpretation that the dynamics of loan volumes following spikes in uncertainty are partially driven by banks' supply decisions. Given our results, the lending behavior of banks may represent another channel through which uncertainty shocks are transmitted and amplified. An interesting avenue for future research would be to further explore the quantitative nature of the relationship between uncertainty, bank lending, and the business cycle.

While our analysis is based on data from the US banking sector, comparisons with other countries appear to be another interesting direction for future research. Since the strength of supply side variations may depend on the institutional and regulatory environment as well as on characteristics of the financial system, cross-country comparisons may provide valuable additional insights.

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Table 1: Definition of bank balance sheet variables

Variable	Period	Definition
C&I loan volume	1984Q1-2007Q3	rcon1766
Size (total assets)	1984Q1-2007Q3	rcfd2170
Liquidity	1984Q1-1993Q4	(rcfd0390+rcfd2146+rcfd1350)/rcfd2170
	1994Q1-2001Q4	(rcfd1754+rcfd1773+rcfd1350)/rcfd2170
	2002Q1-2002Q4	(rcfd1754+rcfd1773+rconb987+rcfdb989)/rcfd2170
	2003Q1-2007Q3	(rcfd1754+rcfd1773+rcfdb987+rcfdb989)/rcfd2170
Capital	1984Q1-1989Q4	(rcfd3230+rcfd3240+rcfd3247)/rcfd2170
	1990Q1-1993Q4	(rcfd3230+rcfd3839+rcfd3632-rcfd0297)/rcfd2170
	1994Q1-2007Q3	(rcfd3230+rcfd3839+rcfd3632+rcfd8434)/rcfd2170
Multi-Bank Holding Company (MBHC)	1984Q1-2007Q3	In a given quarter, there is at least one other bank that has the same direct (RSSD9364), regulatory (RSSD9348), or financial (RSSD9379) high holder.
Securitization	1984Q1-2007Q3	see Loutskina (2011)

Notes: The codes in the definitions refer to the item numbers used in the Call Reports. Detailed descriptions of these items are available from the Federal Reserve Board's *Micro Data Reference Manual* at `http://www.federalreserve.gov/apps/mdrm/data-dictionary`. The Call Report data are available from the Federal Reserve Bank of Chicago's website at `http://www.chicagofed.org/webpages/banking/financial_institution_reports/commercial_bank_data.cfm`. As described in the text, the data was adjusted for mergers using the merger file provided by the Federal Reserve Bank of Chicago available at `http://www.chicagofed.org/webpages/publications/financial_institution_reports/merger_data.cfm`. The aggregate securitization data used in the calculation of the securitization possibility index are available from Elena Loutskina's webpage at `http://faculty.darden.virginia.edu/loutskinae/research.htm`.

Table 2: Summary statistics on loan growth

	pre-event mean	post-event mean	pre-event s.d.	post-event s.d.	mean	s.d.
1987Q4	0.632	1.690	17.959	18.007		
1990Q3	1.208	0.156	16.770	16.778		
1997Q4	3.128	3.592	14.149	14.601		
2001Q3	3.094	0.586	13.610	13.749		
loan growth (1984Q1-2007Q3)					1.813	15.734
loan growth in pre-event sample					1.802	16.106
loan growth in post-event sample					1.455	16.295
loan growth in estimation sample					1.874	15.814

Notes: This table collects average loan growth rates and their standard deviations over various subsamples. The pre-event period refers to the eight quarters preceding an event. The post-event period comprises the event quarter and the two subsequent quarters. The estimation sample includes all periods except periods with surges in uncertainty and the three subsequent quarters.

Table 3: Pooled & panel regressions

	(I)	(II)	(III)
Liquidity	0.156***	0.151***	0.281***
	(0.0120)	(0.0122)	(0.0237)
Capital	-0.0282	-0.0648	0.162
	(0.0572)	(0.0603)	(0.132)
Size	0.178	0.182	-5.873***
	(0.134)	(0.138)	(0.787)
$CALG^{prior}$	0.103***	0.103***	0.0697***
	(0.0121)	(0.0121)	(0.0143)
EV_{1990Q3}		-4.670***	-4.275***
		(0.385)	(0.419)
EV_{1997Q4}		2.730***	6.711***
		(0.401)	(0.711)
EV_{2001Q3}		-4.314***	2.080**
		(0.440)	(0.910)
Constant	-2.502***	-0.950***	-3.057***
	(0.149)	(0.271)	(0.377)
Observations	30,322	30,322	30,322
R-squared	0.010	0.024	0.045
Bank fixed effects	No	No	Yes

