Accepted Manuscript

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PII: S0378-4266(18)30050-5
DOI: 10.1016/j.jbankfin.2018.03.002
Reference: JBF 5313

To appear in: *Journal of Banking and Finance*

Received date: 6 March 2016
Revised date: 27 February 2018
Accepted date: 8 March 2018

Please cite this article as: Ujjal K. Chatterjee , Bank Liquidity Creation and Recessions, *Journal of Banking and Finance* (2018), doi: 10.1016/j.jbankfin.2018.03.002

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ABSTRACT

We investigate the relationship between bank liquidity creation and recessions in the U.S. For the 1984–2010 sample, we find that (i) lower bank on-balance sheet liquidity creation signals recessions four quarters into the future; (ii) off-balance sheet liquidity creation is not a robust predictor of recessions at longer forecast horizons; (iii) off-balance sheet liquidity creation falls in tandem with on-balance sheet liquidity creation one quarter prior to recessions, and aggregate, on- and off-balance sheet bank liquidity creation continue to decline during and up to five quarters after recessions; and (iv) liquidity creation of larger banks contains more information about future recessions than that of smaller ones.

Keywords: Treasury yield curve; Bank liquidity creation; Recessions; Financial Stability; Monetary Policy.

JEL classification: E43; E47; E52; E58; G17; G18; G21; O40; O43

¶ We thank John Sedunov (FMA 2015, Orlando, FL, USA, discussant) Klaus Schaeck, Christa Bouwman, Allen Berger, Xavier Freixas, Hans Degryse, and Kundan Kishor for their suggestions in the formative stages of the paper. We extend sincere thanks to seminar participants at FMA 2015, the American University of Sharjah, University of Wisconsin-Milwaukee, UAE University and Universitat Pompeu Fabra for their comments and suggestions.

1. Introduction

Forecasting recessions is important for many stakeholders including households, investors, businesses, and policymakers. The existing literature (e.g., Harvey, 1988, 1989) has shown that the Treasury yield curve contains information about future economic growth. Specifically, the slope of Treasury yield curve, the spread between long- and short-term interest rates forecasts National Bureau of Economic Research (NBER) recessions (e.g., Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998). In this study, we focus on bank liquidity creation as a forecasting variable for NBER recessions. Monetary policy is generally altered to change bank liquidity creation and it further changes the slope of the yield curve. If monetary policy aims to change how banks create liquidity, then bank liquidity creation is likely to contain information about the real economy and may help predict recessions.[1] However, while banks play a central role in virtually all financial crises (e.g., Diamond and Rajan, 2005), the existing banking literature does not investigate the relationship between bank liquidity creation and

[1] Financial intermediation theories posit that banks exist to create liquidity and transform credit risk (e.g., Diamond, 1984; Diamond and Rajan, 2001; Kashyap et al., 2002; Berger and Bouwman, 2009), and thereby promote economic growth (e.g., Berger and Sedunov 2015). Banks not only create liquidity on the balance sheet by activities, such as providing loans to businesses and individuals funded from deposits (e.g., Diamond and Dybvig, 1983; Berger and Bouwman, 2009), but also create liquidity off the balance sheet by activities, such as extending standby letters of credit and loan commitments to their customers (e.g., Holmstrom and Tirole, 1998; Kashyap et al., 2002; Thakor, 2005; Diamond and Rajan, 2005; Berger and Bouwman, 2009).

recessions. Using the Berger and Bouwman (2009) bank liquidity creation measure, we find that bank liquidity creation contains information about the onset of NBER recessions. Bank liquidity creation contracts up to four quarters prior to recessions and continues to fall for approximately five quarters past recessions. We further show that bank liquidity creation significantly improves the ability of the term spread to forecast recessions.

The existing literature linking bank lending and economic activity provides inconclusive evidence of a "credit crunch" (e.g., Bernanke and Lown, 1991; Kashyap and Stein, 1994). One potential reason for the inconclusive results is that for reputational reasons, commercial banks act as a buffer for long-standing customers with pre-arranged credit lines, which is an off-balance sheet bank activity (e.g., Thakor, 2005). In this study, we investigate both on- and off-balance sheet bank liquidity creation prior to recessions since banks' inability to manage their balance sheet is believed to be the root cause of the most recent financial crisis.

Berger and Sedunov (2015) study the relationship between bank liquidity creation and economic development at the U.S. state level. They find that higher bank liquidity creation in the present quarter leads to higher per capita GDP for the next quarter. Contrary to expectations, the authors show that liquidity creation of small banks rather than that of large banks has higher impact on economic growth. They further do not find significant relationship between bank liquidity creation and per capita GDP during the 2007–2009 subprime crisis. However, Acharya and Mora (2015) show that during the last crisis, banks were unable to provide liquidity. Importantly, Berger and Sedunov (2015) do not investigate whether bank liquidity creation contains leading information about recessions.

Investigating the link between bank liquidity creation and crises, Berger and Bouwman (2014) use NBER recession quarters and events, such as the Long-Term Capital Management

(LTCM) bailout and the Russian debt crisis. The authors show that higher aggregate U.S. bank liquidity creation relative to a linear trend leads to crises, but their results contradict those of Berger and Sedunov (2015). We try to reconcile these findings in the literature by investigating whether bank liquidity creation forecasts NBER recessions. While predicting recessions with precision is one of the objectives of this study, we are particularly interested in investigating the dynamics of bank on- and off-balance sheet liquidity creation prior to and after recessions since this knowledge may help influence monetary policy.

Our study differs from that of Berger and Bouwman (2014) in several important ways. First, we investigate recessions, including the recent subprime crisis rather than exogenous shock-driven crises, such as the Russian debt crisis. We argue that liquidity creation of U.S. banks is unlikely to cause such one-time extreme events. Second, while their model predicts crises one quarter ahead of the events, we forecast recessions one to four quarters into the future. Finally, we investigate the dynamics of bank liquidity creation *during* and *after* recessions.

Our results show that bank liquidity creation is an important predictor of recessions. In particular, we show that bank on-balance sheet liquidity creation decreases at about four quarters prior to recessions and continues to fall leading up to recessions. We further show that on-balance sheet liquidity creation of large banks rather than that of small and medium ones decreases before recessions. This set of results is robust to the exclusion of the recent 2007–2009 recession. In contrast, we do not find that bank off-balance sheet liquidity creation is a robust predictor of recessions. The results are further robust to the inclusion of the term spread.

Our results further suggest that the fall in aggregate, on- and off-balance sheet liquidity creation continues after recessions. However, the term spread turns positive after recessions. The results thus imply that, while monetary policy is loosened around recession quarters and market participants expect such accommodating policies (resulting in an upward sloping yield curve), banks continue to shrink their balance sheet. This relationship between the term spread and bank liquidity creation (before and after recessions) is not investigated in the existing literature.

Our findings contribute to the strand of the literature that investigates the relationship between financial intermediation and economic growth. Since Bagehot (1873), the importance of banking to spur economic development and future growth has been debated. The connection between the components of bank liquidity creation and economic growth is theoretically and empirically grounded in the literature (e.g., Bencivenga and Smith, 1991; Boot et al., 1993; Jayaratne and Strahan, 1996; Bernanke and Blinder, 1988; Kashyap et al., 2002). Our study contributes to this strand of the literature by showing that lower bank liquidity creation leads to recessions.

The rest of the paper proceeds as follows. Section 2 describes bank liquidity creation and other data, reports data sources, and investigates data characteristics. Section 3 presents the main empirical results, while Section 4 conducts several robustness checks. Section 5 discusses monetary policy implications and Section 6 concludes.

2. Data and sample construction

The sample under investigation dates from the first quarter of 1984 to the fourth quarter of 2010 since the Federal Deposit Insurance Corporation (FDIC) call report data is available only from 1984.[2] Since we augment the Estrella and Hardouvelis (1991) Treasury term spread model

[2] The related literature (see, e.g., Haubrich and Dombrosky, 1996; Rudebusch and Williams, 2009) argues for recent data for reasons such as lowered inflation expectations in recent years, to investigate the relationship between recessions and term spread.

