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# Bank liquidity creation, monetary policy, and financial crises

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ABSTRACT

This paper examines the interplay among bank liquidity creation (which incorporates all bank on- and off-balance sheet activities), monetary policy, and financial crises. We find that: (1) high liquidity creation (relative to trend) – particularly off-balance sheet liquidity creation – helps predict crises, controlling for other factors; (2) monetary policy has statistically significant, but economically minor effects on liquidity creation by small banks during normal times, and these effects are even weaker during financial crises; (3) monetary policy has very little effects on medium and large bank liquidity creation during both normal times and crises. These findings suggest that authorities may wish to monitor bank liquidity creation closely in order to predict and perhaps lessen the likelihood of financial crises. They might also consider other tools to control bank liquidity creation, such as capital and liquidity requirements.



## 1. Introduction

Liquidity creation is a key reason why banks exist. Banks create liquidity on the balance sheet by financing relatively illiquid assets such as business loans with relatively liquid liabilities such as transactions deposits (e.g., Bryant, 1980; Diamond and Dybvig, 1983). The loans provide bank customers with the necessary funds to make investments, while the deposits deliver liquidity and payment services to the public to make purchases. Banks also create liquidity off the balance sheet through loan commitments and similar claims to liquid funds (e.g., Holmstrom and Tirole, 1998; Kashyap et al., 2002). For example, loan commitments allow customers to plan their investments and expenditures, knowing that the required funds will be forthcoming when needed (e.g., Boot et al., 1993). Empirical evidence confirms that on- and off-balance sheet liquidity creation have positive effects on the economy (Berger and Sedunov, 2017).

While bank liquidity creation is important for the macroeconomy, it may also sow the seeds of a financial crisis. Acharya and Naqvi (2012) argue that during uncertain times, deposits flow into banks, who may lower their lending standards and lend more. This increases on-balance sheet liquidity creation and may generate asset price bubbles that heighten the fragility of the banking sector. Thakor (2005) shows that excessive risk-taking and greater bank liquidity creation may also occur off the balance sheet during booms, when banks shy away from exercising material adverse change clauses in loan commitment contracts due to reputational concerns. Brunnermeier et al. (2011) argue that models that assess systemic risk should include liquidity build-ups in the financial sector. Nonetheless, studies of early warning systems for financial crises do not use bank liquidity creation. Instead, they usually focus on macroeconomic variables, such as GDP growth, balance of payments problems, and real interest rates, and include banks only as part of domestic credit growth (e.g., Demirguc-Kunt and Detragiache, 1998; Kaminsky and Reinhart, 1999; Edison, 2003; Bussiere and Fratzscher, 2006; Reinhart and Rogoff, 2009).[1]

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[1] The one early warning study to our knowledge that includes an aggregate bank liquidity ratio uses liquid assets over total assets (Barrell et al., 2010). This excludes

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Our first contribution is to fill this void by addressing empirically whether aggregate bank liquidity creation indicates an impending crisis. Our main bank liquidity creation measure is Berger and Bouwman's (2009) preferred measure (see Appendix A for details), which is also used in a number of other studies (e.g., Distinguin et al., 2013; Horvath et al., 2014; Jiang et al., 2016; Berger and Sedunov, 2017). We use five U.S. financial crises described in Berger and Bouwman (2013): 1) the 1987 stock market crash; 2) the credit crunch of the early 1990s; 3) the Russian debt crisis plus the Long-Term Capital Management meltdown in 1998; 4) the bursting of the dot.com bubble plus the September 11 terrorist attack of the early 2000s; and 5) the subprime lending crisis of the late 2000s. We find that high liquidity creation relative to trend tends to be followed by financial crises – even after controlling for other macroeconomic factors and market returns – suggesting that abnormally high liquidity creation may be a harbinger of a crisis. This result is driven primarily by off-balance sheet liquidity creation.

The importance of bank liquidity creation in the macroeconomy and in foreshadowing financial crises raises the issue of controlling this liquidity creation. We therefore next focus on the effects of monetary policy on bank liquidity creation. Theory predicts that monetary policy may affect both on- and off-balance sheet liquidity creation. For example, expansionary monetary policy may increase bank deposits as well as loans, both of which expand bank liquidity creation, but may have ambiguous effects on off-balance sheet loan commitments. These effects are not examined in the extant empirical literature on how monetary policy affects the economy through banking. That literature employs the bank lending channel, in which the effects of monetary policy are transmitted through bank lending, rather than bank liquidity creation, of which lending is only a part (e.g., Bernanke and Gertler, 1995; Kashyap and Stein, 2000).

Moreover, there is no evidence of which we are aware on whether the effectiveness of monetary policy in changing bank behavior differs during financial crises and normal times. During financial crises, banks may hoard loanable funds due to the difficulty of accessing liquidity in the market and be less responsive to incentives to lend (Diamond and Rajan, 2011; Caballero and Simsek, 2013). The demand for and supply of loan commitments and other off-balance sheet guarantees may also be affected by financial crises (e.g., Thakor, 2005).

The second and third contributions of our paper are to fill these gaps in the monetary policy literature. We address how monetary policy affects total bank liquidity creation and its on-balance sheet and off-balance sheet components during normal times and during financial crises. For these analyses, we divide banks into small, medium, and large size classes. We find that during normal times, monetary policy has statistically significant, but economically small effects on small bank liquidity creation. This effect is reduced further during financial crises. Monetary policy has very little effects on liquidity creation by medium and large banks during both normal times and crises. Our stronger results for small banks are consistent with the literature that uses bank lending rather than bank liquidity creation (e.g., Kashyap and Stein, 2000), while our results on the differences between normal times and crisis effects are entirely novel.

The remainder of the paper is organized as follows. Section 2 describes our data sample and provides summary statistics on liquidity creation. Section 3 examines the relationship between liquidity creation and financial crises. Section 4 addresses the effects of monetary policy on bank liquidity creation during normal times and financial crises. Section 5 concludes.

the liquidity contributions of other on-balance sheet activities and all off-balance sheet activities, which together account for most of bank liquidity creation.

## 2. Data sample and summary statistics on liquidity creation

We include virtually all commercial and credit card banks in the U.S. in our study.[2] For each bank, we obtain quarterly Call Report data from 1984:Q1 to 2008:Q4. We stop the data in 2008:Q4 because this marked the end of the monetary policy regime in which the Federal Reserve targeted the federal funds rate with open market operations as its main policy instrument. Monetary policy was later dominated by quantitative easing, forward guidance, setting rates on reserves, and other measures. We keep a bank in the sample if it: 1) has commercial real estate or commercial and industrial loans outstanding; 2) has deposits; 3) has gross total assets (GTA) exceeding $25 million[3]; 4) has an equity capital to GTA ratio of at least 1%.

For each bank, we calculate the dollar amount of liquidity creation in each quarter (933,209 bank-quarter observations from 18,294 distinct banks) using the process described in the Appendix A. We aggregate these amounts to obtain the dollar amount of liquidity creation by the banking sector, and put these (and all other financial values) into real 2008:Q4 dollars using the implicit GDP price deflator. Our final sample contains 100 inflation-adjusted, quarterly liquidity creation amounts.

Fig. 1 *Panel A* shows the dollar amount of liquidity created by the banking sector over our sample period. It also shows the breakout into on- and off-balance sheet liquidity creation. Dotted lines indicate when the five financial crises occurred. As shown, liquidity creation increased substantially over time: it almost quadrupled from $1.398 trillion in 1984:Q1 to $5.304 trillion in 2008:Q4 (in real 2008:Q4 dollars). Since the mid-1990s, off-balance sheet liquidity creation has exceeded and grown faster than on-balance sheet liquidity creation, primarily due to growth in unused loan commitments. Fig. 1 *Panel B* shows that most of the liquidity in the banking sector is created by large banks and their share of the total has increased from 76% in 1984:Q1 to 86% in 2008:Q4. Over this same time frame, the shares of medium and small banks dropped from 8% to 5% and from 16% to 9%, respectively.

## 3. Predicting financial crises

This section first formulates our hypothesis on the relationship between liquidity creation and financial crises. It then discusses our methodology, followed by the results.

### 3.1. Hypothesis development

**Hypothesis**: High liquidity creation (relative to trend) indicates an impending financial crisis.

**Motivation**: Acharya and Naqvi (2012) provide a theoretical argument why an excessive build-up of liquidity may be the precursor to a crisis. They show that when macroeconomic risk increases, more deposits flow into the banking sector, which causes banks to lower their lending standards and lend more. This increases on-balance sheet bank liquidity creation that results in an asset bubble

[2] Berger and Bouwman (2009) include only commercial banks. We also include credit card banks to avoid an artificial $0.19 trillion drop in bank liquidity creation in the fourth quarter of 2006 when Citibank N.A. moved its credit-card lines to Citibank South Dakota N.A., a credit card bank.

[3] GTA equals total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve (a reserve for certain foreign loans). Total assets on Call Reports deduct these two reserves, which are held to cover potential credit losses. We add these reserves back to measure the full value of the loans financed and the liquidity created by the bank on the asset side.

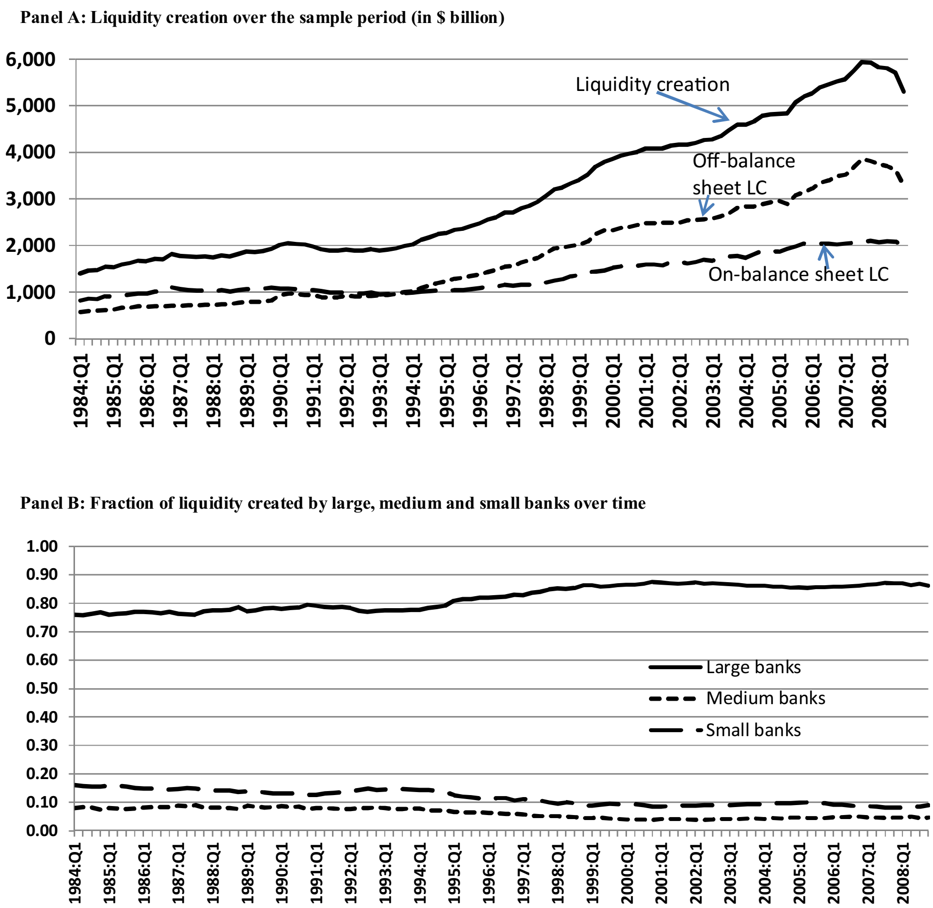



**Fig. 1. Liquidity creation over time.**
Panel A of this figure shows the dollar amount of total liquidity created by the banking sector, calculated using Berger and Bouwman's (2009) preferred liquidity creation measure, as well as on- and off-balance sheet liquidity creation (LC). The sample includes virtually all commercial and credit card banks in the U.S. from 1984:Q1–2008:Q4. Panel B contains the fraction of liquidity creation by small banks (GTA up to $1 billion), medium banks (GTA $1 billion–$3 billion), and large banks (GTA exceeding $3 billion). GTA equals total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve (a reserve for certain foreign loans). All dollar values are expressed in 2008:Q4 dollars.

that may burst and lead to future bank failures. Thakor (2005) shows that banks may also engage in excessive liquidity creation off the balance sheet. Specifically, reputational concerns will cause banks to shy away from exercising material adverse change clauses in loan commitment contracts during economic booms. This results in excessive risk taking and greater bank liquidity creation during such times. Collectively, these papers suggest that increased supplies of on- and off-balance sheet bank liquidity creation may increase the probability of bank failures and future financial crises. Some empirical evidence that the abundant availability of liquidity prior to the recent crisis may have contributed to the crisis by inducing banks to lower their credit standards is provided by Keys et al. (2010) and Dell'Ariccia et al. (2012).

### 3.2. Methodology

This section first explains why and how we detrend the bank liquidity creation data. It then explains the regression setup to test the link between bank liquidity creation and financial crises.