Notes: The event window has a length of three quarters and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal C&I loan growth during the event period. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal loan growth, averaged over the eight quarters preceding the event. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. All explanatory variables are demeaned. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Table 4: Splitting up event fixed effects

	(I)	(II)
$Liquidity \times EV_{1987Q4}$	0.170***	0.240***
	(0.0218)	(0.0338)
$Liquidity \times EV_{1990Q3}$	0.159***	0.331***
	(0.0228)	(0.0329)
$Liquidity \times EV_{1997Q4}$	0.107***	0.256***
	(0.0258)	(0.0348)
$Liquidity \times EV_{2001Q3}$	0.124***	0.262***
	(0.0261)	(0.0378)
$Capital \times EV_{1987Q4}$	0.0696	0.592***
	(0.130)	(0.220)
$Capital \times EV_{1990Q3}$	0.0416	0.367**
	(0.121)	(0.170)
$Capital \times EV_{1997Q4}$	-0.179	0.0206
	(0.124)	(0.170)
$Capital \times EV_{2001Q3}$	-0.160	-0.137
	(0.106)	(0.172)
$Size \times EV_{1987Q4}$	1.722***	-4.165***
	(0.244)	(0.928)
$Size \times EV_{1990Q3}$	-0.742***	-6.691***
	(0.263)	(0.901)
$Size \times EV_{1997Q4}$	-0.236	-6.296***
	(0.280)	(0.878)
$Size \times EV_{2001Q3}$	-0.638**	-6.604***
	(0.303)	(0.853)
$CALG^{prior}$	0.0980***	0.0568***
	(0.0121)	(0.0143)
EV_{1990Q3}	-5.160***	-5.122***
	(0.397)	(0.444)
EV_{1997Q4}	2.515***	6.314***
	(0.422)	(0.764)
EV_{2001Q3}	-4.420***	1.949**
	(0.492)	(0.952)
Constant	-0.530*	-2.357***
	(0.281)	(0.423)
Observations	30,322	30,322
R-squared	0.027	0.049
Bank fixed effects	No	Yes

Notes: The event window has a length of three quarters and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal C&I loan growth during the event period. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal loan growth, averaged over the eight quarters preceding the event. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. EV_{1987Q4}, EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. All explanatory variables are demeaned. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Table 5: Capitalization and Bank Holding Companies

	(I)	(II)	(III)	(IV)
Liquidity		0.281***	0.289***	0.280***
		(0.0237)	(0.0257)	(0.0237)
Capital	0.290**	0.162	0.229*	0.110
	(0.132)	(0.132)	(0.131)	(0.126)
Size	-5.808***	-5.872***	-5.535***	-5.966***
	(0.791)	(0.787)	(0.817)	(0.784)
$CALG^{prior}$	0.0664***	0.0697***	0.0695***	0.0682***
	(0.0143)	(0.0143)	(0.0143)	(0.0143)
EV_{1990Q3}	-4.363***	-4.281***	-4.304***	-4.251***
	(0.423)	(0.421)	(0.420)	(0.419)
EV_{1997Q4}	5.817***	6.699***	6.640***	6.849***
	(0.707)	(0.719)	(0.721)	(0.708)
EV_{2001Q3}	-0.0837	2.067**	2.002**	2.225**
	(0.887)	(0.917)	(0.922)	(0.907)
Constant	-2.451***	-3.079***	-3.030***	-3.202***
	(0.373)	(0.408)	(0.417)	(0.380)
$MBHC$		0.105	0.162	
		(0.759)	(0.787)	
$Liquidity \times MBHC$			-0.0351	
			(0.0471)	
$Capital \times MBHC$			-0.324	
			(0.334)	
$Size \times MBHC$			-1.283*	
			(0.682)	
$Capital * Size$				-0.140
				(0.0979)
Observations	30,322	30,322	30,322	30,322
R-squared	0.035	0.045	0.045	0.045
F-Test for Column (III)		Coef.	Std. Err.	p-value
$Capital + Capital \times MBHC$		-.095	.326	0.771