(with bank liquidity creation measures that are described in subsection 2.1), one of our primary predictor variables is the term spread (*TS* hereafter). *TS* is computed as the difference between the yields on the 3-month Treasury-bill and the 10-year Treasury bond index.

As is standard in the literature (e.g., Estrella and Mishkin, 1998), we further use other predictors such as real GDP, stock market returns (*RET* hereafter), stock market volatility (*VOL* hereafter) and the Federal funds rate (*FED* hereafter). Stock market variables are computed using all New York Stock Exchange (NYSE) stocks as in Næs et al. (2011). Since the literature finds that asset market liquidity and corporate bond credit spread (*CS* hereafter) are important determinant for bank liquidity creation (e.g., Chatterjee, 2015), we use those variables as controls. We obtain the Moody's corporate AAA and BAA rated bond indices yield data to compute credit spreads, the difference between the yields on 10-year AAA and BAA rated corporate bonds. Asset market liquidity measures are described in subsection 2.2. We include quarterly unemployment and inflation rates as additional predictors.[3]

To compare the estimates of recession probabilities of our models with that of the Survey of Professional Forecasters (SPF hereafter), we also use the SPF estimates in the analysis. Every quarter, SPF asks its participants to provide estimates of the probability of negative real GDP for the current and next four quarters, and hence following Rudebusch and Williams (2009) and Lahiri et al. (2013), we analyze the recession forecasting ability of bank liquidity creation for up to four quarters forecast horizons.

Unless noted otherwise, all data are collected from the U.S. Federal Reserve Bank. The Treasury bonds and stocks trading data are obtained from the Center for Research in Security

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[3] We thank an anonymous referee for the suggestion.

Prices. The GDP, unemployment, and inflation data are obtained from the U.S. Bureau of Economic Analysis.

2.1. Bank liquidity creation

Berger and Bouwman (2009) propose an all-inclusive measure of bank output factoring in both banks' on- and off-balance sheet activities such as loans, deposits, equity, derivatives, and loan commitments. Bank liquidity creation is computed for almost all commercial banks in the U.S. using the call reports data from the FDIC. We obtain the bank liquidity creation (BLC hereafter) data of individual banks from Christa Bouwman's website.[4] The BLC variables in our paper are presented as LC, LC^{ON}, and LC^{OFF}. LC is the weighted sum of bank on-balance sheet (loans, deposits, equity, etc.) and off-balance sheet (standby letter of credits, etc.) variables, where weights are assigned based on the liquidity and location (whether on- or off-balance sheet) of each item; $LC^{ON}$and LC^{OFF} variables consider only bank on- and off-balance sheet items, respectively. Following Berger and Bouwman (2014), we aggregate the BLC measures of each bank in the dataset. Fig. 1 graphically presents those aggregated measures.[5]

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[4] We sincerely thank Christa Bouwman for providing the data.

[5] Berger and Bouwman (2009) argue that the "cat" measure (by bank loan *category*) is better than the "mat" measure (by bank loan *maturity*) of bank liquidity creation. Some of the reasons are as follows: (1) business loans, while having short maturity, are not as liquid, and hence maturity-based measurements may not capture bank liquidity creation; and (2) the "mat" measure does not include off-balance sheet items, and hence the "mat" measures are not consistent with the literature (e.g., Holmstrom and Tirole, 1998, Kashyap et al., 2002). Thus, we restrict our analysis to the "cat" measures.

[Fig. 1 about here]

2.2. Asset market liquidity

Chatterjee (2015) shows that asset market liquidity explains BLC. In particular, the author finds that illiquidity of off-the-run T-bills of short maturity has a higher impact on bank on-balance sheet liquidity creation, and stock market illiquidity (computed by Amihud illiquidity ratio, Amihud, 2002) explains both on- and off-balance sheet liquidity creations. Thus, we control for these two variables while testing the forecasting power of BLC.

2.2.1. Stock market illiquidity measure

The Amihud illiquidity ratio (ILR) measure is based on the price impact to the order flow, and is calculated as the ratio of the price movement to the trading volume of a stock and is defined as:

$$ILR_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} |R_{i,d,t}|/VOL_{i,d,t} \quad (1)$$

where $\left|R_{i,d,t}\right|$ and $VOL_{i,d,t}$ are absolute returns and the dollar volume of security *i* on date *d*, respectively, and $D_{i,t}$ is the number of days over which ILR is calculated. It is customary to multiply ILR by 10^6. Consistent with the literature (e.g., Amihud, 2002), we consider stocks that have share prices of more than \$5 and less than \$1000; additionally, stocks must be traded for 20 days in a month to be included in the sample. We first calculate the liquidity of each stock based on the ILR proxy. Next, we calculate the equally weighted quarterly average liquidity of all NYSE stocks to obtain a measure of stock market liquidity, which we denote as ILR. Note that the measure is a proxy for market illiquidity.

2.2.2. Bond illiquidity measure

We use off-the-run illiquidity (*OFFSHORT* hereafter) measure of T-bills with maturities up to one year for the investigation.[6] Following the literature (e.g., Goyenko and Ukhov, 2009), the quoted spread of T-bills is used to measure bond illiquidity. The quoted spread of each bond of specific maturity is calculated daily and the equally weighted average over each quarter is computed as follows:

$$\mathrm{QS}_{i,t} = \frac{1}{D_{i,t}} \sum_{d=1}^{D_{i,t}} \frac{(ASK-BID)_{i,d,t}}{0.5(ASK+BID)_{i,d,t}} \qquad (2)$$

where *i* in the above equation is a bond of specific maturity.

We conduct Augmented Dickey–Fuller (ADF; Dickey and Fuller, 1979) and Kwiatkowski–Phillips–Schmidt–Shin (KPPS; Kwiatkowski et al., 1992) tests to ascertain that the variables are stationary. The transformed variables are reported with a prefix "Δ." For example, ΔLC, and ΔGDP are the log first difference of *LC* and real GDP.

[TABLE 1 about here]

Table 1, Panel A reports the sample summary statistics for two important variables: liquidity creation measures and the term spread. Table 1, Panel B presents the pairwise correlation among the variables of interest. We investigate three BLC variables: ΔLC, ΔLC^{ON},

[6] Once a bond of certain maturity is issued, it is on-the-run and older bonds of the same maturity become off-the-run. We investigate but do not report the results for T-bonds of higher maturities for parsimony since the results show that liquidity of higher maturity T-bonds have no information about recessions; the results are available on request.

and ΔLC^{OFF}. The correlation analysis shows that these variables are negatively correlated to recessions and positively correlated to ΔGDP. While the contemporaneous correlation results may not hold in predictive probit regressions, the correlation analysis highlights the expected relationship between BLC and recessions. Table 1, Panel C further shows that BLC growth variables have low auto-correlations.

3. In-sample forecasting of recessions with bank liquidity creation

Following Estrella and Hardouvelis (1991) and Estrella and Mishkin (1995), we estimate the probability of recessions using the following probit model:

$$P(X_t = 1) = \Phi(\alpha + \beta * TS_{t-l} + \gamma * V_{t-l}) \quad (3)$$

where $X_t = 1$ if the economy is in the NBER recession quarters and 0 otherwise, *TS* is the term spread, V is a vector of augmenting variables that includes one of the three BLC variables, and *l* is the number of lags used for the estimation. We evaluate the model performance using the Pseudo R-squared values.[7]

[TABLE 2 about here]

To understand the dynamics between BLC and the recent recession, we conduct our studies using the full sample of 1984:Q1 to 2010:Q4 and a subsample from 1984:Q1 to 2002:Q4, which includes both the 1990–1991 and 2001 recessions, but not the 2007–2009 recession. In Table 2, we present the coefficient estimates of Eq. (3) with different measures of BLC for up to

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[7] Pseudo $R^2 = 1 - \left[\frac{\log(L_u)}{\log(L_c)}\right]^{-\left(\frac{2}{n}\right)\log(L_c)}$

where L_u is the likelihood of the full model and L_c is the likelihood of the intercept-only model.

four quarters prior to recessions.

First, we present the results for the subsample in Table 2, Panel A. Next, we present the results for the full sample in Table 2, Panel B. We restrict our investigation to four quarters before recessions for two reasons. First, *TS* is shown to perform the best at that forecast horizon (e.g., Estrella and Hardouvelis, 1991). Second, we do not find that the BLC variables have robust predictive power at forecast horizons higher than four quarters.