#### 3.2.1. Detrended bank liquidity creation

Liquidity creation has grown dramatically over time (see Section 2.2) and may contain seasonal components. This poses a problem because an examination of whether high levels of liquidity creation precede financial crises may be strongly affected by trends and seasonal components. We are interested in *deviations* from the trend and seasonality. To link liquidity creation to the advent of a crisis, we therefore use an approach widely employed in the macroeconomics literature (e.g., Barro, 1997): we first deseasonalize and then detrend the data.

To deseasonalize the data, we use the U.S. Census Bureau X11 procedure, which identifies and adjusts for outliers. For detrending, we use the Hodrick and Prescott (1997) (HP) filter, originally created to fit US GDP data but generally used to remove cyclical components from macroeconomic data.[4] Henceforth, we call deseasonalized and detrended data "detrended data" for brevity.

To ensure that the detrended amounts are based purely on historical data, we use the following approach. Since the HP filter requires that at least twelve quarterly observations are used, we first detrend the initial twelve quarters in the sample period (1984:Q1–1986:Q4). We drop the first eleven quarterly detrended amounts since they are in part based on forward-looking data. Thus, the first detrended amount in our analyses is from the twelfth quarter, 1986:Q4. For the following quarter, we use data from 1984:Q1 to 1987:Q1 in our detrending process and only keep the result for 1987:Q1. We follow a similar procedure for subsequent quarters.

[4] Assuming the original series has a trend component and a cyclical component, the HP filter identifies the cyclical component by trading off smoothness and goodness of fit. The trade-off parameter is set to 1600, which is customary for quarterly data. The HP filter is known to be sensitive to the endpoints, but since no obvious remedies exist, we present the results as they are.

### 3.2.2. Logit regressions to predict the onset of a crisis

To predict the onset of a crisis, we keep the normal time period quarters and the first quarter of each crisis (e.g., Demirguc-Kunt and Detragiache, 2001). We drop the remaining crisis quarters because a crisis cannot start if one is already underway. As a result, the sample used here is smaller than the one used above. We create a crisis dummy that equals 1 during the first quarter of each crisis.

Ideally, we would use data from a sample period with many crises, obtain the regression coefficients, and use them to predict the advent of several subsequent crises. However, our sample period includes only five crises. Therefore, the models we use to obtain the regression coefficients always include the first four crises and our focus is on predicting the start of the next crisis.

To predict the start of the fifth crisis, we run 19 logit regressions that each adds one additional quarter of data and predicts the probability of a crisis in the next quarter.[5] The first logit regression uses data through 2002:Q4, one quarter after the end of the fourth crisis. At this point in time, it is reasonable to assume that the start of the first four crises is generally known and thus could be used in a forecasting model. We regress the log odds ratio of a crisis striking on (lagged) detrended total liquidity creation and various (lagged) macroeconomic variables discussed below which may help predict the start of a crisis. The coefficients from this regression are used to predict the probability of a crisis occurring one quarter hence (i.e., in 2003:Q1). Each of the next 18 regressions adds one quarter of data. The last one uses data through 2007:Q2, the quarter before the subprime lending crisis of the late 2000s started.

Specifically, we estimate the following regression equations:

$$\log\left(\frac{Prob\,(CRISIS_t)}{1-Prob\,(CRISIS_t)}\right) = a_0 + a_1 DETRENDED\quad LC_{t-1} + a_2 DETRENDED\ \ GDP_{t-1} + a_3 MONPOL_{t-1} + a_4 MKTRETURN_{t-1} \quad (1)$$

where *DETRENDED LC* is detrended liquidity creation. *LC* is alternatively defined as total liquidity creation (*LC TOTAL*) or one of its components, on- or off-balance sheet liquidity creation (*LC ON BS* or *LC OFF BS*, respectively). *DETRENDED GDP* is detrended GDP. *MONPOL* is monetary policy measured as the level of the federal funds rate. *MKTRETURN* is the performance of the stock market as proxied by the average quarterly return on the value-weighted CRSP index.[6]

### 3.3. Results

We first provide some graphical evidence suggesting that liquidity creation, particularly its off-balance sheet component, tends to be abnormally high relative to trend before crises. Fig. 2 *Panel A* shows that detrended liquidity creation was high around the beginning of the credit crunch, and also from late 1994 through late 1999, which includes the Russian debt crisis and the prelude to the bursting of the dot.com bubble. It was also high prior to the subprime lending crisis.[7] Fig. 2 *Panel B* shows a far less pronounced pattern for detrended on-balance sheet liquidity creation, with somewhat elevated levels in the mid-1990s and more pronounced peaks in the late 1990s, including around the start of the Russian debt crisis and the bursting of the dot.com bubble. In Fig. 2 *Panel C*, the pattern for detrended off-balance sheet liquidity creation is very similar to that for total liquidity creation in *Panel A*.

Table 1 *Panel A* shows the results of the logit regressions. We report odds ratios obtained by exponentiating the logit coefficients. When *DETRENDED LC* has an odds ratio that exceeds (is less than) 1, a higher level of detrended liquidity creation is associated with higher (lower) odds of a crisis striking. *Subpanel A1* shows that the odds ratios of *DETRENDED LC TOTAL* exceed 1 in all cases and are significant at the 10% level or better in 18 out of 19 cases suggesting that higher detrended total liquidity creation is associated with a higher risk of a crisis striking one quarter hence. The odds ratios of about 1.03 in almost all the models suggest that a $1 billion increase in detrended liquidity creation increases the odds of a crisis occurring one quarter hence by about 3.0%. The odds ratios for the other variables suggest that a higher level of detrended GDP reduces the probability of a crisis striking and a higher federal funds rate is associated with a higher probability of a crisis occurring.[8] The odds ratios for the return on the stock market are never significant. *Subpanels A2* and *A3* show comparable results based on detrended on- and off-balance sheet liquidity creation, respectively.

Table 1 *Panel B* uses the results from *Panel A* to calculate the predicted probabilities of a crisis occurring one quarter hence starting in 2002:Q4 (first quarter after the fourth crisis) and ending in 2007:Q2 (last quarter before the fifth crisis). The results show that the probability of a crisis striking was close to zero soon after the fourth crisis was over, but started to increase in 2005:Q4. Detrended total liquidity creation (*Subpanel B1*) and detrended off-balance sheet liquidity creation (*Subpanel B3*) appear to predict the onset of a crisis best. As of 2006:Q3, the probability of a crisis occurring in the next quarter was close to 25% based on detrended total liquidity creation and close to 76% based on detrended off-balance sheet liquidity creation, but less than 2% based on on-balance sheet liquidity creation. Two quarters before the subprime lending crisis started, the probability of a crisis striking had increased to around 90% based on detrended total and off-balance sheet liquidity creation, although this dropped to 33% the quarter before the crisis.[9] Detrended on-balance sheet liquidity creation appears to be less important in predicting the fifth crisis, likely because it is smaller and has less variation than the other two series.

## 4. Effects of monetary policy on bank liquidity creation during normal times and crises

This section focuses on the effects of monetary policy on bank liquidity creation, which is important given the roles of liquidity creation in the macroeconomy and in presaging financial crises. It first develops two hypotheses on how monetary policy affects total, on-balance sheet, and off-balance sheet liquidity creation during normal times and during financial crises. Next, it discusses our methodology, which uses both a VAR approach and a single-equation model. It also describes the two measures of the change in monetary policy – the change in the federal funds rate and Romer and Romer (2004) monetary policy shocks. Finally, it presents regression results.

5 The finance literature often uses hazard models to predict a variety of "failures," such as companies going bankrupt (e.g., Shumway, 2001). However, those models assume that the time that has elapsed since the last failure matters in determining the probability of occurrence of the next failure. This assumption is not economically justifiable in our context since a financial crisis can happen at any time, and the time since the last crisis occurred is not an economically sensible variable on which one can condition the probability of occurrence of the next crisis.

6 Regressions based on the equal-weighted CRSP index or the S&P 500 yield similar results.

7 Detrended liquidity creation peaked in 2006:Q2, then dropped for three quarters afterward (until 2007:Q1). It rose dramatically in 2007:Q2. Importantly, as discussed in Section 4.3, the predictability of crises is driven by the level of detrended liquidity creation (which was high even after it dropped).

8 We are not asserting causation here – the federal funds rate may have been generally high before crises because the authorities were trying to slow the economy.

9 This drop in the last quarter is driven primarily by an increase in detrended GDP.

**Table 1**
**Detrended liquidity creation as an indicator of an impending financial crisis**.

Panel A: Logit regression results

Subpanel A1: Crisis dummy regressed on DETRENDED LC TOTAL and other factors

| Model estimated using data through: | 2002:Q4 | 2003:Q1 | 2003:Q2 | 2003:Q3 | 2003:Q4 | 2004:Q1 | 2004:Q2 | 2004:Q3 | 2004:Q4 | 2005:Q1 | 2005:Q2 | 2005:Q3 | 2005:Q4 | 2006:Q1 | 2006:Q2 | 2006:Q3 | 2006:Q4 | 2007:Q1 | 2007:Q2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DETRENDED LC TOTAL $_{t-1}$ | **1.030** | **1.031** | **1.031** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.033** | **1.031** | **1.033** | 1.024 |
| | *(1.94)* | *(2.01)* | *(2.05)* | *(2.07)* | *(2.07)* | *(2.07)* | *(2.07)* | *(2.07)* | *(2.08)* | *(2.08)* | *(2.08)* | *(2.08)* | *(2.08)* | *(2.07)* | *(2.08)* | *(2.06)* | *(1.99)* | *(1.99)* | *(1.61)* |
| DETRENDED GDP $_{t-1}$ | **0.950** | **0.951** | **0.952** | **0.952** | **0.952** | **0.952** | **0.952** | **0.952** | **0.952** | **0.952** | **0.951** | **0.951** | **0.951** | **0.951** | **0.950** | **0.949** | **0.950** | **0.950** | **0.971** |
| | *(1.92)* | *(1.90)* | *(1.88)* | *(1.87)* | *(1.87)* | *(1.88)* | *(1.88)* | *(1.88)* | *(1.88)* | *(1.88)* | *(1.88)* | *(1.88)* | *(1.89)* | *(1.88)* | *(1.90)* | *(1.93)* | *(1.88)* | *(1.88)* | *(1.90)* |
| MONPOL $_{t-1}$ | 2.030 | 2.190 | 2.250 | **2.273** | **2.273** | **2.273** | **2.273** | **2.273** | **2.275** | **2.275** | **2.275** | **2.275** | **2.280** | **2.335** | **2.342** | **2.382** | **2.421** | **2.467** | 2.312 |
| | *(1.31)* | *(1.56)* | *(1.64)* | *(1.68)* | *(1.68)* | *(1.68)* | *(1.68)* | *(1.69)* | *(1.69)* | *(1.69)* | *(1.69)* | *(1.69)* | *(1.70)* | *(1.74)* | *(1.74)* | *(1.77)* | *(1.75)* | *(1.77)* | *(1.62)* |
| MKTRETURN $_{t-1}$ | 0.796 | 0.775 | 0.774 | 0.770 | 0.770 | 0.770 | 0.770 | 0.770 | 0.770 | 0.770 | 0.770 | 0.770 | 0.770 | 0.766 | 0.766 | 0.768 | 0.764 | 0.756 | 0.810 |
| | *(0.73)* | *(0.83)* | *(0.81)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.84)* | *(0.83)* | *(0.82)* | *(0.85)* | *(0.67)* |
| Constant | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.000** | **0.000** | **0.000** | **0.000** | **0.000** | **0.000** |
| | *(1.77)* | *(2.05)* | *(2.15)* | *(2.19)* | *(2.19)* | *(2.19)* | *(2.19)* | *(2.20)* | *(2.20)* | *(2.20)* | *(2.20)* | *(2.20)* | *(2.21)* | *(2.25)* | *(2.26)* | *(2.29)* | *(2.26)* | *(2.27)* | *(2.04)* |
| Observations | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 | 52 | 53 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 |

Subpanel A2: Crisis dummy regressed on DETRENDED ON BS LC and other factors

| Model estimated using data through: | 2002:Q4 | 2003:Q1 | 2003:Q2 | 2003:Q3 | 2003:Q4 | 2004:Q1 | 2004:Q2 | 2004:Q3 | 2004:Q4 | 2005:Q1 | 2005:Q2 | 2005:Q3 | 2005:Q4 | 2006:Q1 | 2006:Q2 | 2006:Q3 | 2006:Q4 | 2007:Q1 | 2007:Q2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DETRENDED ON BS LC $_{t-1}$ | **1.045** | **1.047** | **1.048** | **1.049** | **1.049** | **1.049** | **1.049** | **1.049** | **1.049** | **1.049** | **1.049** | **1.049** | **1.049** | **1.049** | **1.049** | **1.050** | **1.050** | **1.050** | **1.051** |
| | (1.70) | (1.77) | (1.82) | (1.84) | (1.84) | (1.84) | (1.84) | (1.85) | (1.85) | (1.85) | (1.85) | (1.86) | (1.86) | (1.85) | (1.85) | (1.86) | (1.88) | (1.89) | (1.87) |
| DETRENDED GDP $_{t-1}$ | **0.967** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.970** | **0.969** | **0.969** | **0.969** | **0.969** | **0.972** |
| | (1.85) | (1.83) | (1.81) | (1.79) | (1.80) | (1.80) | (1.80) | (1.80) | (1.81) | (1.81) | (1.81) | (1.82) | (1.83) | (1.82) | (1.84) | (1.86) | (1.86) | (1.87) | (1.80) |
| MONPOL $_{t-1}$ | 1.882 | **2.086** | **2.122** | **2.143** | **2.146** | **2.146** | **2.146** | **2.147** | **2.153** | **2.153** | **2.154** | **2.159** | **2.163** | **2.197** | **2.209** | **2.216** | **2.229** | **2.233** | **2.271** |
| | (1.41) | (1.77) | (1.84) | (1.89) | (1.90) | (1.90) | (1.90) | (1.90) | (1.92) | (1.92) | (1.92) | (1.93) | (1.94) | (1.97) | (1.98) | (1.99) | (2.01) | (2.01) | (1.96) |
| MKTRETURN $_{t-1}$ | 0.839 | 0.800 | 0.799 | 0.795 | 0.794 | 0.794 | 0.794 | 0.794 | 0.794 | 0.794 | 0.794 | 0.794 | 0.793 | 0.792 | 0.791 | 0.791 | 0.790 | 0.789 | 0.793 |
| | (0.63) | (0.82) | (0.81) | (0.84) | (0.84) | (0.85) | (0.85) | (0.85) | (0.84) | (0.85) | (0.85) | (0.85) | (0.85) | (0.84) | (0.85) | (0.84) | (0.85) | (0.85) | (0.79) |
| Constant | **0.003** | **0.002** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** |
| | (1.95) | (2.33) | (2.43) | (2.48) | (2.49) | (2.49) | (2.49) | (2.49) | (2.51) | (2.51) | (2.51) | (2.53) | (2.54) | (2.56) | (2.58) | (2.59) | (2.61) | (2.62) | (2.54) |
| Observations | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 | 52 | 53 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 |