Notes: The event window has a length of three quarters and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal C&I loan growth during the event period. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal loan growth, averaged over the eight quarters preceding the event. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. $MBHC$ is a dummy variable that takes the value of one if a bank was part of a multi-bank holding company in the quarter preceding an event. EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. All explanatory variables are demeaned. All equations include bank fixed effects. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Table 6: Varying event length

	(I) 1 quarter	(II) 2 quarters	(III) 3 quarters
Liquidity	0.0906***	0.174***	0.281***
	(0.0135)	(0.0195)	(0.0237)
Capital	-0.0593	0.00966	0.162
	(0.0677)	(0.115)	(0.132)
Size	-2.647***	-4.099***	-5.873***
	(0.420)	(0.641)	(0.787)
$CALG^{prior}$	0.0801***	0.0695***	0.0697***
	(0.0242)	(0.0167)	(0.0143)
EV_{1990Q3}	-0.626***	-1.513***	-4.275***
	(0.243)	(0.344)	(0.419)
EV_{1997Q4}	3.630***	5.335***	6.711***
	(0.397)	(0.578)	(0.711)
EV_{2001Q3}	2.039***	2.240***	2.080**
	(0.507)	(0.750)	(0.910)
Constant	-1.983***	-2.769***	-3.057***
	(0.213)	(0.310)	(0.377)
Observations	32,069	31,111	30,322
R-squared	0.015	0.025	0.045
Number of banks	13,293	12,974	12,686

Notes: The event window has a length of 1, 2, and 3 quarters in columns (I), (II), and (III), respectively, and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal C&I loan growth during the event period. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal loan growth, averaged over the eight quarters preceding the event. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. All explanatory variables are demeaned. All equations include bank fixed effects. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Table 7: Dynamics

	(I)	(II)	(III)	(IV)
$Liquidity \times Quarter_1$				0.0890***
				(0.0105)
$Liquidity \times Quarter_2$				0.0930***
				(0.0108)
$Liquidity \times Quarter_3$				0.0998***
				(0.0106)
$Capital \times Quarter_1$				0.0537
				(0.0550)
$Capital \times Quarter_2$				0.0521
				(0.0587)
$Capital \times Quarter_3$				0.0561
				(0.0544)
$Size \times Quarter_1$				-1.572***
				(0.292)
$Size \times Quarter_2$				-2.108***
				(0.290)
$Size \times Quarter_3$				-2.193***
				(0.292)
$CALG^{prior}$			0.0795***	0.0697***
			(0.0153)	(0.0154)
$Quarter_2$	0.435***	0.435***	0.435***	0.435***
	(0.124)	(0.133)	(0.133)	(0.133)
$Quarter_3$	0.349***	0.349***	0.349***	0.349***
	(0.122)	(0.131)	(0.131)	(0.131)
EV_{1990Q3}	-1.468***	-1.702***	-1.745***	-1.425***
	(0.129)	(0.146)	(0.146)	(0.151)
EV_{1997Q4}	1.047***	1.051***	0.883***	2.237***
	(0.128)	(0.154)	(0.155)	(0.255)
EV_{2001Q3}	-1.509***	-1.513***	-1.651***	0.693**
	(0.136)	(0.168)	(0.169)	(0.327)
$Constant$	-0.619***	-0.552***	-0.480***	-1.280***
	(0.115)	(0.117)	(0.117)	(0.157)
Observations	90,966	90,966	90,966	90,966
R-squared	0.005	0.018	0.019	0.022
Bank fixed effects	No	Yes	Yes	Yes

Notes: The event window has a length of three quarters and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal C&I loan growth during the event period. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal loan growth, averaged over the eight quarters preceding the event. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. $Quarter_{1-3}$ are dummies for the three quarters of the event window. All explanatory variables are demeaned. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Table 8: Securitization and liquidity