Table 2, Panel A results show that TS and ΔLC^{ON} are negatively related to recessions in each quarter over a four-quarter forecast horizon. At each forecast horizon, we further find ΔLC^{ON}-augmented models have higher pseudo R-squared values relative to that of the benchmark *TS* model. Thus, we find some evidence that bank on-balance sheet liquidity creation falls before recessions. Note that the coefficient of *TS* increases in absolute term when we add bank on-balance sheet liquidity creation to the term spread model. Thus, our results suggest that the *TS*-only model underestimates the true impact of *TS* in forecasting recessions. Higher pseudo R-squared values of the BLC-augmented *TS* model imply that BLC has additional recession forecasting information. In the next section (Section 3.1), we formally show that BLC reacts to *TS* during recessions.

We further observe that ΔLC^{OFF} is positively related to recessions at four- and three-quarter forecast horizons at the 1% level of significance. However, one quarter prior to recessions, ΔLC^{OFF} is negatively related to recessions at the 1% level of significance. Thus, we find some evidence that bank off-balance sheet liquidity creation compensates for the on-balance sheet liquidity creation in the third and fourth quarters prior to recessions. The result is supportive of the arguments in the literature that prior to recessions, banks create liquidity through off-balance sheet activities (e.g., Thakor, 2005). Eventually, at the one-quarter forecast horizon, off-balance sheet liquidity creation catches up with that of on-balance sheet liquidity creation and it falls.

We next investigate the relationship between ΔLC and recessions. Four quarters prior to recessions, the results show that ΔLC is positively and significantly (at the 5% level of significance) related to recessions. This result suggests that bank off-balance sheet liquidity creation rises more than the fall in the on-balance sheet liquidity creation, and aggregate liquidity creation rises before recessions. For two- and three-quarter forecast horizons, ΔLC has no predictive power for recessions. However, for a one-quarter forecast horizon, the coefficient estimate of ΔLC is negatively related to recessions at the 1% level of significance. The overall evidence thus suggests that at some point between four and one quarters before recessions, bank aggregate liquidity creation switches from positive to negative.

Looking next at Table 2, Panel B, where we present the results for the full sample, we find qualitatively similar results as presented in Table 2, Panel A. ΔLC^{ON} falls in all four quarters prior to recessions and the statistical significance of the corresponding coefficients is generally higher than the 10% level of significance. In addition, the ΔLC^{ON}-augmented models have higher pseudo R-squared values than those of the *TS* model. One quarter prior to recessions, both ΔLC and ΔLC^{OFF} are inversely related to recessions at the 1% level of significance.

However, while the sign of the coefficient of ΔLC^{OFF} is similar to that of the 1984–2002 subsample, none of them is statistically significant at forecast horizons greater than one. Thus, the results indicate that banks may have created less off-balance sheet liquidity before the last recession/crisis. Unreported results further show that during the prior four quarters (2006:Q4–2007:Q3) before the most recent recession (2007:Q4–2009:Q2), the mean of ΔLC^{OFF} was 1.64% per quarter, while the average of the same for the prior two recessions (1990 and 2001 recessions) was 4.08% per quarter. Similarly, ΔLC has no statistically significant relationship at longer forecast horizons. Since we find that the predictive power of bank on-balance sheet is more robust at longer forecast horizons, which is more valuable for policymakers, we primarily focus on ΔLC^{ON} for the rest of our analysis.

Fig. 2 graphically shows the estimates of recession probability of two models for a four-quarter forecast horizon for the full sample. The figure shows that the ΔLC^{ON}-augmented TS model performed better than the *TS* model for the past three recessions. In particular, it is shown that the ΔLC^{ON}-augmented *TS* model has better performance than the *TS* model predicting the 1990–1991 and 2007–2009 recessions—the recessions that are known to be primarily driven by banking crises.

[Fig. 2 about here]

3.1. Term spread and bank liquidity creation

It is an established fact that the Treasury term structure is the primary driver of bank on-balance sheet activities since the Treasury term structure is one of the determinants of bank short-term borrowing and long-term lending. Thus, we conduct both Granger causality tests and regression analyses to investigate whether *TS* contains information about BLC and vice versa.

Table 3, Panel A presents the pairwise Granger causality test results for three variables: *TS*, ΔLC^{ON}, and ΔLC^{OFF}. The optimal lag length of "one" for the Granger causality tests is chosen in a vector autoregression (VAR) framework and is based on both the Schwarz information criterion (SIC) and Akike information criterion (AIC).

Looking from the top in Table 3, Panel A, we show that while *TS* Granger causes

ΔLC^{ON} at the 10% level of significance, there is no reverse Granger causality. These results suggest that *TS* contains information about ΔLC^{ON}, which is consistent with the notion that the Treasury term structure is a determinant of bank on-balance sheet activities. By contrast, *TS* and ΔLC^{OFF} do not Granger cause each other. Finally, ΔLC^{ON} Granger causes ΔLC^{OFF} at the 5% level of significance, but the reverse is not true. Thus, the Granger causality results indicate that *TS* has information about ΔLC^{ON}**.** However, the Granger causality tests are pairwise causality tests and do not account for other variables, and hence we formally test whether *TS* is related to BLC, especially during recessions.

[TABLE 3 about here]

We use the following equation, where X is one of the three BLC variables, Y is a vector of variables such as *TS*, R is the binary NBER recession variable, c_t is the intercept term, and θ_t is the error term.

$$\mathrm{X}_t = c_t + \Phi_t X_{t-1} + \omega_t Y_{t-1} + \nu_t (TS)_{t-1} * R_t + \theta_t \tag{4}$$

Table 3, Panel B presents the results, where we do not report the coefficient estimates of some of the control variables to save space. Looking from the left (Model 1), we observe that *TS* is positively related to ΔLC at the 5% level of significance. However, looking next at the coefficient of the interaction term of Model 2 with a number of control variables, we observe that *TS* is inversely related to ΔLC during recessions. By comparing the adjusted R-squared values of Models 1 and 2, one can conclude that ΔLC contains information that is not captured by *TS* or other variables. Models 3 and 4 similarly show that *TS* is inversely related to both ΔLC^{OFF} and LC^{ON} during recessions. Since *TS* affects BLC, especially during recessions, we employ a two-stage probit model for robust coefficient estimates. In the first stage, we estimate the orthogonal (to *TS* and other variables) components ($\widehat{\mathrm{X}}_t = \theta_t$) of the BLC variables using Eq. (4).

In the second stage, we use $\hat{X}_t$, the orthogonalized BLC variables, to forecast recessions using Eq. (3). We focus on ΔLC^{ON}, since the results for this variable are robust to different samples as shown in Table 2. Table 3, Panel C shows that the results for orthogonalized ΔLC^{ON} (hereafter $\Delta\widehat{LC}^{ON}$) as a predictor of recessions. Table 3, Panel C results are qualitatively similar to the results presented in Table 2 and do not change our main conclusion that bank on-balance sheet liquidity creation is an important predictor of recessions. Since *TS* is inversely related to the BLC variables during recessions, we use the orthogonalized version of the BLC variables for the most of our remaining analyses.

3.2. Two-stage Probit models with additional control variables

In this subsection, we use a set of control variables to ensure robustness of the results presented earlier.[8] The primary predictor variables are *TS* and one of the three orthogonalized BLC variables ($\Delta\widehat{LC}^{ON} or\ \Delta\widehat{LC}^{OFF} or\ \Delta\widehat{LC}$). We use a comprehensive set of control variables that are described in the data section (Section 2). The results of the extended probit models are presented in Table 4.