Subpanel A3: Crisis dummy regressed on DETRENDED OFF BS LC and other factors

| Model estimated using data through: | 2002:Q4 | 2003:Q1 | 2003:Q2 | 2003:Q3 | 2003:Q4 | 2004:Q1 | 2004:Q2 | 2004:Q3 | 2004:Q4 | 2005:Q1 | 2005:Q2 | 2005:Q3 | 2005:Q4 | 2006:Q1 | 2006:Q2 | 2006:Q3 | 2006:Q4 | 2007:Q1 | 2007:Q2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| DETRENDED OFF BS LC $_{t-1}$ | **1.049** | **1.051** | **1.052** | **1.053** | **1.053** | **1.053** | **1.053** | **1.053** | **1.053** | **1.053** | **1.053** | **1.053** | **1.053** | **1.053** | **1.054** | **1.051** | **1.034** | **1.030** | 1.018 |
| | (1.94) | (2.03) | (2.05) | (2.08) | (2.08) | (2.08) | (2.08) | (2.08) | (2.08) | (2.08) | (2.09) | (2.09) | (2.09) | (2.10) | (2.10) | (2.00) | (1.82) | (1.69) | (1.20) |
| DETRENDED GDP $_{t-1}$ | **0.945** | **0.946** | **0.947** | **0.947** | **0.947** | **0.947** | **0.947** | **0.947** | **0.947** | **0.947** | **0.947** | **0.947** | **0.947** | **0.946** | **0.946** | **0.945** | **0.960** | **0.963** | 0.979 |
| | (1.97) | (1.94) | (1.93) | (1.92) | (1.92) | (1.92) | (1.93) | (1.93) | (1.93) | (1.93) | (1.93) | (1.93) | (1.94) | (1.95) | (1.96) | (1.92) | (1.87) | (1.78) | (1.61) |
| MONPOL $_{t-1}$ | 1.795 | 1.904 | 2.007 | 2.031 | 2.031 | 2.032 | 2.033 | 2.033 | 2.034 | 2.034 | 2.034 | 2.034 | 2.038 | **2.074** | **2.077** | **2.128** | **1.935** | **1.928** | 1.771 |
| | (1.20) | (1.42) | (1.56) | (1.60) | (1.60) | (1.61) | (1.61) | (1.61) | (1.61) | (1.61) | (1.61) | (1.61) | (1.62) | (1.66) | (1.67) | (1.72) | (1.75) | (1.74) | (1.62) |
| MKTRETURN $_{t-1}$ | 0.810 | 0.789 | 0.786 | 0.780 | 0.780 | 0.780 | 0.780 | 0.780 | 0.779 | 0.779 | 0.779 | 0.779 | 0.779 | 0.776 | 0.776 | 0.800 | 0.837 | 0.829 | 0.883 |
| | (0.68) | (0.79) | (0.78) | (0.82) | (0.82) | (0.82) | (0.82) | (0.82) | (0.82) | (0.82) | (0.82) | (0.82) | (0.82) | (0.82) | (0.83) | (0.73) | (0.64) | (0.69) | (0.49) |
| Constant | **0.003** | **0.002** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.001** | **0.002** | **0.002** | **0.003** |
| | (1.74) | (1.99) | (2.15) | (2.20) | (2.20) | (2.21) | (2.21) | (2.21) | (2.21) | (2.21) | (2.21) | (2.21) | (2.23) | (2.27) | (2.28) | (2.34) | (2.43) | (2.43) | (2.33) |
| Observations | 44 | 45 | 46 | 47 | 48 | 49 | 50 | 51 | 52 | 53 | 54 | 55 | 56 | 57 | 58 | 59 | 60 | 61 | 62 |

Panel B: Predicted probabilities of the occurrence of a crisis one quarter hence

| Prediction based on: | 2002:Q4 | 2003:Q1 | 2003:Q2 | 2003:Q3 | 2003:Q4 | 2004:Q1 | 2004:Q2 | 2004:Q3 | 2004:Q4 | 2005:Q1 | 2005:Q2 | 2005:Q3 | 2005:Q4 | 2006:Q1 | 2006:Q2 | 2006:Q3 | 2006:Q4 | 2007:Q1 | 2007:Q2 |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Subpanel B1: | | | | | | | | | | | | | | | | | | | |
| DETRENDED LC TOTAL | 10.0% | 3.2% | 0.9% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.1% | 5.3% | 0.4% | 5.5% | 24.2% | 5.6% | 90.4% | 33.2% |
| Subpanel B2: | | | | | | | | | | | | | | | | | | | |
| DETRENDED ON BS LC | 25.9% | 2.6% | 1.3% | 0.1% | 0.0% | 0.0% | 0.0% | 0.3% | 0.0% | 0.1% | 0.3% | 0.2% | 6.2% | 1.4% | 0.8% | 1.6% | 0.3% | 26.7% | 1.5% |
| Subpanel B3: | | | | | | | | | | | | | | | | | | | |
| DETRENDED OFF BS LC | 7.8% | 10.3% | 1.4% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.0% | 0.2% | 3.8% | 0.2% | 26.3% | 76.9% | 35.5% | 85.6% | 40.3% |

This table examines whether abnormally high detrended liquidity creation presages a financial crisis. The data are first deseasonalized using the X11 procedure developed by the U.S. Census Bureau, and then detrended using the Hodrick and Prescott (1997) filter. We refer to the modified data as detrended for brevity. The sample includes the normal time period quarters and the first quarter of every crisis. We drop the remaining crisis quarters because a crisis cannot start if one is already ongoing. The crisis dummy equals 1 during the first quarter of each crisis. Panel A reports the results of 19 logit regressions in which the probability of a crisis occurring is regressed on DETRENDED LC, the dollar amount of detrended liquidity creation, with LC alternatively defined as total liquidity creation (Subpanel A1) or its on- or off-balance sheet component (Subpanels A2 and A3, respectively), macroeconomic factors that may affect the likelihood of a crisis (detrended GDP; and monetary policy as measured by MONPOL, the federal funds rate) and MKTRETURN, the quarterly return on the stock market measured as the average monthly return during the quarter. The regressors are lagged one quarter. The first regression uses data through 2002:Q4, one quarter after the end of the fourth crisis. Each of the next 18 regressions includes one additional quarter of data. The last regression uses data through 2007:Q2, the last quarter before the start of the subprime lending crisis of the late 2000s, the last crisis in the sample. Odds ratios, i.e., exponentiated regression coefficients, are reported. t-statistics are in parentheses. **Bold font** denotes significance at least at the 10% level. Panel B uses the results from Panel A to calculate the predicted probabilities of a crisis striking one quarter hence.

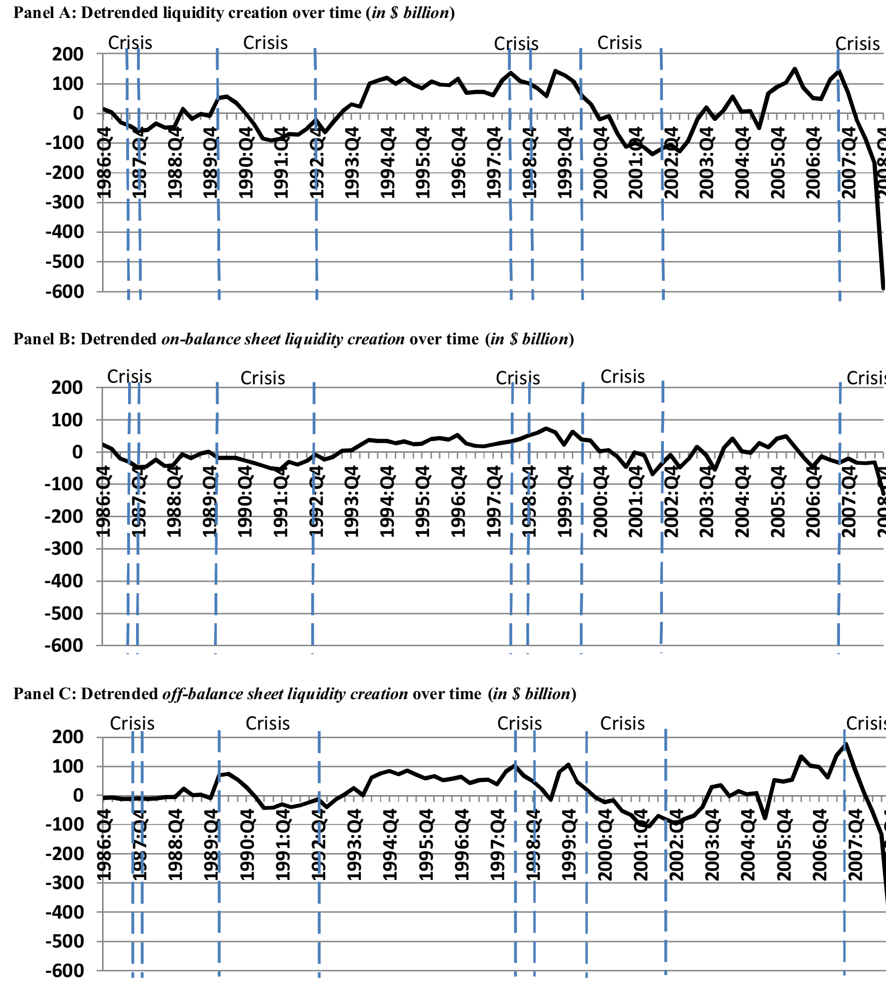



**Fig. 2. Detrended liquidity creation over the sample period**.
This figure shows the total amount of detrended liquidity created by the banking sector (Panel A) and its on- and off-balance sheet components (Panels B and C, respectively). The data are first deseasonalized using the X11 procedure developed by the U.S. Census Bureau, and then detrended using the Hodrick and Prescott (1997) (HP) filter. To ensure that the detrended amounts are purely based on historical data, we do the following. Since the HP filter requires that at least twelve quarterly observations are used, we first detrend the initial twelve quarters in the sample period (1984:Q1–1986:Q4). We drop the first eleven quarterly detrended amounts since they are in part based on forward-looking data. Thus, the first detrended amount in our sample is from the twelfth quarter, 1986:Q4. To obtain the detrended amount in the next quarter, we use data from 1984:Q1–1987:Q1 in our detrending process and only keep the result for 1987:Q1. We follow a similar procedure for every subsequent quarter and end up with a detrended liquidity creation series from 1986:Q4–2008:Q4 that is based on historical data in every quarter. All dollar values are expressed in real 2008:Q4 dollars. Each panel also shows the five financial crises studied in this paper (marked with dotted lines) – the 1987 stock market crash, the credit crunch of the early 1990s, the Russian debt crisis plus LTCM bailout in 1998, the bursting of the dot.com bubble plus Sept. 11, and the subprime lending crisis of the late 2000s.

### *4.1. Hypothesis development*

For ease of exposition we focus on monetary policy loosening (MPL), but in line with the literature, we assume symmetry – opposite effects are expected for monetary policy tightening (MPT).

**Hypothesis**: During normal times, MPL: (a) increases on-balance sheet liquidity creation for banks of all sizes and this effect is strongest for small banks; (b) has an ambiguous effect on off-balance sheet liquidity creation for banks of all sizes; and (c) increases total liquidity creation by small banks, with ambiguous effects on medium and large banks.

**Motivation**: Monetary policy affects on- and off-balance sheet liquidity creation differently during normal times.

On-balance sheet liquidity creation: MPL is expected to increase on-balance sheet liquidity creation by increasing loans (see bank lending channel survey papers by Bernanke and Gertler, 1995; Kashyap and Stein, 1997) and deposits. To elaborate, MPL expands bank reserves, which may increase bank deposits. This may expand the loanable funds available and/or decrease the cost of funds by replacing higher-cost sources such as federal funds or large CDs with cheaper deposits (e.g., Bernanke and Blinder, 1992; Stein, 1998). Banks may respond by lending more, including granting loans to some applicants that might otherwise be rationed (e.g., Stiglitz and Weiss, 1981).[10] The effect is expected to be greater for small banks because they have less access to non-deposit sources of funds (Kashyap and Stein, 2000).