	(I)	(II)
Securitization	0.000907	0.478***
	(0.0770)	(0.0842)
Liquidity		0.337***
		(0.0260)
Capital	0.290**	0.179
	(0.132)	(0.132)
Size	-5.809***	-6.425***
	(0.796)	(0.798)
$CALG^{prior}$	0.0664***	0.0740***
	(0.0143)	(0.0143)
EV_{1990Q3}	-4.364***	-5.108***
	(0.449)	(0.447)
EV_{1997Q4}	5.810***	3.467***
	(0.909)	(0.908)
EV_{2001Q3}	-0.0928	-2.282*
	(1.202)	(1.197)
Constant	-2.447***	-1.350***
	(0.485)	(0.484)
Observations	30,322	30,322
R-squared	0.035	0.047

Notes: The event window has a length of three quarters and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal C&I loan growth during the event period. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal loan growth, averaged over the eight quarters preceding the event. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. All explanatory variables are demeaned. All equations include bank fixed effects. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Table 9: Alternative outlier adjustment

	(I)	(II)	(III)
Liquidity	0.156***	0.150***	0.277***
	(0.0120)	(0.0123)	(0.0235)
Capital	-0.0433	-0.0770	0.194
	(0.0577)	(0.0608)	(0.130)
Size	0.230*	0.242*	-5.632***
	(0.134)	(0.138)	(0.782)
$CALG^{prior}$	0.102***	0.102***	0.0657***
	(0.0121)	(0.0122)	(0.0143)
EV_{1990Q3}		-4.617***	-4.348***
		(0.383)	(0.417)
EV_{1997Q4}		2.671***	6.404***
		(0.399)	(0.703)
EV_{2001Q3}		-4.372***	1.745*
		(0.439)	(0.899)
Constant	-2.482***	-0.922***	-2.891***
	(0.148)	(0.270)	(0.372)
Observations	30,092	30,092	30,092
R-squared	0.01	0.024	0.044
Bank fixed effects	No	No	Yes

Notes: This table shows the results obtained by applying the filter suggested by Loutskina (2011). The event window has a length of three quarters and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal C&I loan growth during the event period. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal loan growth, averaged over the eight quarters preceding the event. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. All explanatory variables are demeaned. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Table 10: Total loans

	(I)	(II)	(III)
Liquidity	0.144***	0.137***	0.275***
	(0.00559)	(0.00576)	(0.00964)
Capital	-0.171***	-0.145***	-0.0583
	(0.0324)	(0.0342)	(0.0560)
Size	-0.268***	-0.160**	-3.760***
	(0.0615)	(0.0642)	(0.360)
$CALG^{prior}$	0.318***	0.329***	0.314***
	(0.0112)	(0.0113)	(0.0128)
EV_{1990Q3}		-2.800***	-2.334***
		(0.150)	(0.158)
EV_{1997Q4}		0.0255	2.506***
		(0.174)	(0.298)
EV_{2001Q3}		-3.229***	1.106***
		(0.192)	(0.390)
Constant	-1.828***	-0.437***	-1.891***
	(0.0621)	(0.113)	(0.159)
Observations	35,706	35,706	35,706
R-squared	0.076	0.092	0.147
Bank fixed effects	No	No	Yes

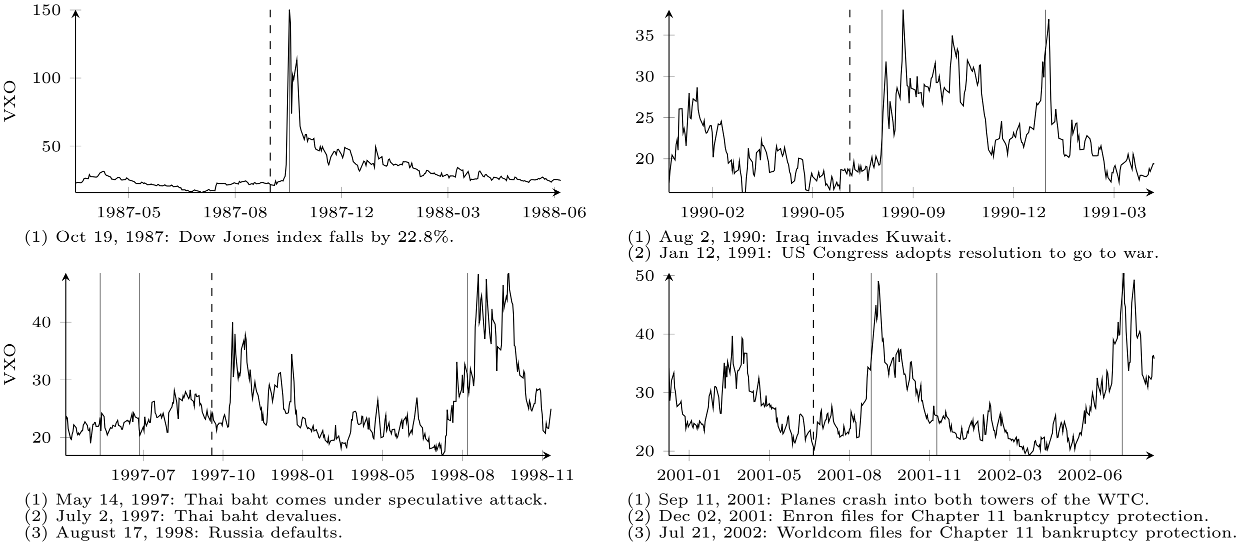
Notes: The event window has a length of three quarters and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal total loan growth during the event period. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal total loan growth, averaged over the eight quarters preceding the event. EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. All explanatory variables are demeaned. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Table 11: Alternative measures of abnormal loan growth