[TABLE 4 about here]

For a one-quarter forecast horizon, it is shown that $\Delta\widehat{LC}$, $\Delta\widehat{LC}^{ON}$, and $\Delta\widehat{LC}^{OFF}$ are negatively related to recessions after we control for other predictor variables. We find that ΔGDP

[8] We thank an anonymous seminar participant for suggesting the inclusion of those control variables.

is an important predictor at shorter forecast horizons, which is consistent with the results in Estrella and Hardouvelis (1991). However, we further observe that *VOL* and *CS* have some predictive power for recessions, but those two variables are not robust predictors at each forecast horizon.[9]

For a two-, three-, and four-quarter forecast horizons, $\Delta\widehat{LC}^{ON}$ is negatively related to recessions in conformity with Table 2. Because the results for $\Delta\widehat{LC}$ and $\Delta\widehat{LC}^{OFF}$ at different forecast horizons are qualitatively similar to the estimates presented in Table 2, we do not report some of those results. Overall, our results with a larger set of control variables do not change our main conclusions.[10]

4. Robustness checks

This section conducts several robustness checks of the results presented earlier. First, we investigate the relationship between alternative measures of BLC and recessions. Next, we conduct out-of-sample tests to ascertain that in-sample results hold. Finally, we conduct a vector-autoregressive analysis to ensure that the BLC variables are positively related to real GDP.

[9] The inclusion of unemployment and inflation in the analysis does not change our conclusions. While inflation is positively related to recessions, especially at longer forecast horizons, unemployment rises one quarter before recessions. Those results are available on request.

[10] Since stock market returns are calculated using the NYSE stocks, to ascertain that the results are insensitive to the choice of indices, we include all stocks in the NYSE, NASDAQ, and AMEX indices to measure stock market returns. Unreported results show that the inclusion of all indices to compute stock market returns does not have qualitative effects on our main results. We do not report those results for brevity and are available on request. We thank an anonymous referee for the suggestion.

4.1. Alternative measures of bank liquidity creation

Berger and Bouwman (2009) provide alternative measures of BLC, where off-balance sheet items are computed differently. For example, while *LC* uses *available* loan commitments and standby letters of credits, an alternative measure of liquidity creation, LCA (CATFATSECADJ in Berger and Bouwman, 2009) considers the *likelihood* of usage of loan commitments and standby letters of credits. The reason for this adjustment is that customers may not fully drawdown available loan commitments and standby letters of credit. In Table 5, we present the results for alternative measures of BLC, where ΔLCA, ΔLCA^{ON}, and ΔLCA^{OFF} are alternative measures of aggregate, on- and off-balance sheet liquidity creation growth, respectively, for the 1984–2002 subsample. We find that alternative measures of BLC have qualitatively similar recession forecasting power as our preferred measures. The results for the full sample are qualitatively similar to the full-sample results in Table 2, Panel B, and hence those are not reported for brevity.

[TABLE 5 about here]

4.2. Out-of-sample tests

In this section, we conduct pseudo-out-of-sample tests to verify that the in-sample results hold out-of-sample. We further investigate how the estimates of recession probabilities of our models compare to the *SPF* estimates. First, we present a short description of the methodologies.

Next, we present the results.

We use 1984:Q1–1991:Q4 data for estimation, which includes at least one of the recessions, and then predict the recession probabilities for 1992:Q1 through 2010:Q4. Following Rudebusch and Williams (2009), we use MAE (mean absolute error) and RMSE (root mean squared error) as performance measures.[11] We also use the DM-statistics (Diebold and Mariano, 1995) to test for equal MAEs. We test the statistical significance for equal MSEs since the DM-statistics is not available for the RMSE loss function. The loss differentials at a horizon *h* for the MAE and MSE loss functions are as follows:

$$diff(MAE)_t = |(error1)_{t|t-h}| - |(error2)_{t|t-h}| \tag{5}$$

$$diff(MSE)_t = (error1)^2{}_{t|t-h} - (error2)^2{}_{t|t-h} \tag{6}$$

where *error* is the forecast error of the two competing models 1 and 2. We regress the loss differential on a constant, and test the resulting *t*-statistics for a zero coefficient and reject the null that models have the same MAE or RMSE based on the differentials with HAC corrections.

4.3. Out-of-sample test results

Looking at the out-of-sample results in Table 6 from the top, we show MAE and RMSE values of the baseline *TS* model, the *TS*-augmented BLC models, the *SPF* estimates, and the *TS*-augmented extended models, respectively. We show the results for models that are comparable to the *TS* model and the *SPF* estimates for brevity. At each forecast horizon, bold MAE/RMSE represents that the corresponding model has higher statistically significant (at least at the 10%

[11] Rudebusch and Williams (2009) show that at forecast horizons greater than one quarter, other evaluation methods, such as the log probability score (LPS), produce similar results. The authors further argue that a forecast horizon longer than one quarter is more important for policymakers. Thus, we prefer the MAE and RMSE loss functions.

level) forecast errors than that of the lowest MAE/RMSE model.

[TABLE 6 about here]

For a single quarter forecast horizon, based on MAEs and RMSEs, all BLC-augmented models (Models B through D) perform better than a parsimonious *TS* model (Model A). Thus, BLC-augmented *TS* models have more information about recessions than the *TS* model.

Based on MAEs, the *SPF* estimates (Model E) are better than Models A through D. However, Models F and G with the *TS*, BLC growth, *RET*, and ΔGDP as predictors are better than the *SPF* estimates in terms of forecast accuracy. Based on RMSEs, the *SPF* estimates are better than Models A through D, where we have two predictors: *TS* and one of the three BLC variables. However, the *SPF* estimates are not statistically different from those of Model F (where we have four predictor variables: *TS*, ΔLC, *RET*, and ΔGDP) and Model G where we have four predictor variables: *TS*, ΔLC^{ON}, *RET*, and ΔGDP). Thus, we show that the *SPF* one-quarter estimates, while better than those of the *TS* model, are similar to the models that include observable variables such as ΔLC.

Looking at two- and three-quarter forecast horizons and based on MAEs, we observe Model G forecast recessions better than both the *SPF* estimates and the *TS* model. However, based on MSEs, we find mixed evidence. For a two-quarter forecast horizon, the *SPF* estimates are better, while for a three-quarter forecast horizon, Model F has lower forecast error than both the *SPF* and the *TS* model.

For a four-quarter forecast horizon based on both MAEs and MSEs, we observe that the BLC-based models perform better than both the *SPF* and the *TS* models. In sum, we find that the out-of-sample test results generally conform to our in-sample findings.

4.3. Vector-autoregression (VAR) estimates of real GDP growth

If the BLC variables forecast recessions, they may have information about economic growth, and hence we investigate the dynamic responses of Δ*GDP* to Δ*LC* shocks using a vector- autoregressive (VAR) model. Specifically, we employ Bayesian vector autoregression (BVAR), which uses Bayesian methods to estimate a vector autoregression (VAR). Koop and Korobilis (2010), among others, argue that for the limited length of macroeconomic datasets, such as ours, Bayesian methods are perhaps a better way of dealing with the problem of over-parameterization.

The endogenous VAR variables are Δ*FED*, Δ*GDP*, Δ*LC*, *TS*, *CS*, Δ*ILR*, *RET,* and *VOL*. Following the literature (e.g., Thorbecke, 1997), we order the endogenous VAR variables as follows: first, monetary policy variable; then, macro variables; finally, micro variables. However, alternative ordering of the variables has an insignificant impact on the VAR results. Based on the Schwarz information criterion (SIC) and the Akaike information criterion (AIC), we find VAR(1) describes the dynamics. We use "Minnesota prior" as is common in the BVAR literature. For parsimony, we report impulse responses of Δ*GDP* to Δ*FED*, Δ*LC*, *TS*, and *CS* shocks in Fig. 3.[12]

[Fig. 3 about here]

[12] Unreported standard VAR or Structural VAR results are qualitatively similar, and hence are not reported. We further do not report BVAR parameter estimates for parsimony. Unreported results further show that ΔLC^{ON} rather than ΔLC^{OFF} is the driver for Δ*GDP*. These results are available on request.

The impulse responses show that ΔLC has a significant positive impact on ΔGDP. After one quarter, the impact of ΔLC shock is approximately 13% of mean ΔGDP and is larger than that of *CS* and *TS* shocks. The positive impact of ΔLC on ΔGDP is consistent with our recession forecasting results that BLC is negatively related to recessions. While Berger and Sedunov (2015) do not investigate the relationship between U.S. GDP growth and ΔLC, our VAR results are consistent with their findings. Our results are also consistent with the findings in Jarkoet et al. (2015) that BLC in Russia contributes to economic development.