Off-balance sheet liquidity creation: The effects of MPL on off-balance sheet liquidity creation are ambiguous for banks of all size classes. On the one hand, customers who obtain more credit in the spot market may reduce their demand for loan commitments and other off-balance sheet guarantees (Thakor, 2005). On the other hand, banks may supply more guarantees because of the greater availability of loanable funds and/or a reduction in the cost of these funds.[11] It is unclear *ex ante* which effect dominates.

[10] Additionally, a decrease in market interest rates caused by MPL increases the present value of fixed-rate loans in a bank's portfolio, which improves the bank's net worth, thereby also enhancing bank loan supply.

[11] Because of complementarities between offering deposits and selling loan commitments, an increase in deposits can also induce the bank to provide more liquidity to its customers via loan commitments (Kashyap et al., 2002).

Total liquidity creation: The effect of MPL on total liquidity creation by small banks is hypothesized to be positive. The positive effect of MPL on on-balance sheet liquidity creation is expected to dominate any effect on off-balance sheet liquidity creation because these banks create the vast majority of their liquidity on the balance sheet (Berger and Bouwman, 2009, 2016). In contrast, medium and large banks create much of their liquidity off the balance sheet. Therefore, the ambiguous effect on off-balance sheet liquidity creation may dominate the positive effect on on-balance sheet liquidity creation, yielding an ambiguous effect of MPL on total liquidity creation by medium and large banks.

**Hypothesis**: The effects of monetary policy on liquidity creation is weaker during crises than during normal times for banks of all size classes. This holds for: (a) on-balance sheet liquidity creation; (b) off-balance sheet liquidity creation; and (c) total liquidity creation.

**Motivation**: Monetary policy affects on- and off-balance sheet liquidity creation differently during crises.

On-balance sheet liquidity creation: The response of on-balance sheet liquidity creation to MPL may be muted during crises relative to normal times because banks may hoard loanable funds and be less responsive to incentives to lend. In addition, asymmetric information problems become more acute during crises and the possibility of asset markets freezing up can also make banks more averse to taking positions in some assets or engaging in interbank lending that could have enabled other banks to make loans (Diamond and Rajan, 2011; Caballero and Simsek, 2013).

Off-balance sheet liquidity creation: The effect of monetary policy on off-balance sheet liquidity creation is also expected to be weaker during crises. As discussed above, during normal times, the demand for loan commitments and other off-balance sheet guarantees may go down as a result of MPL, while the supply of such guarantees may go up, yielding an ambiguous overall effect. During crises, the reduction in demand for these off-balance sheet guarantees due to MPL is smaller because greater asymmetric information and moral hazard frictions lead to more rationing in the spot market (Stiglitz and Weiss, 1981), so some borrowers who would have gone to the spot market shift instead to loan commitments (Thakor, 2005). Similarly, banks may increase the supply of these guarantees less in response to MPL during crises because they are less responsive to changes in loanable funds and the cost of funding during crises. Consequently, since MPL is predicted to have an ambiguous effect on off-balance sheet liquidity creation during normal times, it will have a smaller positive effect or a stronger negative effect during crises. For ease of exposition, we refer to this as a weaker effect.

Total liquidity creation: The effect of MPL on total liquidity creation is the sum of the on- and off-balance sheet effects. Since both are weaker during crises, the overall effect is also weaker.

### 4.2. Methodology

This section explains the methodology used to test the two hypotheses formulated in the previous subsection. It first discusses the two monetary policy measures. It then explains the two methods used to examine the effects of monetary policy on liquidity creation during normal times and crises.

Since the hypothesized effects of monetary policy on liquidity creation differ by bank size, we also split the sample into small, medium, and large banks, and perform our analyses separately for these three sets of banks. Small banks have GTA up to \$1 billion, medium banks have GTA exceeding \$1 billion and up to \$3 billion, and large banks have GTA exceeding \$3 billion. Small banks correspond to the usual definition of community banks and the \$3 billion cutoff between medium and large banks results in approximately equal numbers of banks in those two size classes.

Merged banks are included in all the analyses. Banks are not necessarily in the same size category at each point in time. They are included in whichever size category they belong in a particular period. For example, if two small banks merge and move beyond one of the thresholds, they are counted in the bigger bank size category in subsequent time periods.

#### 4.2.1. Two monetary policy measures

To examine how monetary policy affects liquidity creation, we focus on the change in monetary policy based on two measures. These are the change in the federal funds rate and the monetary policy shocks developed by Romer and Romer (2004).

Since the Federal Reserve explicitly targeted the federal funds rate over our entire sample period, the change in the federal funds rate proxies for the change in monetary policy.[12] A drawback of this measure, however, is that it may contain anticipatory movements. That is, changes in the federal funds rate may respond to information about future developments in the economy, making it harder to isolate the effect of monetary policy on bank output. The Romer and Romer measure takes into account such endogeneity.

Romer and Romer (2004) construct their measure as follows. First, the intended federal funds rate changes around meetings of the Federal Open Market Committee (FOMC) are gleaned by examining narratives of each FOMC meeting. Next, anticipatory movements are removed by regressing the intended federal funds rate on the Federal Reserve's internal forecasts of inflation and real activity. The residuals from this regression are the monetary policy shocks, i.e., the changes in the federal funds rate that are not responsive to forecasts of economic conditions. While Romer and Romer's (2004) data end in 1996:Q4, Barakchian and Crowe (2013) extend the data through 2008:Q2, and Crowe provides a further extension to 2008:Q4.[13]

Fig. 3 shows the change in the federal funds rate (*Panel A*) and the Romer and Romer monetary policy shocks (*Panel B*). The five financial crises are indicated with dotted lines. The figure shows that MPL is prevalent during crises – loosening took place in 83% of the crisis quarters based on the change in the federal funds rate and in 58% of these quarters based on the Romer and Romer (2004) policy shocks. The reason why the fractions are different for the two measures is as follows. When the federal funds rate is reduced, it is always recorded as MPL based on the change in the federal funds rate. However, it is only recorded as MPL based on the Romer and Romer policy shocks if the reduction in the federal funds rate was more than it normally would be based on the Federal Reserve's internal forecasts of inflation and growth.

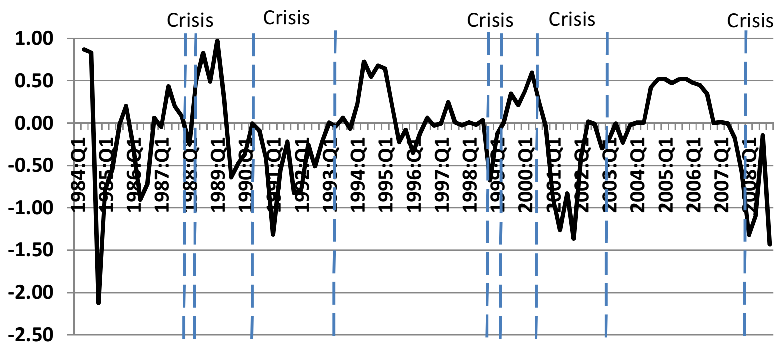
#### 4.2.2. Two methods to examine the effects of monetary policy on liquidity creation

To examine the effect of monetary policy on liquidity creation, we use both a vector autoregression (VAR) model (e.g., Cochrane, 1998; Christiano et al., 1999; Stock and Watson, 2001) and a single-equation approach (e.g., Romer and Romer, 2004). In the VAR

[12] We use the actual federal funds rate (as in Romer and Romer, 2004) rather than the target federal funds rate since bank behavior will be affected most by the actual rate.

[13] We are grateful to Christopher Crowe for making these data available to us. Note that a strength of Romer and Romer's original measure is that it controls for the Federal Reserve's own Greenbook forecasts. However, since Greenbook forecasts are released only with a five-year lag, Barakchian and Crowe (2013) substitute the consensus forecast available from the Blue Chip Economic Indicators for the Greenbook forecasts towards the end of the sample.

**Panel A: Change in the federal funds rate (%)**




**Panel B: Romer and Romer monetary policy shocks (%)**

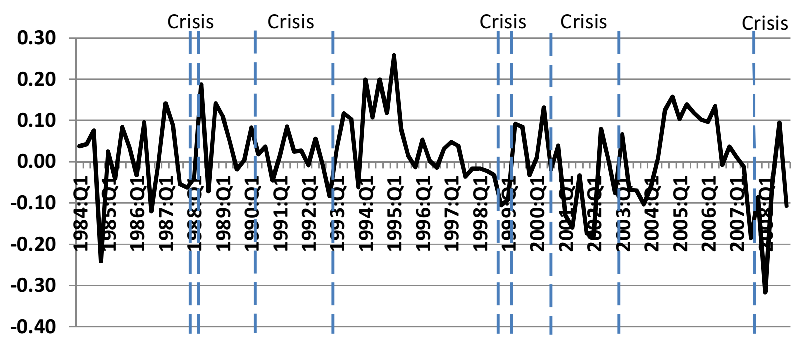



**Fig. 3. Changes in monetary policy.**
This figure shows the change in monetary policy over the sample period using two measures. Panel A uses the change in the federal funds rate. Panel B uses the Romer and Romer monetary policy shocks, which are regression residuals that measure the changes in the federal funds rate that do not reflect anticipatory movements related to forecasts of economic conditions. Each panel also shows the five financial crises studied in this paper (marked with dotted lines) – the 1987 stock market crash, the credit crunch of the early 1990s, the Russian debt crisis plus LTCM bailout in 1998, the bursting of the dot.com bubble plus Sept. 11, and the subprime lending crisis of the late 2000s.

model, monetary policy is allowed to respond to bank liquidity creation. The VAR model may be more appropriate if monetary policy responds significantly to aggregate bank liquidity creation. In the single-equation approach, lagged monetary policy may affect liquidity creation, but lagged liquidity creation does not influence monetary policy. This model may be most appropriate if monetary policy is essentially exogenous to liquidity creation. We account for both possibilities by running the two models and obtain similar results below.[14]

As discussed above, we follow standard practice in the monetary policy literature and treat tightening and loosening symmetrically (e.g., Bernanke and Blinder, 1992; Christiano et al., 1999). For expositional purposes, we mostly discuss loosening, but the effects of tightening should be understood as the exact opposite. In the interest of brevity, we also follow the applied macroeconomic literature and simply show the impulse response functions and their confidence intervals for both the VAR and single-equation models in the figures below.[15]

*4.2.2.1. Single-equation approach.* Because it is simpler, we explain our single-equation approach first. To analyze how monetary policy affects liquidity creation during normal times and whether the effect differs during financial crises, we use the following regression setup[16]:

$$
\begin{aligned}
\%\Delta LC_{X,t} = {} & \alpha + \sum_{i=1}^{4} \beta_i \Delta MONPOL_{t-i} \\
& + \sum_{j=1}^{4} \gamma_j \Delta MONPOL_{t-j} * D\ CRIS_{t-j} + \sum_{k=1}^{4} \delta_k D\ CRIS_{t-k} \\
& + \sum_{l=1}^{4} \varepsilon_l\ \%\Delta LC_{X,t-l} + \sum_{m=1}^{4} \zeta_m\ \%\Delta GDP_{t-m} + \sum_{n=1}^{4} \eta_n \Delta PRICE_{t-n} \\
& + \theta\ \ \Delta INNOVATION_{t-1} + \vartheta\ \ \Delta RISKAVERSION_{t-1} \\
& + \iota\ \ \Delta UNCERTAINTY_{t-1} + \kappa\, D\ RISKAV\ UNCERT\ AVAIL_{t-1} \\
& + \lambda\ \ \Delta CAPITAL\ \ RATIO_{X,t-1} + \mu\ \ \Delta NPL\ \ RATIO_{X,t-1} \\
& + \sum_{p=1}^{3} \nu_p D\ SEASON_p
\end{aligned}
\tag{2}
$$

[14] This is in line with Romer and Romer (2004, p. 1079), who study the effect of a monetary policy shock on output (GDP) using a single-equation approach and a VAR model, and find the effect to be "broadly similar."

[15] Tables with all the regression coefficients are available from the authors upon request.