	(I) Seasonal Dummies	(II) + Aggregate loan growth	(III) + autoreg. lag
Liquidity	0.280***	0.250***	0.259***
	(0.0237)	(0.0244)	(0.0253)
Capital	0.204	0.193	0.223*
	(0.132)	(0.135)	(0.130)
Size	-5.774***	-5.291***	-5.240***
	(0.789)	(0.815)	(0.815)
$CALG^{prior}$	0.0801***	0.0816***	0.0626***
	(0.0144)	(0.0150)	(0.0156)
EV_{1990Q3}	-1.951***	0.506	0.470
	(0.422)	(0.430)	(0.438)
EV_{1997Q4}	6.672***	5.662***	5.650***
	(0.714)	(0.736)	(0.743)
EV_{2001Q3}	4.203***	5.881***	5.877***
	(0.914)	(0.937)	(0.948)
Constant	-4.303***	-4.477***	-4.128***
	(0.378)	(0.386)	(0.390)
Observations	30,322	30,322	30,322
R-squared	0.031	0.017	0.016

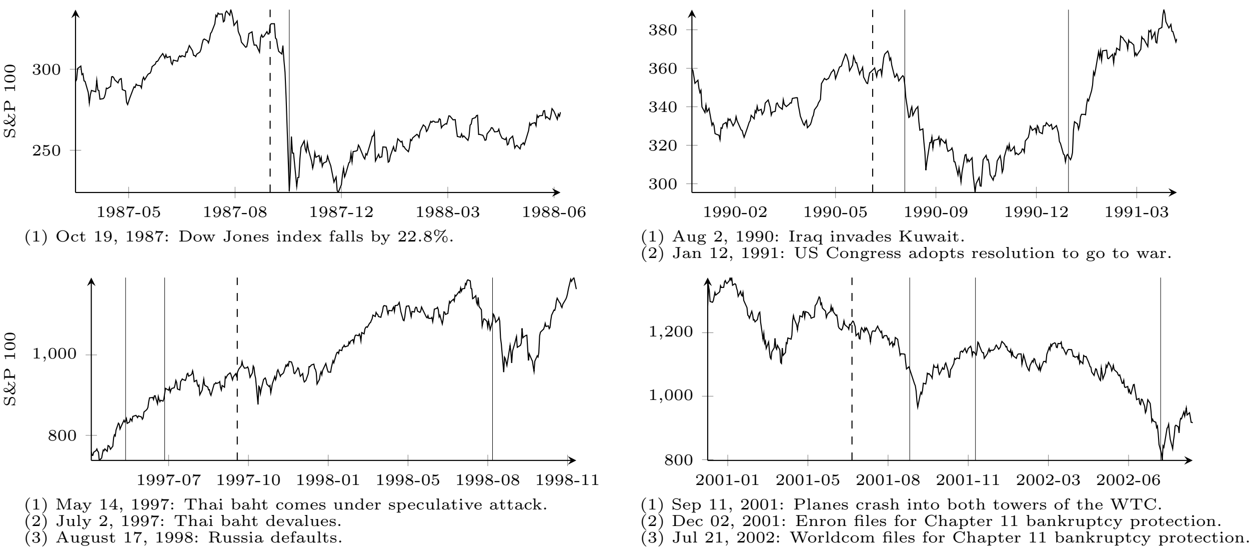
Notes: The event window has a length of three quarters and starts in the quarter in which the event occurs. The dependent variable is cumulative, abnormal C&I loan growth during the event period, where abnormal loan growth has been calculated using a different specification of the market equation in each of the columns. The explanatory variables are liquidity, capitalization, size, and cumulative, abnormal loan growth, averaged over the eight quarters preceding the event. $CALG^{prior}$ is normalized by multiplying average $CALG$ over the eight pre-event quarters by the event length. EV_{1990Q3}, EV_{1997Q4}, and EV_{2001Q3} are event dummies. All explanatory variables are demeaned. All equations include bank fixed effects. Robust standard errors (in parentheses) are clustered at the bank level. ***/**/* correspond to significance levels of 0.01/0.05/0.10.