5. Monetary Policy Implications

In this section, we outline the monetary policy implications of our results. First, we investigate the relationship between liquidity creation of banks of different sizes and recessions. Next, we examine the dynamics between BLC and *TS* during and after recessions. Finally, we discuss the potential monetary policy implications.

5.1. Liquidity creation of large banks and recessions

Since the recent crisis, much has been discussed about "too large to fail" banks and their role in the economy. However, Berger and Sedunov (2015) find that liquidity creation of small banks rather than that of large banks has a higher impact on economic growth.[13] This may seem counterintuitive given that large banks create more than 90% of bank liquidity, which motivates us to examine whether large banks have had any role in other recessions. To conduct our

[13] Bank size is often an important factor to examine the role of banking on economic development (e.g., Carter and McNulty, 2005; Berger and Black, 2011).

analysis, we study the relationship between recessions and liquidity creation of banks of different sizes. Following Berger and Bouwman (2014), bank size is defined by bank gross total assets, which is bank total assets (FDIC call report code RCFD 2170) plus allowance for loan and lease losses (RCFD 3123) and the allocated transfer risk reserve (RCFD 3128)—a reserve for certain foreign loans losses. Large, medium, and small banks have more than \$3 billion, between \$1 billion and \$3 billion, and up to \$1 billion gross total assets, respectively.

[TABLE 7 about here]

In Table 7, we show the relationship between on-balance sheet liquidity creation of banks of different sizes and recessions for the full sample. The results show that on-balance sheet liquidity creation of larger banks rather than that of smaller banks forecasts recessions. Thus, our findings suggest that the forecasting power of ΔLC^{ON} for recessions (see Table 2) is driven by the on-balance sheet liquidity creation of larger banks. Unreported results similarly show that off-balance sheet and aggregate liquidity creation of large banks drive the recession forecasting power of ΔLC^{ON} and ΔLC.[14] This set of results provides some support for the different policy measures targeted at "too large to fail" banks right after the last financial crisis.

5.2. Term spread and bank liquidity creation during and after recessions

Monetary policy is generally loosened during recessions/crisis so that banks can create more liquidity. To better understand the dynamics, we next investigate the behavior of *TS* and the BLC measures during and for a period of eight quarters after recessions. Specifically, we use the

[14] These results and all unreported findings are available from the author upon request.

following probit model:

$$P(X_t = 1) = \Phi(\alpha + \beta * TERM_{t+l} + \gamma * V_{t+l}) \tag{7}$$

where $X_t = 1$ when the economy is in recession and 0 otherwise, *TS* is the term spread, V is one of the BLC growth measures, and *l* varies from 0 to 8. For parsimony, we present the results in Table 8 for *l* = 0, 1, 3, 5, and 8.

[TABLE 8 about here]

For the 1984–2002 subsample, we find that all three BLC measures fall for up to five quarters after recessions. In contrast, the relationship between *TS* and recessions turns positive approximately one quarter after recessions. The coefficient estimates of *TS* continue rising in each of the five quarters after recessions. The results thus suggest that the Treasury yield curve becomes steeper, possibly because of looser monetary policy around recession quarters. However, the BLC measures fall to its lowest level around the third post-recession quarter.

The results for the 1984–2010 sample are qualitatively similar to those of the 1984–2002 subsample for *TS* and bank on-balance sheet liquidity creation. However, for the 1984–2010 sample, both off-balance sheet and aggregate liquidity creation continue falling beyond five quarters after recessions. Up to eight quarters after recessions with an upward sloping yield curve, we do not find any evidence that liquidity creation expands.

The in-sample probit results of Table 8 could be visualized by an event study. We consider the onset of recessions as the "event" and show the evolution of different variables around the event in Fig. 4. For each recession, we aggregate *TS*, LC^{ON}, and ΔLC^{OFF} for thirteen quarters starting four quarters (R-4) before the first NBER recession quarter. For the 1984–2010 sample, the recessions lasted on average for approximately 4.7 quarters. Therefore, out of thirteen quarters, the first four quarters are shown as R-1 to R-4, the five quarters starting from the first NBER recession quarter are shown as R, and the last four quarters are shown as R+1 to R+4. Since *TS* is in % and the BLC variables are in $ trillion, we plot standardized TS, LC^{ON}, and LC^{OFF} for ease of comparison. The plot shows that there exists a near inverse relationship between *TS* and BLC during and after the recessions. While *TS* starts increasing from the onset of recessions, both bank on- and off-balance sheet liquidity creation continue to decline. Thus, the event study seems to be consistent with the results presented in Table 8.

[Fig. 4 about here]

5.3. Monetary policy implications

Our findings have potential policy implications. First, if contractionary policy is designed to fight against the over-expansion of the economy, our results show that banks, specifically larger ones, create less liquidity through on-balance sheet activities when the term spread contracts. In other words, the level of bank on-balance sheet activities before recessions can provide an important indication to regulators concerning the efficacy of the credit tightening policy, since the feedback is available about four quarters before recessions. Policymakers could use this piece of information, along with other signals such as employment and inflation levels during the credit tightening cycle.

Second, our results show that while *TS* turns positive right after the recessions, possibly because of looser monetary policy, BLC continues to fall for approximately five quarters after the recessions. The results suggest that expansionary policy measures after recessions come too late to have a real impact on the economy through bank liquidity creation. The evidence in Bekaert et al. (2017) suggests that the recent recessions are "aggregate demand recessions," while earlier recessions are "aggregate supply recessions." Given our sample period of 1984–2010, the monetary implications of our results may be more relevant to "aggregate demand recessions."

Finally, the in-sample and out-of-sample results show that the BLC-augmented *TS* models display better performance at longer forecast horizons. Our results thus suggest that policymakers and forecasters may place proper weights on observable variables such as BLC when forecasting recessions.

6. Concluding remarks

Berger and Bouwman (2009) propose a measure of bank liquidity creation that factors in both banks' on- and off-balance sheet activities since banks create liquidity on the balance sheet and off the balance sheet. While measuring bank liquidity creation is important, investigating its impact on economic growth is central to evaluate the efficacy of monetary policy. There is an extensive literature on the relationship between the term spread and recessions (e.g., Estrella and Hardouvelis, 1991; Estrella and Mishkin, 1998), but the relationship between bank liquidity creation and recessions, to the best of our knowledge, has not been investigated in the literature. We examine this particular issue in this study by augmenting the term spread model of Estrella and Hardouvelis (1991) with bank liquidity creation measures of Berger and Bouwman (2009). We show that bank liquidity creation measures, especially on-balance sheet liquidity creation, contain information about future recessions for up to four quarters into the future.

We also provide an additional potential explanation for the severity of the 2007–2009 recession. Thakor (2005) argues that when credits are difficult to obtain, banks provide their long-standing customers with pre-arranged off-balance sheet credit rights such as standby letters of credit. We find an empirical support for this line of argument for the 1984–2002 subsample, which includes two recessions. However, when we investigate the last recession, we find evidence that banks created lower off-balance sheet liquidity prior to the recent crisis. Bank off-balance sheet liquidity creation data show that during the prior four quarters (2006:Q4–2007:Q3) before the recent recession (2007:Q4–2009:Q2), the mean of bank off-balance sheet liquidity creation growth was 1.64% per quarter, while the average for the same for the prior two recessions (1990 and 2001 recessions) was 4.08% per quarter. This may explain why the recent recession has been longer and more severe.

This study may have important macro-prudential policy implications. We find that bank liquidity creation falls prior to recessions and banks continue to create less liquidity after recessions. This information may help influence monetary policy. Our results further suggest that policymakers and forecasters may include bank liquidity creation in their recession forecasting models.

In this paper, while we find evidence that bank on-balance sheet activities contract prior to and after recessions, we do not investigate whether or how banks manage their balance sheet by rebalancing their asset/liability composition around recessions. Future research may investigate how banks shift their cash, liquid assets, and loan portfolios prior to recessions. It would also be interesting to investigate whether banks change their sources of borrowing (e.g., deposits versus non-deposits) during recessions.