[16] The VAR model explained in Section 4.2.2.2 includes four lags of five variables viewed to be endogenous. For parsimony, that model only includes one lag of the exogenous variables, with two exceptions. First, the seasonal dummies are not lagged. Second, although the crisis dummy is exogenous, we include four lags because the crisis dummy interacted with the change in monetary policy is endogenous. For consistency, we use the same lag structure in the single-equation approach. In lag-order tests discussed below, we verify that four quarterly lags are sufficient.

where $\%\Delta LC_{X,t}$ is the percentage change in liquidity creation by banks of size class $X$ in year t, with $X \in \{Small, Medium, Large\}$. $\%\Delta LC_{X,t}$ is alternatively defined as total liquidity creation ($\%\Delta LC\ TOTAL_{X,t}$) or one of its components, on-balance sheet or off-balance sheet liquidity creation ($\%\Delta LC\ ON\ BS_{X,t}$ and $\%\Delta LC\ OFF\ BS_{X,t}$, respectively). $\Delta MONPOL_{t-j}$ is the (lagged) change in monetary policy, alternatively defined as the change in the federal funds rate ($\Delta FEDFUNDS_{t-j}$) and Romer and Romer monetary policy shocks ($RR\ POLICYSHOCKS_{t-j}$). In both cases, a negative number reflects monetary policy loosening and a positive number indicates tightening. $D\ CRIS_{t-k}$ is a crisis dummy that equals one if there was a crisis in quarter *t-k*, with $k \in \{1, 2, 3, 4\}$. $\Delta MONPOL_{t-j}{}^{*}D\ CRIS_{t-j}$ is an interaction term of a (lagged) change in monetary policy with a (lagged) crisis dummy. $\%\Delta GDP_{t-m}$, the (lagged) percentage change in gross domestic product, and $\Delta PRICE_{t-n}$, the (lagged) change in the price level, are included to control for the economic cycle, consistent with the literature. $\Delta INNOVATION_{t-1}$, the (lagged) change in securitization divided by the sum of securitization and lending, aims to capture changes in financial innovation in the banking industry that affect liquidity creation. Following Bekaert et al. (2013), we include two components of the Volatility Index (VIX): (lagged) changes in risk aversion, $\Delta RISKAVERSION_{t-1}$, and uncertainty, $\Delta UNCERTAINTY_{t-1}$, which may both affect the demand and supply for liquidity from banks.[17] Since both variables are calculated from the VIX index, available from 1990 onward, we add $D\ RISKAV\ UNCERT\ AVAIL_{t-1}$, a dummy that equals one if the risk aversion and uncertainty variables are available. We also include two measures of the financial strength of banks in size class $X$: $\Delta CAPITAL\ RATIO_{X,t-1}$, common equity divided by GTA, and $\Delta NPL\ RATIO_{X,t-1}$, non-performing loans divided by GTA. Since these two variables may be conduits through which monetary policy works, we also run the regressions without these variables and obtain comparable results (not shown for brevity). $D\ SEASON_v$ is a quarterly dummy to control for seasonal effects. Inference is based on robust standard errors.

The variables in this analysis other than the dummies are expressed in terms of changes because the hypotheses are about changes in monetary policy, rather than levels. Using changes also eliminates the need to detrend variables because the use of changes essentially eliminates the trend.

The coefficients on the change in monetary policy ($\Delta MONPOL_{t-i}$) pick up the effect of monetary policy during normal times. Negative coefficients would indicate that MPL increases bank liquidity creation, as loosening is indicated by negative values of $\Delta MONPOL_{t-i}$. The coefficients on the interaction terms ($\Delta MONPOL_{t-j} * D\ CRIS_{t-j}$) show whether monetary policy has a different effect during financial crises versus normal times. For example, if monetary policy is less effective during financial crises than during normal times as hypothesized, the coefficients on the interaction term will be positive and significant.

Even in this single-equation approach, the effects of monetary policy on liquidity creation over time are complicated because of the lags of liquidity creation in Eq. (1). For example, the predicted effect of a monetary policy shock two quarters ago on the percentage change in liquidity creation in the current quarter has a direct effect through the coefficient of the second lag of $\Delta MONPOL$ plus a feedback effect through the effect on the first lag of $\%\Delta LC$. Thus, while the predicted effect of a monetary policy shock one quarter ago on liquidity creation in the current quarter during normal times (i.e., when lagged $D\ CRIS = 0$) is simply $\beta_1$, the predicted effect of $\Delta MONPOL_{t-2}$ on $\%\Delta LC_t$ is given by $\beta_2 + \beta_1\varepsilon_1$. Similarly, the one- and two-quarter impulse response functions when the lagged quarters are during financial crises (i.e., lagged $D\ CRIS = 1$) are $\beta_1 + \gamma_1$ and $\beta_2 + \gamma_2 + \left(\beta_1 + \gamma_1\right)\varepsilon_1$, respectively. The differential crisis effects are the differences between the crisis and normal times effects, $\gamma_1$ and $\gamma_2 + \gamma_1\varepsilon_1$, respectively.[18]

*4.2.2.2. VAR model.* We use a reduced-form VAR with five equations for the following five endogenous variables: the change in monetary policy, the change in monetary policy interacted with the crisis dummy, the percentage change in liquidity creation, the percentage change in GDP, and the change in the price level.[19] The other variables from Eq. (2) are included as exogenous variables: the crisis dummy, the change in innovation, the changes in risk aversion and uncertainty (and the associated dummy to indicate if these variables are available), the change in the capital ratio, the change in the non-performing loans ratio, and seasonal effects.

We include four lags of the endogenous variables. For parsimony, we only include one lag of the exogenous variables, with two exceptions. First, the seasonal dummies are not lagged. Second, although the crisis dummy is exogenous, we include four lags because the crisis dummy interacted with the change in monetary policy is endogenous. Importantly, we use two lag-order selection criteria to assess whether four lags are sufficient. The results suggest they are.[20]

### *4.3. Results*

Figs. 4 and 5 present the results based on the VAR model and the single-equation approach, respectively. Each figure shows how monetary policy affects total liquidity creation (*Panel I*), on-balance sheet liquidity creation (*Panel II*), and off-balance sheet liquidity creation (*Panel III*). Each panel shows the implied response of percentage changes in bank liquidity creation to a one percentage point change in the federal funds rate (*Subpanel A*) and a one percentage point Romer and Romer monetary policy shock (*Subpanel B*), together with 90% confidence intervals.[21] Each subpanel shows the results separately for the three size classes (small, medium, and large banks) – the top row focuses on normal times and the bottom row presents the differential crisis effect. We test for the effects of changes in monetary policy on total liquidity creation by examining whether zero lies outside the 90% confidence interval.

Because of the large number of figures – covering two different econometric methods (VAR and single equation), three different liquidity creation measures (total, on-balance sheet, and off-balance sheet liquidity creation), two different monetary policy measures (changes in the federal funds rate and Romer and

[17] We thank Marie Hoerova for making these data available on her website. Bekaert et al. (2013) observe that the VIX index, which measures investor expectations about future stock market volatility, strongly co-moves with measures of the monetary policy stance. They find that monetary policy loosening decreases both VIX components, risk aversion and uncertainty, and that high risk aversion and high uncertainty tend to presage monetary policy loosening.

[18] Similarly, the third- and fourth-quarter impulse response functions during normal times are $\beta_3 + \beta_1\varepsilon_2 + \left(\beta_2 + \beta_1\varepsilon_1\right)\varepsilon_1$ and $\beta_4 + \beta_1\varepsilon_3 + \left(\beta_2 + \beta_1\varepsilon_1\right)\varepsilon_2 + \left(\beta_3 + \beta_1\varepsilon_2 + \left(\beta_2 + \beta_1\varepsilon_1\right)\varepsilon_1\right)\varepsilon_1$, respectively.

[19] Our VAR is non-standard in that it includes monetary policy measures and monetary policy measures interacted with crisis dummies to pick up the differential crisis effect. We emphasize, however, that we also use a single-equation model which includes similar variables and yields similar results.

[20] Ivanov and Kilian (2005) show that "for quarterly VAR models, the Hannan-Quinn Criterion (HQC) appears to be the most accurate criterion with the exception of sample sizes smaller than 120, for which the Schwarz Information Criterion (SIC) is more accurate." Since all our VAR estimations include 95 quarterly observations, we used both. In all cases, they suggest that four lags are sufficient.

[21] Three confidence intervals are generally used in monetary policy papers that use a VAR setup: 95% (e.g., Christiano et al., 2005; Christiano and Vigfusson, 2003), 90% (e.g., Bernanke et al., 2005; Steinsson, 2008), and 68% (e.g., Romer and Romer, 2004; Stock and Watson, 2001). At the 95% level, we find less significance than reported, while at the 68% level, we find more.

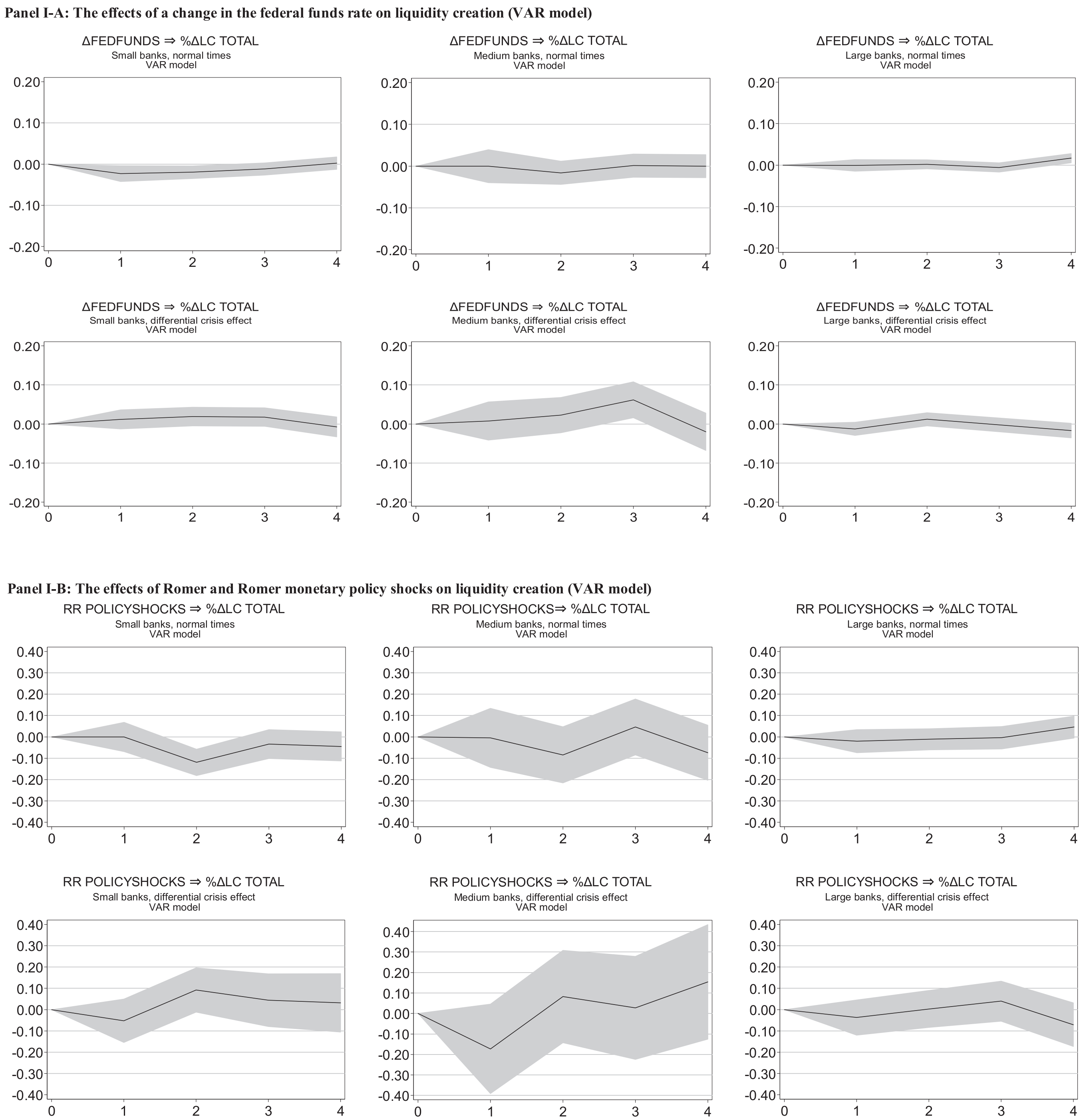
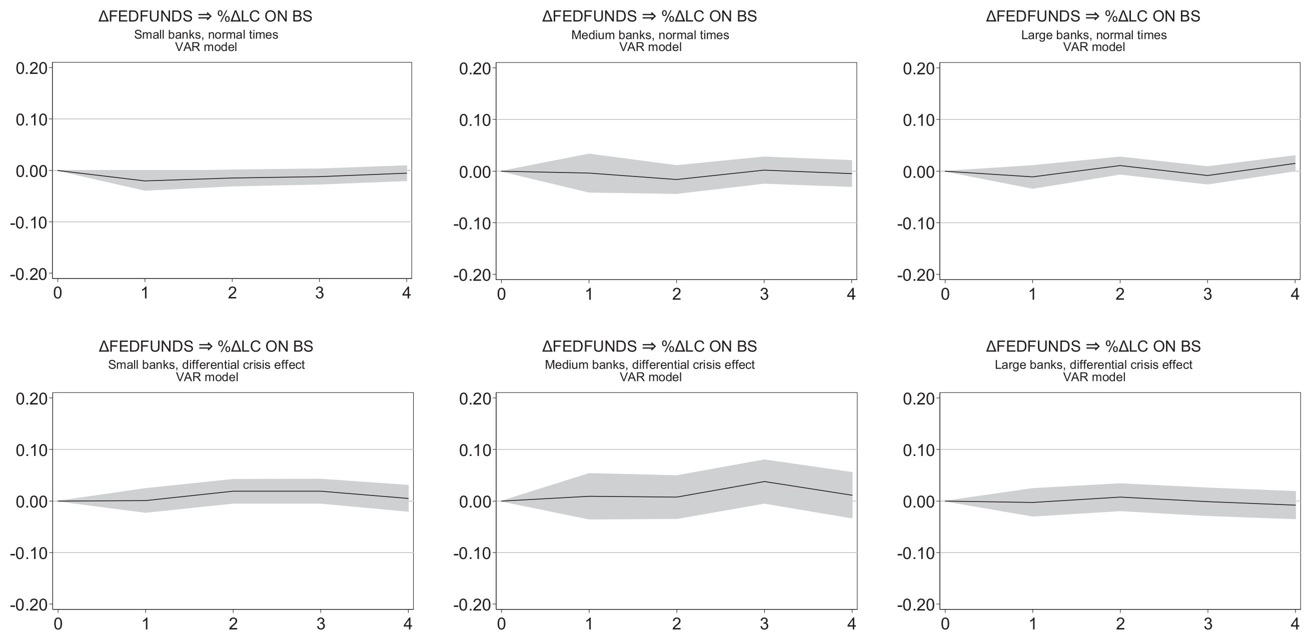