Figure 1: VXO development around the four events



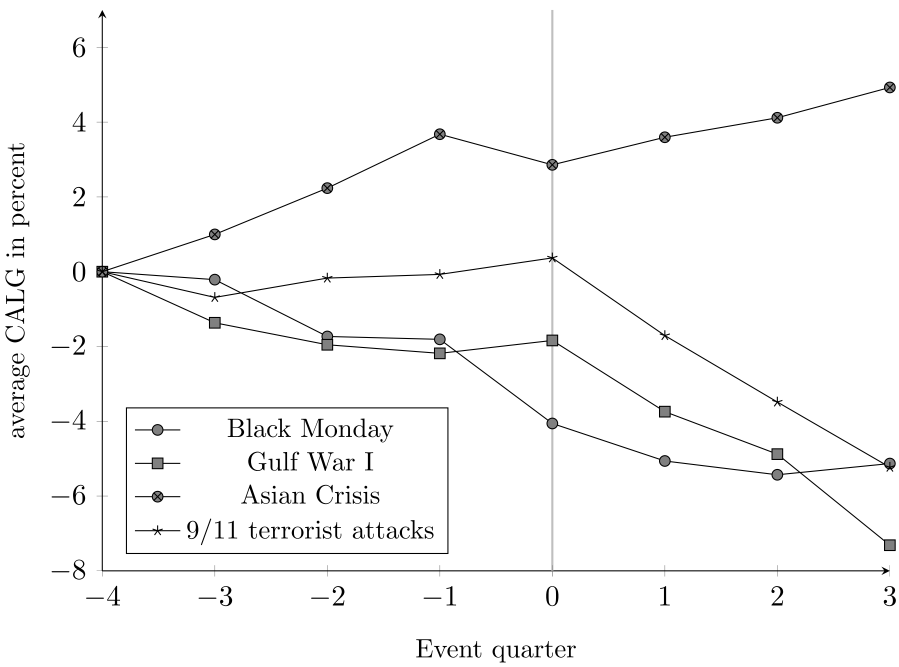
Notes: The figures show the development of the VXO around the four events. The dashed lines indicate the beginning of a quarter in the course of which a volatility event occurs. The solid lines indicate other developments which occured around the time of the events which we analyze. A short description of these events is given below the figures in chronological order.

Figure 2: S&P 100 around the four events



Notes: The figures show the development of the S&P 100 index around the four events. The dashed lines indicate the beginning of a quarter in the course of which a volatility event occurs. The solid lines indicate other developments which occured around the time of the events which we analyze. A short description of these events is given below the figures in chronological order.

Figure 3: Average CALG developments around the four events



Notes: This figure shows the average developments of the cumulative, abnormal loan growth rates around the four events.

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Burkhard Raunig, Johann Scharler, Friedrich Sindermann

Do banks lend less in uncertain times?

Abstract
We study the development of bank lending in the U.S. after four large jumps in uncertainty using an event study approach. We find that more liquid banks reduce lending less than banks with smaller liquidity ratios after a surge in uncertainty. Lending by smaller banks is also less responsive to increases in uncertainty. Banks with a higher capitalization ratio keep up lending to a greater extent, but the effect is only significant for banks which are not part of a multi-bank holding company. This heterogeneity across banks suggests that declines in bank lending following increases in uncertainty are partly the result of a reduced supply of bank loans.

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