Acknowledgements

We thank John Sedunov (FMA 2015, Orlando, FL, USA, discussant) Klaus Schaeck, Christa Bouwman, Allen Berger, and Kundan Kishor for their suggestions in the formative stages of the paper. We extend sincere thanks to seminar participants at FMA 2015, the American University of Sharjah, University of Wisconsin-Milwaukee, and the UAE University for their comments and suggestions.

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Table 1
Summary Statistics.

Panel A: Summary statistics							
	LC^{ON}	LC^{OFF}	LC	ΔLC	ΔLC^{ON}	ΔLC^{OFF}	TS
	(US$ Trillion)						
Mean	1.41	2.19	3.59	0.01	0.01	0.01	1.92
Median	1.17	2.13	3.26	0.01	0.01	0.01	1.95
Maximum	2.14	4.29	6.40	0.08	0.10	0.20	3.70
Minimum	0.84	0.61	1.43	-0.06	-0.05	-0.09	-0.45
Std. Dev.	0.42	1.22	1.62	0.02	0.02	0.03	1.15
Observations	108	108	108	107	107	107	108

Panel B: Pairwise correlation coefficients											
	RECESSION	ΔLC	ΔLC^{ON}	ΔLC^{OFF}	TS	FED	CS	RET	VOL	ΔILR	$\Delta OFFSHORT$
ΔLC	-0.40										
ΔLC^{ON}	-0.19	0.63									
ΔLC^{OFF}	-0.37	0.83	0.12								
TS	0.10	-0.32	-0.15	-0.29							
FED	-0.22	0.35	0.08	0.38	-0.42						
CS	0.51	-0.53	-0.19	-0.52	0.33	-0.17					
RET	-0.09	-0.07	0.06	-0.09	0.08	-0.03	-0.08				
VOL	0.44	-0.31	-0.15	-0.29	0.06	-0.21	0.57	-0.46			
ΔILR	0.11	0.15	0.06	0.16	-0.08	0.07	0.07	-0.50	0.43		
$\Delta OFFSHORT$	0.17	-0.23	-0.10	-0.22	0.11	-0.15	0.17	0.13	0.11	0.05	
ΔGDP	-0.65	0.42	0.29	0.35	0.03	0.22	-0.53	0.18	-0.44	-0.08	-0.17

Panel C: Bank liquidity creation auto-correlation structure			
	Lag 1	Lag 2	Lag 3
ΔLC	0.12	0.26	0.00
ΔLC^{ON}	-0.13	0.10	0.13
ΔLC^{OFF}	0.25	0.03	-0.00

This table shows descriptive statistics. Panel A presents the summary statistics of primary predictor variables for recessions, where LC^{ON}, LC^{OFF}, and LC are bank on-balance sheet, off-balance sheet, and aggregate of on- and off-balance sheet liquidity creation measures, respectively; ΔLC^{ON}, ΔLC^{ON}, and ΔLC are the log first difference of those measures; *TS* is the term spread, the difference between the yield on 3-month Treasury bills and 10-year Treasury bonds. Panel B shows the pairwise correlation analysis, where RECESSION is the NBER recession quarters indicated by a binary variable that takes the value of 1 in recession quarters and 0 otherwise; *FED* is the Federal funds rate; *CS* is the credit spread, which is the difference in yields between Moody's AAA and BAA rated bond indices; *RET* is the stock market returns; *VOL* is the stock market volatility; ΔGDP is the log difference of real GDP; ΔILR is the log difference of ILR, Amihud's (Amihud, 2002) stock market illiquidity measure; and $\Delta OFFSHORT$ is the first difference of illiquidity of off-the-run short-maturity Treasury bills with maturities up to one year. Panel C presents the auto-correlations structure of bank liquidity creation growth. Quarterly sample from 1984:Q1 to 2010:Q4.

Table 2

In-sample Probit estimates of recessions with bank liquidity creation.

Panel A: Bank liquidity creation, Treasury term spread, and prediction of recessions: excluding recent crisis (1984-2002 subsample)								
	One-Quarter		Two-Quarters		Three-Quarters		Four-Quarters	
TS	-0.52	-0.64	-0.95	-1.37	-2.32	-3.01	-3.41	-4.59
	(-3.01)***	(-3.11)***	(-3.07)***	(-2.97)***	(-3.52)***	(-3.74)***	(-3.11)***	(-3.06)***
ΔLC^{ON}		-17.46		-35.02		-41.04		-44.58
		(-2.24)***		(-2.88)***		(-2.50)***		(-2.03)**
Pseudo R-Sq.	0.12	0.17	0.27	0.41	0.52	0.62	0.61	0.70
TS		-0.66		-0.91		-2.63		-6.87
		(-3.02)***		(-2.84)***		(-2.70)***		(-2.06)**
ΔLC^{OFF}		-28.17		6.24		14.97		22.87
		(-2.28)***		(1.02)		(2.83)***		(2.96)***
Pseudo R-Sq.		0.22		0.29		0.59		0.74
TS		-0.79		-0.98		-2.42		-6.22
		(-3.05)***		(-3.15)***		(-2.81)***		(-2.24)***
ΔLC		-35.71		-5.16		14.99		46.52
		(-3.13)***		(-0.31)		(0.74)		(1.92)**
Pseudo R-Sq.		0.24		0.27		0.53		0.69

Table 2 (continued)

Panel B: Bank liquidity creation, Treasury term spread, and prediction of recessions: full sample (1984–2010)

	One-Quarter		Two-Quarters		Three-Quarters		Four-Quarters	
TS	-0.13	-0.22	-0.33	-0.45	-0.61	-0.68	-0.88	-0.95
	(-1.17)	(-1.99)***	(-2.47)***	(-3.07)***	(-3.50)***	(-3.41)***	(-3.38)***	(-3.29)***
ΔLC^{ON}		-17.57		-21.81		-14.46		-14.71
		(-2.73)***		(-2.86)***		(-1.99)**		(-1.74)*
Pseudo R-Sq.	0.01	0.07	0.06	0.16	0.19	0.23	0.30	0.32
TS		-0.31		-0.31		-0.57		-0.84
		(-2.61)***		(-2.44)***		(-3.34)***		(-3.22)***
ΔLC^{OFF}		-20.24		0.22		4.42		14.71
		(-3.12)***		(0.03)		(0.78)		(0.69)
Pseudo R-Sq.		0.13		0.06		0.19		0.32
TS		-0.37		-0.41		-0.62		-0.88
		(-2.88)***		(-3.17)***		(-3.72)***		(-3.56)***
ΔLC		-28.81		-11.08		-2.01		-4.24
		(-4.03)***		(-1.17)		(-0.21)		(-0.09)
Pseudo R-Sq.		0.16		0.09		0.19		0.30

This table shows how bank liquidity creation is related to recessions using the probit model $P(X_t = 1) = \Phi(\alpha + \beta * TS_{t-l} + \gamma * V_{t-l})$, where TS is the term spread, V is one of the bank liquidity creation measures that are described in Table 1. Panel A reports probit results with ΔLC^{ON}, ΔLC^{OFF} and ΔLC, bank on-, off-balance sheet and aggregate liquidity creation measures, respectively, along with TS at different prediction horizons for the quarterly sub-sample from 1984:Q1-2002:Q4. Panel B probit results for the full sample from 1984:Q1 to 2010:Q4. Errors are corrected for heteroscedasticy adjustments. Z-statistics are in the parenthesis; intercepts are not reported for parsimony. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. For parsimony, only β and γ are reported.

Table 3
Term structure and bank on-balance sheet liquidity creation.