**Fig. 4. The effects of monetary policy on liquidity creation (VAR model)**.
This figure shows how monetary policy affects liquidity creation using the VAR model. The VAR has five equations for the following five endogenous variables: the percentage change in liquidity creation, the change in monetary policy, the change in monetary policy interacted with the crisis dummy, the percentage change in GDP, and the change in the price level. Each equation includes the following exogenous variables: crisis dummy, change in innovation, changes in risk aversion and uncertainty (and the associated dummy to indicate if these variables are available), change in the capital ratio, change in the non-performing loans ratio, and seasonal effects. Each equation includes four lags of the endogenous variables and one lag of the exogenous variables (exceptions: the seasonal dummies are not lagged; and while the crisis dummy is exogenous, we include four lags because the crisis dummy interacted with the change in monetary policy is endogenous). The figure presents the impulse responses of total liquidity creation (%ΔLC TOTAL – Panel I), on-balance sheet liquidity creation (%ΔLC ON BS – Panel II), and off-balance sheet liquidity creation (%ΔLC OFF BS – Panel III) to a one percentage point change in the federal funds rate (ΔFEDFUNDS – Subpanels A) and a one percentage point Romer and Romer monetary policy shock (RR POLICYSHOCKS – Subpanels B), together with a 90% confidence band. Romer and Romer monetary policy shocks are regression residuals that measure the changes in the federal funds rate that do not reflect anticipatory movements related to forecasts of economic conditions. Each subpanel shows the results separately for small banks (gross total assets or GTA up to $1 billion), medium banks (GTA exceeding $1 billion and up to $3 billion), and large banks (GTA exceeding $3 billion). GTA equals total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve (a reserve for certain foreign loans). In each subpanel, the top row focuses on normal times and the bottom row presents the differential crisis effect. The coefficients on the change in monetary policy pick up the effect of monetary policy during normal times. Negative coefficients indicate that monetary policy loosening (MPL) increases bank liquidity creation, as loosening is indicated by negative changes in the monetary policy variables. The coefficients on the interaction terms show whether monetary policy has a different effect during financial crises versus normal times. Positive coefficients on the interaction term indicate that monetary policy is less effective during financial crises than during normal times as hypothesized.

**Panel II-A: The effects of changes in the federal funds rate on *on-balance sheet liquidity creation* (VAR model)**




**Panel II-B: The effects of Romer and Romer monetary policy shocks on *on-balance sheet liquidity creation* (VAR model)**

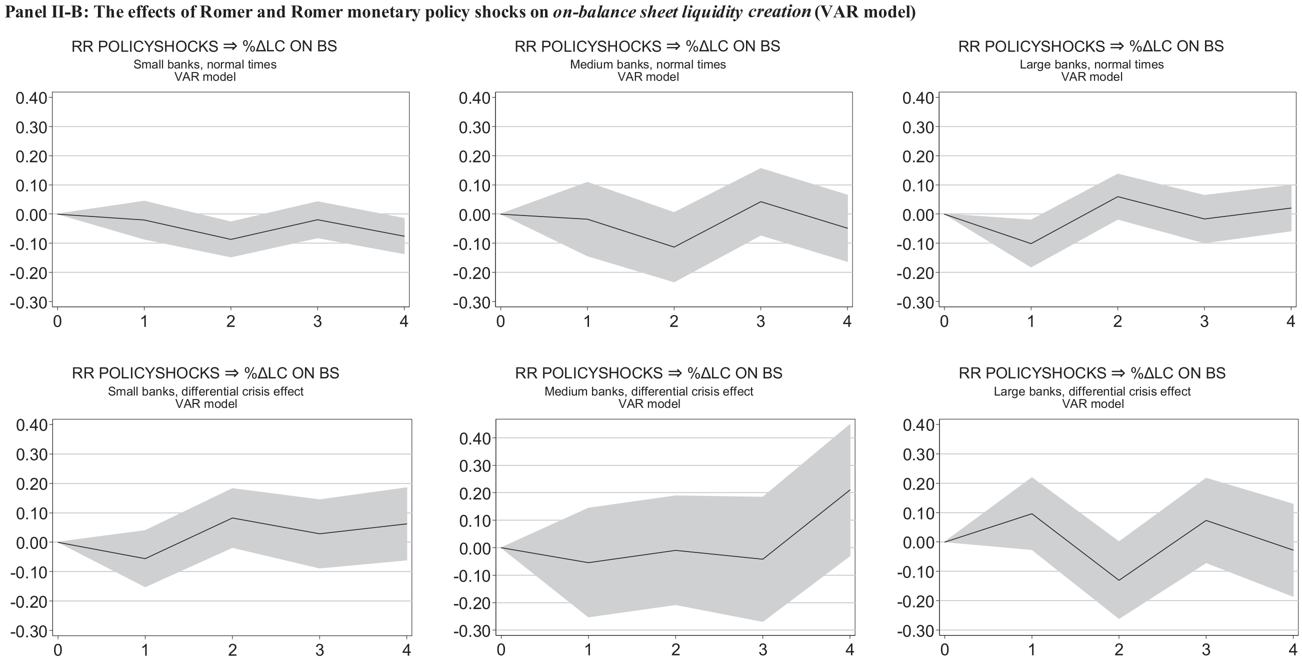



**Fig. 4.** (*Continued*)

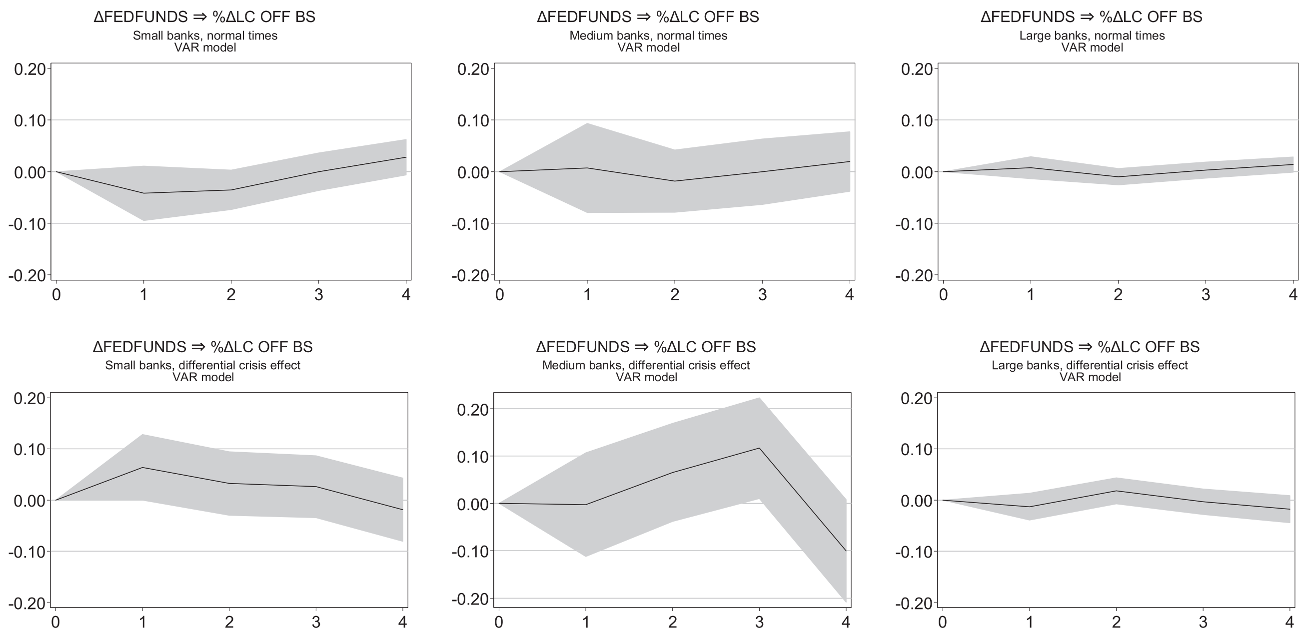
Romer shocks), three different bank size classes (small, medium, and large), and results for normal times and differential crisis effects – we focus on summarizing the results and drawing out the "big picture" conclusions. For the most part, the results for the different econometric methods and the different monetary policy measures are mutually consistent, so we focus on how the results differ by bank size class, type of liquidity creation, and normal versus differential crisis effects.

Most of the effects of monetary policy on bank liquidity creation occur for small banks. For these banks, MPL appears to increase total liquidity creation and its on- and off-balance sheet components during normal times. In some cases, the effects are statistically significant.[22] These results are consistent with our hypothesis.

While the effects of monetary policy on small bank liquidity creation are statistically significant in various cases, the effects are quite small economically. For example, based on the VAR model, a decrease in the federal funds rate of one percentage point (a very large change in monetary policy), is found to yield cumula-

[22] Consistent with Kashyap and Stein (2000), we find that small banks tend to react within one to two quarters to changes in monetary policy, with the effect dying out shortly thereafter. In 75% of the cases in which we find significance at the 10% level, we also find significance at the more stringent 5% level.

**Panel III-A: The effects of changes in the federal funds rate on *off-balance sheet liquidity creation* (VAR model)**




**Panel III-B: The effects of Romer and Romer monetary policy shocks on *off-balance sheet liquidity creation* (VAR model)**

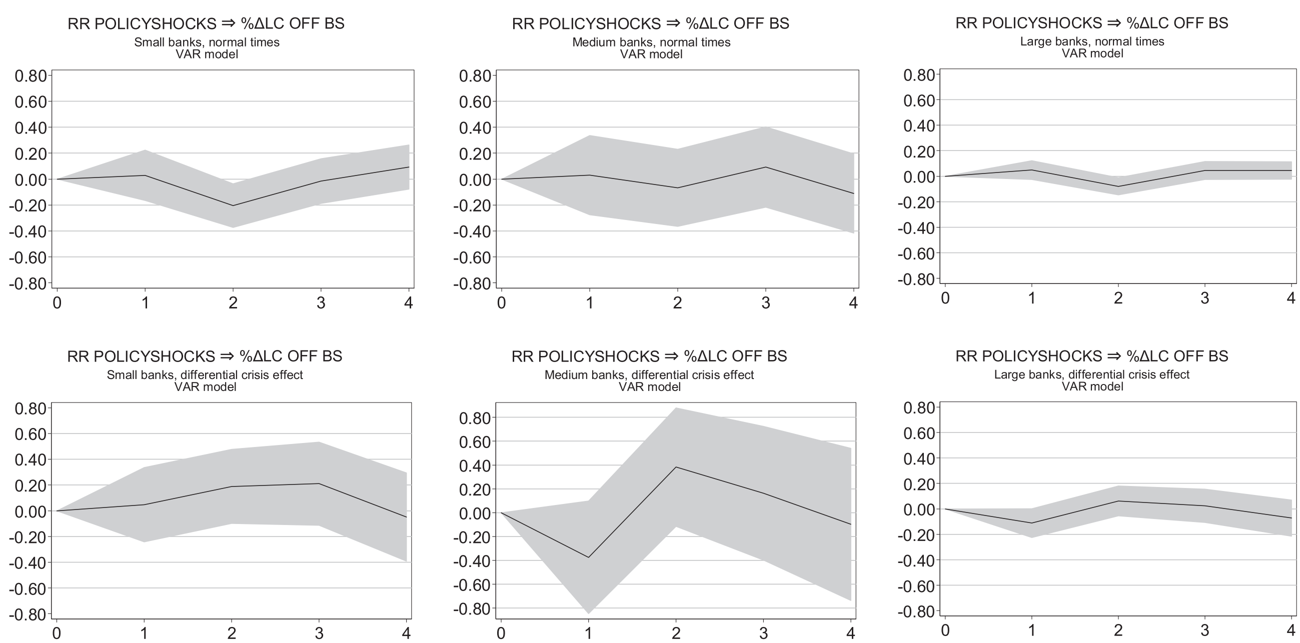


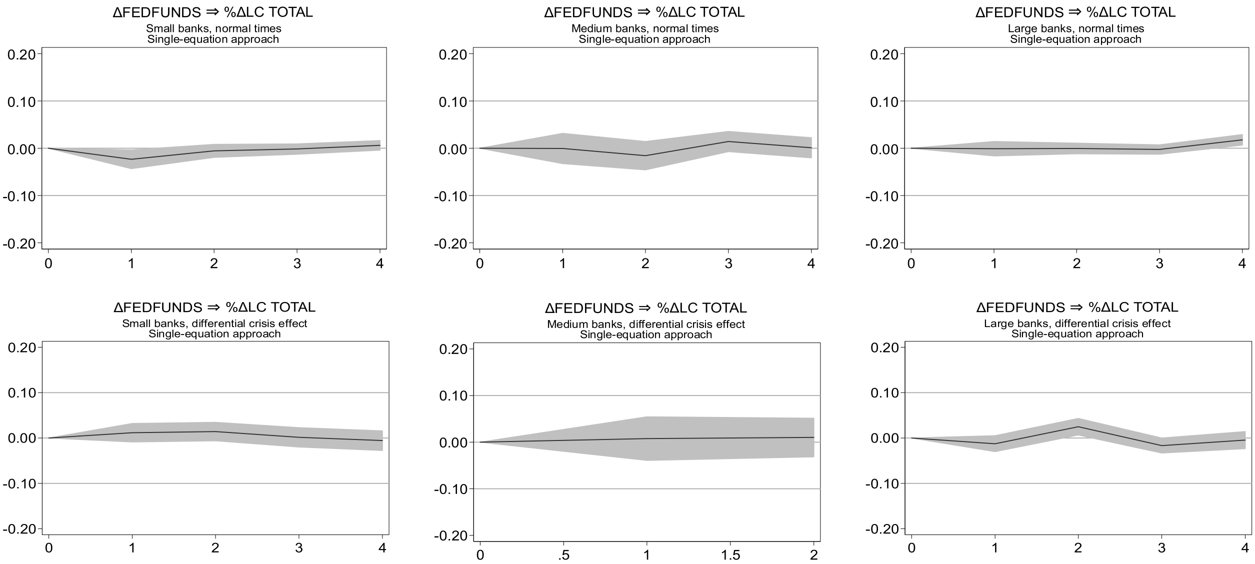

**Fig. 4.** (*Continued*)

tive increases in liquidity creation by small banks of 2.3% and 2.0% after one and two quarters, respectively. Evaluated at the average dollar amount of liquidity created by small banks of $333 billion, this translates into cumulative increases in liquidity creation of only $7.75 billion and $6.57 billion, respectively, only about 0.2% of banking industry liquidity creation. The differential crisis effects figures suggest that, consistent with our hypothesis, monetary policy has an even smaller effect during crises.

The findings for medium and large banks may be summarized briefly as weak and mixed. It does not appear that monetary policy has consistent effects on total, on-balance sheet, or off-balance sheet liquidity creation for these size classes, and there is little in the way of clear results for the differential crisis effects.

Our findings confirm and expand upon the bank lending channel literature. That literature focuses narrowly on bank lending whereas we include all on- and off-balance sheet liquidity creation, which may also have important effects on the macroeconomy and the likelihood of future crises. Our results that monetary policy is only effective for small banks is consistent with Kashyap and Stein (2000). Our results also present the first attempt to examine how the effects of monetary policy differ between normal times and financial crises.

**Panel I-A: The effects of a change in the federal funds rate on liquidity creation (single-equation approach)**




**Panel I-B: The effects of Romer and Romer monetary policy shocks on liquidity creation (single-equation approach)**

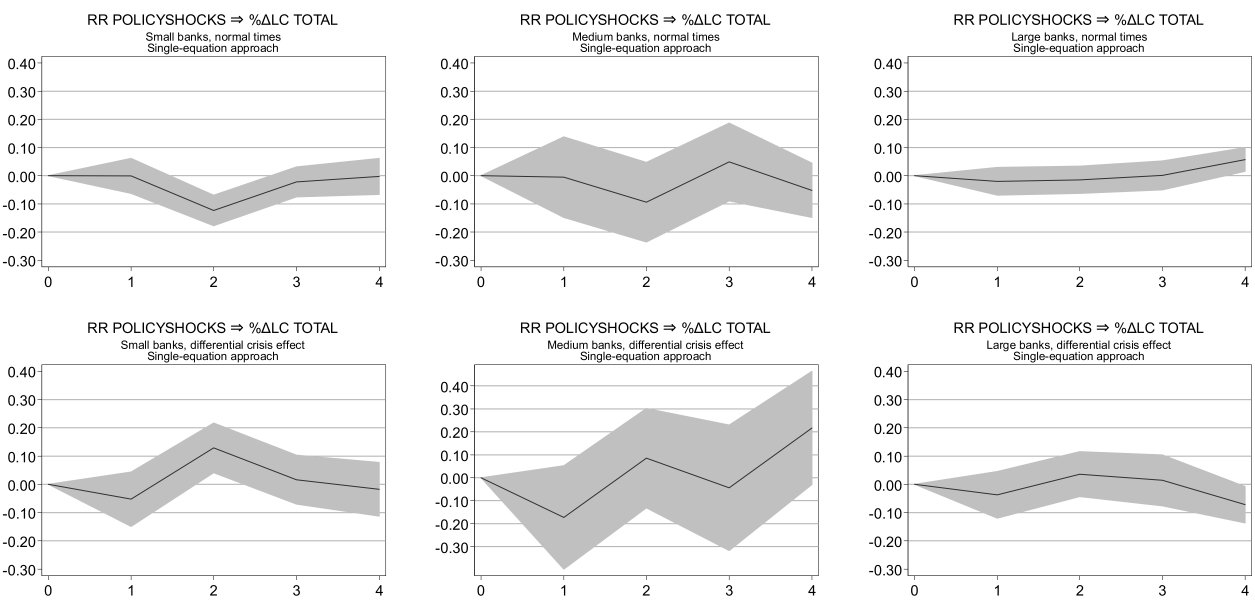
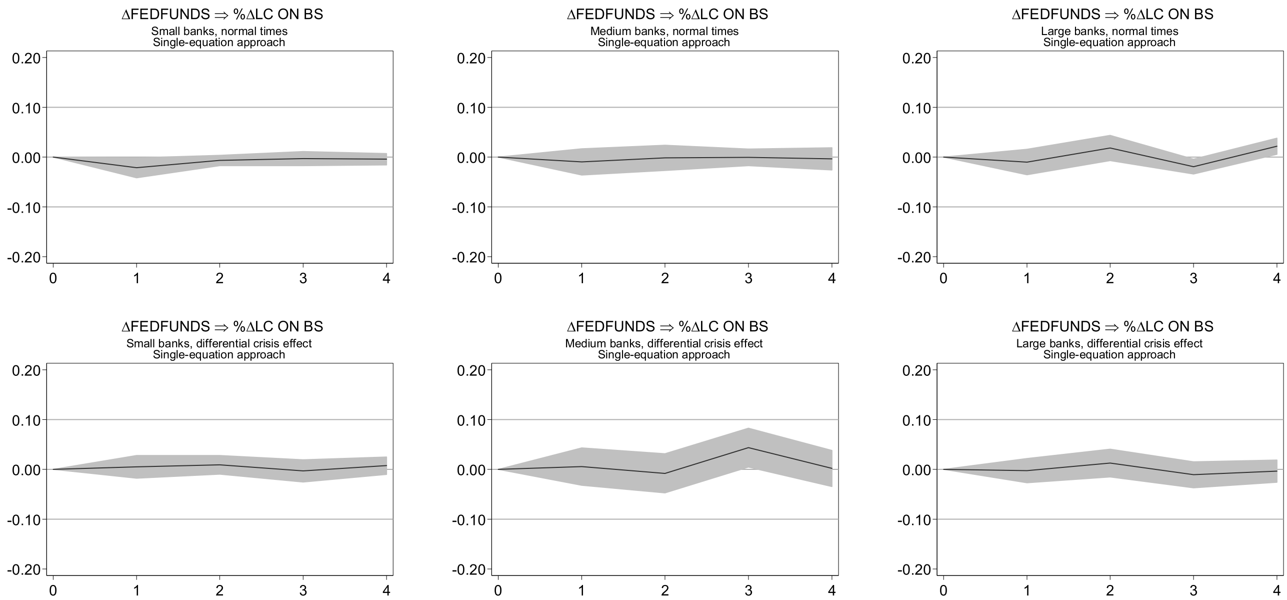



**Fig. 5. The effects of monetary policy on liquidity creation (single-equation approach).**
This figure shows how monetary policy affects liquidity creation using the single-equation approach. The percentage change in liquidity creation is regressed on lagged values of five variables which are considered endogenous in the VAR model: the percentage change in liquidity creation, the change in monetary policy, the change in monetary policy interacted with the crisis dummy, the percentage change in GDP, and the change in the price level. Each equation also includes lagged values of the following variables which are considered exogenous in the VAR model: crisis dummy, change in innovation, changes in risk aversion and uncertainty (and the associated dummy to indicate if these variables are available), change in the capital ratio, change in the non-performing loans ratio, and seasonal effects. We include four lags of the endogenous variables and one lag of the exogenous variables (exceptions: the seasonal dummies are not lagged; and while the crisis dummy is exogenous, we include four lags because the crisis dummy interacted with the change in monetary policy is endogenous). The figure presents the impulse responses of total liquidity creation (%ΔLC TOTAL – Panel I), on-balance sheet liquidity creation (%ΔLC ON BS – Panel II), and off-balance sheet liquidity creation (%ΔLC OFF BS – Panel III) to a one percentage point change in the federal funds rate (ΔFEDFUNDS – Subpanels A) and a one percentage point Romer and Romer monetary policy shock (RR POLICYSHOCKS – Subpanels B), together with a 90% confidence band. Romer and Romer monetary policy shocks are regression residuals that measure the changes in the federal funds rate that do not reflect anticipatory movements related to forecasts of economic conditions. Each subpanel shows the results separately for small banks (gross total assets or GTA up to $1 billion), medium banks (GTA exceeding $1 billion and up to $3 billion), and large banks (GTA exceeding $3 billion). GTA equals total assets plus the allowance for loan and lease losses and the allocated transfer risk reserve (a reserve for certain foreign loans). In each subpanel, the top row focuses on normal times and the bottom row presents the differential crisis effect. The coefficients on the change in monetary policy pick up the effect of monetary policy during normal times. Negative coefficients indicate that monetary policy loosening (MPL) increases bank liquidity creation, as loosening is indicated by negative changes in the monetary policy variables. The coefficients on the interaction terms show whether monetary policy has a different effect during financial crises versus normal times. Positive coefficients on the interaction term indicate that monetary policy is less effective during financial crises than during normal times as hypothesized.

**Panel II-A: The effects of changes in the federal funds rate on *on-balance sheet liquidity creation* (single-equation approach)**




**Panel II-B: The effects of Romer and Romer monetary policy shocks on *on-balance sheet liquidity creation* (single-equation approach)**