Panel A: Pairwise Granger causality of bank on- and off-balance sheet liquidity creation growth and term spread		
Null Hypothesis:	*F*-statistic	*p*-value
TS does not Granger cause ΔLC^{ON}	2.99	0.09*
ΔLC^{ON} does not Granger cause *TS*	2.38	0.13
TS does not Granger cause LC^{OFF}	2.37	0.13
LC^{OFF} does not Granger cause *T*S	2.40	0.12
LC^{OFF} does not Granger cause ΔLC^{ON}	1.90	0.17
ΔLC^{ON} does not Granger cause LC^{OFF}	5.05	0.03**

Panel B: Relationship between bank liquidity creation and Treasury term spread: full sample (1984–2010)				
Dependent:	ΔLC		ΔLC^{ON}	ΔLC^{OFF}
	Model 1	Model 2	Model 3	Model 4
TS(-1)(X100)	0.15	0.17	0.03	0.02
	(1.87)*	(1.35)	(1.42)	(1.67)*
ΔLC(-1)	0.39	0.03		
	(2.35)***	(1.87)*		
ΔLC^{ON}(-1)			-0.21	
			(-2.11)**	
ΔLC^{OFF}(-1)				0.1
				(1.42)
Δ*ILR*(-1)		-0.12	-0.16	-0.09
		(-2.04)**	(-1.93)*	(-1.04)
CS(-1)		-0.02	-0.01	-0.04
		(-3.64)***	(-0.15)	(-7.64)***
TS(-1)*R		-0.03	-0.02	-0.04
		(-4.63)***	(-2.52)***	(-3.39)***
Other control variables	No	YES	YES	YES
Pseudo R-Sq.	0.23	0.48	0.45	0.47

Table 3 (continued)

Panel C: Orthogonalized bank on-balance sheet liquidity creation and Treasury term spread: full sample (1984–2010)				
	One-Quarter	Two-Quarters	Three-Quarters	Four-Quarters
TS	-0.17	-0.41	-0.65	-0.92
	(-1.58)	(-2.82)***	(-3.33)***	(-3.27)***
$\Delta\widehat{LC}^{ON}$	-19.76	-24.78	-16.53	-16.41
	(-3.02)***	(-3.18)***	(-2.25)***	(-1.93)**
Pseudo R-Sq.	0.09	0.17	0.23	0.33

This table shows the relationship between the Treasury term spread and bank liquidity creation. Panel A presents Granger causality results for TS, ΔLC^{ON}, and ΔLC^{OFF}. Using Eq. (4) in the text, Panel B shows how TS is related to the BLC measures, (-1) implies a lag of one quarter; R is the binary NBER recession variable. Panel C shows how orthogonal component of ΔLC^{ON} (to TS, ΔILR, CS, etc.) is related to recessions; $\Delta\widehat{LC}^{ON}$, the orthogonal component of ΔLC^{ON} is as per Eq. (4) in the text. Sample: Quarterly data from 1984:Q1 to 2010:Q4. Errors are corrected for heteroscedasticity adjustments. Z-statistics are in the parentheses; intercepts are not reported for parsimony. *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively. For parsimony, intercepts are not reported.

Table 4
Two-stage Probit estimates of recessions with extended models.

Aggregate bank liquidity creation, asset market liquidity, Treasury term spread, and recessions: full sample (1984–2010)							
	1-Quarter			2-Quarters	3-Quarters	4-Quarters	
TS	-0.42	-0.22	-0.35	-0.58	-0.75	-0.96	-1.05
	(-2.58)***	(-1.38)	(-2.34)***	(-2.46)***	(-3.07)***	(-3.48)***	(-3.07)***
$\Delta\widehat{LC}$	-36.75					-4.36	
	(-3.46)***					(-0.32)	
$\Delta\widehat{LC}^{ON}$		-9.54		-20.70	-12.05		-19.66
		(-1.73)*		(-2.20)***	(-1.70)*		(-2.21)***
$\Delta\widehat{LC}^{OFF}$			-32.16				
			(-3.03)***				
ΔGDP	-127.11	-116.56	-147.77	-34.09	-12.97	27.48	38.06
	(-2.14)***	(-1.92)*	(-2.61)***	(-0.74)	(-0.34)	(0.60)	(0.92)
RET	-2.07	-1.44	-2.59	-1.53	-3.12	-4.52	-3.91
	(-0.75)	(-0.54)	(-0.87)	(-0.52)	(-1.28)	(-1.63)	(-1.36)
VOL	87.84	102.76	73.80	72.71	13.69	-10.59	-4.09
	(1.93)*	(2.23)***	(1.66)*	(1.52)	(0.39)	(-0.27)	(-0.12)
FED	-0.05	-0.12	-0.03	-0.12	-0.11	-0.07	-0.05
	(-0.67)	(-1.35)	(-0.43)	(-1.34)	(-1.06)	(-0.64)	(-0.56)
CS	0.68	0.78	-0.53	0.35	1.99	7.40	5.24
	(0.59)	(1.00)	(-0.38)	(0.47)	(1.12)	(2.03)**	(1.51)
ΔILR	1.01	0.18	1.15	1.26	0.92	1.16	1.29
	(0.67)	(0.12)	(0.81)	(0.73)	(0.54)	(0.57)	(0.66)
$\Delta OFFSHORT$	-3.87	-2.86	-4.55	-2.70	-1.05	2.86	3.48
	(-1.52)	(-1.19)	(-1.64)	(-1.12)	(-0.39)	(1.29)	(1.58)
Pseudo R-Sq.	0.45	0.37	0.47	0.34	0.34	0.38	0.41

This table shows how bank liquidity creation is related to recessions using the extended probit model $P(X_t = 1) = \Phi(\alpha + \beta * TS_{t-l} + \gamma * V_{t-l})$, where TS is the term spread, V is a vector of predictors variables that are described in Table 1. One of the predictor variables is one of the orthogonalized bank liquidity creation measures: $\Delta\widehat{LC}^{ON}$, $\Delta\widehat{LC}^{OFF}$, and $\Delta\widehat{LC}$; orthogonal components are computed as per equation (4) in the text. Errors are corrected for heteroscedasticy adjustments. Z-statistics are in the parenthesis; intercepts are not reported for parsimony. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. For parsimony, only β and γ are reported. Quarterly sample from 1984:Q1 to 2010:Q4.

Table 5
Predicting recessions with alternative measures of bank liquidity creation.

Alternative measures of bank liquidity creation, Treasury term spread and recessions: excluding recent crisis (1984–2002 subsample)				
	One-Quarter	Two-Quarters	Three-Quarters	Four-Quarters
TS	-0.56	-1.14	-2.64	-3.86
	(-2.98)***	(-2.76)***	(-3.88)***	(-3.09)***
ΔLCA^{ON}	-13.52	-25.35	-27.98	-19.19
	(-1.99)**	(-2.59)***	(-2.14)**	(-2.04)**
Pseudo R-Sq.	0.16	0.36	0.58	0.64
TS	-0.54	-0.75	-2.55	-6.87
	(-3.28)***	(-3.01)***	(-2.34)***	(-2.06)**
ΔLCA^{OFF}	-27.39	6.83	16.56	22.87
	(-2.15)***	(1.10)	(3.01)***	(2.96)***
Pseudo R-Sq.	0.22	0.29	0.59	0.73
TS	-0.75	-1.04	-2.36	-7.92
	(-3.03)***	(-3.07)***	(-3.00)***	(-2.40)***
ΔLCA	-34.45	-13.30	11.15	94.43
	(-2.98)***	(-0.80)	(0.40)	(1.98)*
Pseudo R-Sq.	0.23	0.28	0.52	0.70

This table shows how alternative measures of bank liquidity creation growth is related to recessions using the probit model $P(X_t = 1) = \Phi(\alpha + \beta * TS_{t-l} + \gamma * V_{t-l})$, where TS is the term spread, where V is one of probit results with $\Delta LCSA^{ON}$, $\Delta LCSA^{OFF}$ and ΔLCSA, bank on-, off-balance sheet and aggregate alternative liquidity creation measures, respectively, where the measures accounts for bank off-balance sheet activities differently. For example, LCSA considers the *likelihood of usage* rather than *available* lines of credit, an off-balance sheet item. Other variables are described in Table 1. Sample: Quarterly data from 1984:Q1 to 2002:Q4. Errors are corrected for heteroscedasticy adjustments. Z-statistics are in the parenthesis; intercepts are not reported for parsimony. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. For parsimony, only β and γ are reported.

Table 6
Out-of-sample tests.