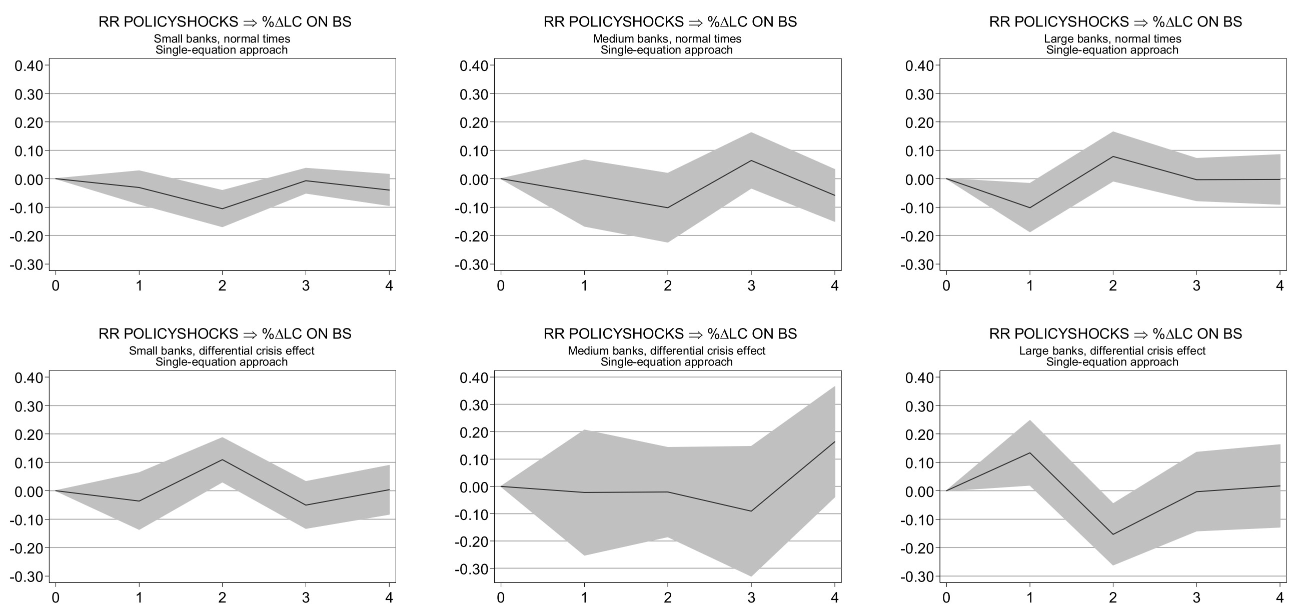



**Fig. 5.** (*Continued*)

## 5. Conclusions

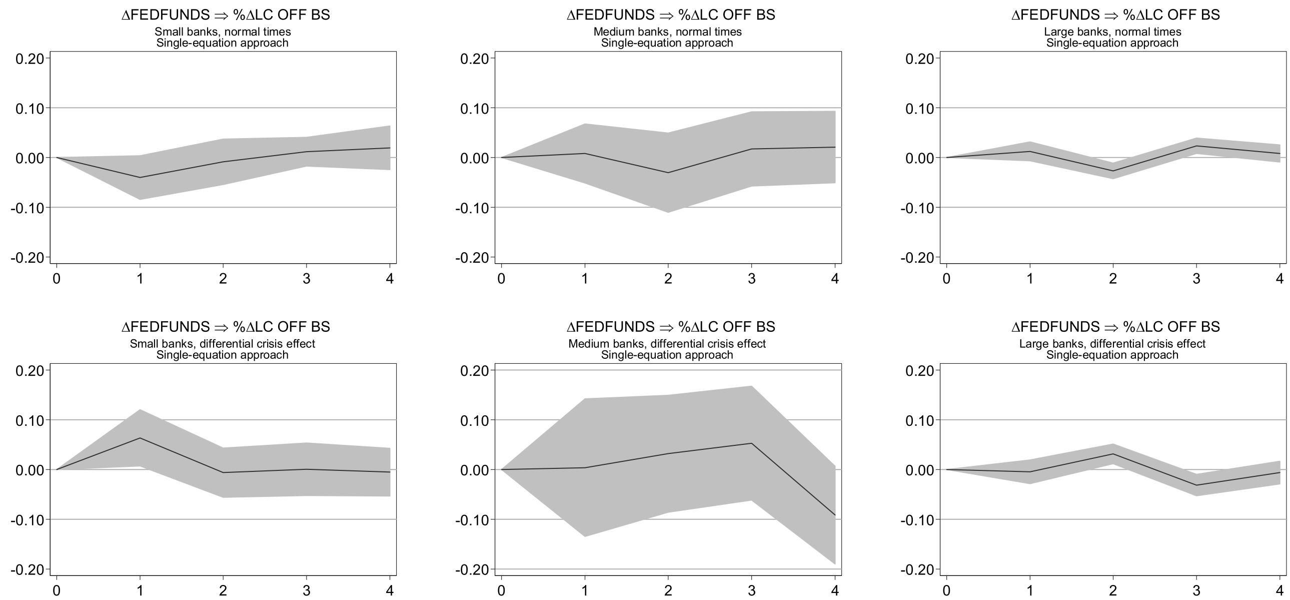
This paper empirically examines the interplay among bank liquidity creation, monetary policy, and financial crises. We show that high liquidity creation (relative to trend) tends to be followed by financial crises, even after controlling for other macroeconomic factors and market returns. This result is driven primarily by off-balance sheet liquidity creation. We also find that during normal times, monetary policy has statistically significant, but economically minor effects on liquidity creation by small banks, and weak and mixed effects on liquidity creation by medium and large banks. In addition, our empirical results suggest that the effects of monetary policy are weaker during financial crises.

Our findings generally support existing theories. Our paper adds to the financial crisis early warning literature that does not consider bank liquidity creation. It also expands upon the bank lending channel literature by broadening the focus to bank liquidity creation – which includes much more than lending – and by examining for the first time the effectiveness of monetary policy during financial crises.

In terms of policy implications, our findings suggest that authorities might consider monitoring bank liquidity creation closely in order to predict and perhaps lessen the likelihood of financial crises. Based on our results, monetary policy does not appear to be a very effective tool in this regard. These findings suggest further investigation into other tools, such as capital and liquidity requirements, which might be more effective in this regard.

In terms of research implications, we acknowledge that our study is limited by being confined to only one country with only five financial crises to analyze. We suggest that future research

**Panel III-A: The effects of changes in the federal funds rate on *off-balance sheet liquidity creation* (single-equation approach)**




**Panel III-B: The effects of Romer and Romer monetary policy shocks on *off-balance sheet liquidity creation* (single-equation approach)**

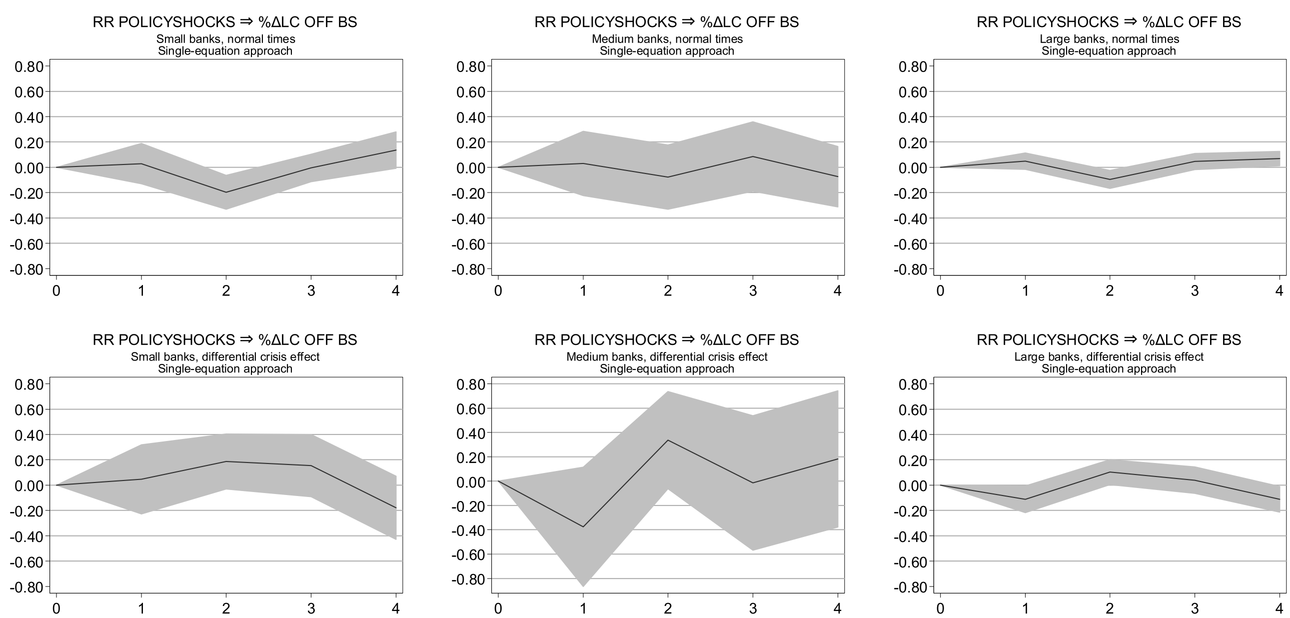



**Fig. 5.** (*Continued*)

extend these findings to other nations and/or cross-country settings which often have many more financial crises to analyze. There are a number of studies which calculate bank liquidity creation for other individual nations, including China, Germany, Japan, and Russia, as well as for groups of countries (see Berger and Bouwman, 2016, p. 220, Box 15.1 for a list). Presumably, data from these studies could be used to test whether high bank liquidity creation in these nations foreshadows financial crises, and test the effects of monetary policy in these nations on bank liquidity creation during normal times and financial crises. The results could either affirm or contradict the findings here and advance the state of knowledge on these topics.

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## Appendix A. Bank liquidity creation: preferred and alternative measures

To measure liquidity creation, we follow Berger and Bouwman's (2009) three-step procedure shown in Table A1. Below, we briefly discuss these three steps.

In Step 1, all bank activities are classified as liquid, semi-liquid, or illiquid. For assets, this is based on the ease, cost, and time for banks to dispose of their obligations to meet these liquidity demands. For liabilities and equity, this is based on the ease, cost, and time for customers to obtain liquid funds from the bank. Off-balance sheet activities are classified based on functionally similar on-balance sheet activities. For all activities other than loans, this process uses information on both product category and maturity. Due to data restrictions, loans are classified entirely by category.

In Step 2, weights are assigned to all of the bank activities classified in Step 1. The weights are consistent with liquidity creation theory, which argues that banks create liquidity on the balance sheet when they transform illiquid assets into liquid liabilities. Positive weights are therefore applied to illiquid assets and liquid liabilities. Following similar logic, negative weights are applied to liquid assets and illiquid liabilities and equity, since banks destroy liquidity when they use illiquid liabilities to finance liquid assets. Weights of ½ and −½ are used because only half of the total amount of liquidity created is attributable to the source or use of funds

**Table A1**
Liquidity classification of bank activities and construction of the liquidity creation measure.

| | | |
|---|---|---|
| **Step 1: Classify all bank activities as liquid, semi-liquid, or illiquid. For activities other than loans, information on product category and maturity are combined. Due to data limitations, loans are classified entirely by product category.** | | |
| **Step 2: Assign weights to the activities classified in Step 1.** | | |
| **ASSETS:** | | |
| Illiquid assets (weight = ½) | Semi-liquid assets (weight = 0) | Liquid assets (weight = −½) |
| Commercial real estate loans (CRE) | Residential real estate loans (RRE) | Cash and due from other institutions |
| Loans to finance agricultural production | Consumer loans | All securities (regardless of maturity) |
| Commercial and industrial loans (C&I) | Loans to depository institutions | Trading assets |
| Other loans and lease financing receivables | Loans to state and local governments | Fed funds sold |
| Other real estate owned (OREO) | | |
| Investment in unconsolidated subsidiaries | Loans to foreign governments | |
| Intangible assets | | |
| Premises | | |
| Other assets | | |
| **LIABILITIES PLUS EQUITY:** | | |
| Liquid liabilities (weight = ½) | Semi-liquid liabilities (weight = 0) | Illiquid liabilities plus equity (weight = − ½) |
| Transactions deposits | Time deposits | Subordinated debt |
| Savings deposits | Other borrowed money | Other liabilities |
| Overnight federal funds purchased | | Equity |
| Trading liabilities | | |
| **OFF-BALANCE SHEET GUARANTEES (notional values):** | | |
| Illiquid guarantees (weight = ½) | Semi-liquid guarantees (weight = 0) | Liquid guarantees (weight = −½) |
| Unused commitments | Net credit derivatives | Net participations acquired |
| Net standby letters of credit | Net securities lent | |
| Commercial and similar letters of credit | | |
| All other off-balance sheet liabilities | | |
| **OFF-BALANCE SHEET DERIVATIVES (gross fair values):** | | |
| | | Liquid derivatives (weight = −½) |
| | | Interest rate derivatives |
| | | Foreign exchange derivatives |
| | | Equity and commodity derivatives |

**Step 3: Combine bank activities as classified in Step 1 and as weighted in Step 2 to construct the liquidity creation (LC) measure.**

| | | | |
|---|---|---|---|
| LC= | +½ * illiquid assets | +0 * semi-liquid assets | −½ * liquid assets |
| | +½ * liquid liabilities | +0 * semi-liquid liabilities | −½ * illiquid liabilities |
| | | | −½ * equity |
| | +½ * illiquid guarantees | +0 * semi-liquid guarantees | −½ * liquid guarantees |
| | | | −½ * liquid derivatives |

This table explains the Berger and Bouwman (2009) methodology to construct their preferred liquidity creation measure (cat fat) that classifies loans by category and includes off-balance sheet activities in three steps.

alone.[23] An intermediate weight of 0 is applied to semi-liquid assets and liabilities. Weights for off-balance sheet activities are assigned using the same principles.

In Step 3, the activities classified in Step 1 and weighted in Step 2 are combined to construct Berger and Bouwman's (2009) preferred liquidity creation measure (cat fat). This measure classifies loans by category, while all activities other than loans are classified using information on product category and maturity, and includes off-balance sheet activities.[24] To obtain the dollar amount of liquidity creation at a particular bank, we multiply the weights times the dollar amounts of the corresponding bank activities and add the weighted dollar amounts.

Since the ability to securitize assets has changed greatly over time, we also construct an alternative liquidity creation measure as in Berger and Bouwman (2009). It is identical to the preferred measure, except for the way loans are classified. For each loan category, we use U.S. Flow of Funds data on the total amount of loans outstanding and the total amount of loans securitized to calculate the fraction of loans that has been securitized in the market at each point in time. Following Loutskina (2011), it is assumed that each bank can securitize that fraction of its own loans.[25] This alternative measure faces a significant drawback. While the theories suggest that it is the ability to securitize that matters for liquidity creation, this measure uses the actual amount of securitization. Thus, while the vast majority of these residential real estate loans may be securitizable, this alternative measure treats only about half of them as such. Since we obtain qualitatively similar regression results based on the alternative measure, all reported regression results are based on the preferred measure for brevity.

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[23] To give a few examples: when $1 of liquid liabilities is used to finance $1 in illiquid assets, liquidity creation equals ½ * $1 + ½ * $1 = $1. In this case, maximum liquidity is created. When $1 of liquid liabilities is used to finance $1 in liquid assets, liquidity creation equals ½ * $1 + –½ * $1 = $0. In this case, no liquidity is created as the bank holds items of approximately the same liquidity as those it gives to the nonbank public. Maximum liquidity is destroyed when $1 of illiquid liabilities or equity is used to finance $1 of liquid assets. In this case, liquidity creation equals –½ * $1 + –½ * $1 = –$1.

[24] Berger and Bouwman (2009) construct four liquidity creation measures by alternatively classifying loans by category or maturity, and by alternatively including or excluding off-balance sheet activities. However, they argue that the measure we use here is the preferred measure since for liquidity creation, banks' ability to securitize or sell loans is more important than loan maturity, and banks do create liquidity both on and off the balance sheet.

[25] For example, in 1993:Q4, $3.1 trillion in residential real estate loans were outstanding in the market, and 48.4% of these loans were securitized. If a bank has $10 million in residential real estate loans in that quarter, we assume that 48.4% of it can be securitized. Hence, we classify $4.84 million of these loans as semi-liquid and the remainder as illiquid.


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