Panel A: Forecasting recessions by bank liquidity creation									
Estimation sample		1984:Q1–1991:Q4							
Forecasts for 1992:Q1–2010:Q4		One-quarter		Two-quarters		Three-quarters		Four-quarters	
Model	Predictor Variables	MAE	RMSE	MAE	RMSE	MAE	RMSE	MAE	RMSE
Model A	*TS*	**22.02**	**35.91**	**20.97**	**34.29**	**18.55**	**33.03**	**15.46**	**33.42**
Model B	TS, $\Delta\widehat{LC}$	**19.18**	**34.24**	**21.45**	**34.19**	**19.13**	**33.75**	12.47	31.09
Model C	TS, $\Delta\widehat{LC}^{ON}$	**20.14**	**34.51**	17.77	**34.01**	**15.84**	**32.82**	12.94	**32.18**
Model D	TS, $\Delta\widehat{LC}^{OFF}$	**20.22**	**33.97**	**20.74**	**34.02**	**24.35**	**46.94**	**13.11**	**33.77**
Model E	*SPF*	**16.83**	23.06	**19.91**	27.02	**22.17**	30.22	**23.61**	**32.08**
Model F	TS, $\Delta\widehat{LC}$, RET, ΔGDP	11.56	23.73	16.87	**29.37**	**17.24**	29.71	**16.21**	28.68
Model G	TS, $\Delta\widehat{LC}^{ON}$, RET, ΔGDP	9.61	23.78	16.23	**30.01**	12.89	**33.95**	11.95	**33.61**

This table presents the out-of-sample tests results for different models. Panel A presents out-of-sample results for the Term spread model, bank liquidity creation-augmented term spread models, and the SPF estimates for lags up to four quarters prior to recessions, where SPF refers to the Survey of Professional Forecaster's estimates and other variables are described in earlier tables; for each model, same lags for each predictor variable is used. Models are evaluated based on both the MAE (mean absolute error) and RMSE (root mean squared error); bold MAE/RMSE represents higher statistically significant (at least at the 10% level) MAE/RMSE relative to the model with the lowest MAE/RMSE using the test-statistics described in the text.

Table 7
On-balance sheet liquidity creation of banks of different sizes and recessions.

On-balance sheet liquidity creation growth of banks of different sizes, Treasury term spread, and recessions								
	Excluding the recent crisis (1984–2002 subsample)				Full sample (1984–2010)			
	One-Quarter	Two-Quarters	Three-Quarters	Four-Quarters	One-Quarter	Two-Quarters	Three-Quarters	Four-Quarters
TS	-0.50	-1.10	-2.96	-4.65	-0.23	-0.47	-0.69	-0.97
	(-3.22)***	(-3.14)***	(-3.85)***	(-3.04)***	(-2.13)***	(-2.58)***	(-3.35)***	(-3.71)***
Large-Sized	-14.56	-30.48	-42.23	-43.90	-17.92	-22.27	-14.52	-15.35
	(-2.06)**	(-2.78)***	(-2.33)***	(-1.94)*	(-2.82)***	(-2.97)***	(-2.04)**	(-1.89)*
Pseudo R-Sq.	0.13	0.35	0.63	0.71	0.08	0.15	0.22	0.32
TS	-0.45	-0.77	-2.07	-3.43	-0.12	-0.31	-0.59	-0.87
	(-3.29)***	(-3.54)***	(-3.47)***	(-3.26)***	(-0.82)	(-2.01)**	(-3.09)***	(-3.47)***
Mid-Sized	4.47	0.22	-6.21	-8.12	0.10	-0.93	-2.37	-0.52
	(0.75)	(0.03)	(-0.51)	(-0.56)	(0.02)	(-0.19)	(-0.44)	(-0.09)
Pseudo R-Sq.	0.09	0.23	0.53	0.64	0.01	0.06	0.19	0.30
TS	-0.50	-0.85	-2.13	-3.46	-0.18	-0.37	-0.63	-0.91
	(-3.28)***	(-3.67)***	(-3.38)***	(-3.25)***	(-1.14)	(-2.28)**	(-3.16)***	(-3.48)***
Small-Sized	5.46	3.04	-1.99	-2.33	3.81	2.94	1.22	1.66
	(1.80)*	(0.73)	(-0.33)	(-0.34)	(1.30)	(1.01)	(0.39)	(0.49)
Pseudo R-Sq.	0.14	0.24	0.52	0.63	0.03	0.08	0.19	0.30

This table shows how bank liquidity creation of banks of different sizes is related to recessions using the probit model $P(X_t = 1) = \Phi(\alpha + \beta * TERM_{t-l} + \gamma * V_{t-l})$, where TS is the term spread, V is on-balance sheet liquidity creation measure based on bank size. The results reports probit results for the quarterly full sample from 1984:Q1 to 2010:Q4 and the sub-sample from 1984:Q1-2002:Q4. Bank size is defined by bank gross total assets: large-, mid- and small-sized banks have more than $3 billion, between $1 billion-$3 billion and up to $1 billion gross total assets, respectively. Errors are corrected for heteroscedasticy adjustments. Z-statistics are in the parenthesis; intercepts are not reported for parsimony. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. For parsimony, only β and γ are reported.

Table 8
Bank liquidity creation during and after recessions.

	Bank liquidity creation and Treasury term spread during and after recessions									
	Excluding recent crisis (1984–2002 subsample)					Full sample (1984–2010)				
	R-Q	Plus 1	Plus 3	Plus 5	Plus 8	R-Q	Plus 1	Plus 3	Plus 5	Plus 8
TS	0.14	0.42	1.00	1.21	1.47	-0.19	0.18	0.57	0.95	1.36
	(1.23)	(2.94)***	(3.94)***	(3.94)***	(2.45)***	(-0.99)	(1.10)	(2.83)***	(3.36)***	(3.13)***
$\Delta\widehat{LC}$	-31.90	-32.02	-25.80	-15.00	0.85	-26.25	-32.80	-36.12	-26.43	-3.42
	(-3.18)***	(-3.13)***	(-2.51)***	(-1.57)	(0.55)	(-1.84)***	(-3.22)***	(-3.16)***	(-3.22)***	(-0.39)
Pseudo R-Sq.	0.17	0.23	0.32	0.33	0.37	0.10	0.28	0.39	0.37	0.35
TS	0.14	0.38	0.97	1.15	1.49	0.12	0.36	0.97	1.11	1.43
	(1.30)	(2.93)***	(3.97)***	(4.19)***	(2.45)***	(1.08)	(2.83)***	(3.97)***	(3.19)***	(3.23)***
$\Delta\widehat{LC}^{ON}$	-15.88	-17.39	-22.16	-6.03	5.24	-15.93	-17.42	-22.31	-6.53	6.78
	(-2.04)***	(-2.14)***	(-2.50)***	(-0.80)	(0.55)	(-2.03)***	(-2.15)***	(-2.56)***	(-1.40)	(1.19)
Pseudo R-Sq.	0.08	0.15	0.33	0.31	0.38	0.07	0.14	0.33	0.31	0.36
TS	0.10	0.38	0.92	1.16	1.43	-0.07	0.20	0.55	0.94	1.37
	(0.91)	(2.65)***	(4.16)***	(4.01)***	(2.53)***	(-0.64)	(1.35)	(3.01)***	(3.52)***	(3.04)***
$\Delta\widehat{LC}^{OFF}$	-24.49	-24.20	-18.28	-9.98	-10.05	-22.00	-22.92	-21.93	-17.69	-5.57
	(-3.23)***	(-3.12)***	(-2.07)***	(-1.50)	(-0.87)	(-3.56)***	(-3.01)***	(-2.93)***	(-2.93)***	(0.81)
Pseudo R-Sq.	0.15	0.21	0.30	0.32	0.37	0.18	0.26	0.33	0.36	0.36

This table shows how bank liquidity creation is related to during and after recession quarters using the probit model $P(X_t = 1) = \Phi(\alpha + \beta * TS_{t+l} + \gamma * V_{t+l})$, where TS is the term spread, V is one of the orthogonalized bank liquidity creation measures described in Table 4. The results reports probit results for the quarterly full sample from 1984:Q1 to 2010:Q4 and the sub-sample from 1984:Q1-2002:Q4 during and after recessions. Errors are corrected for heteroscedasticy adjustments. Z-statistics are in the parenthesis; intercepts are not reported for parsimony. *, ** and *** denote significance at the 10%, 5% and 1% levels, respectively. For parsimony, only β and γ are reported. R-Q and Plus 1-8 imply recession quarters and 1 to 8 quarters after recessions, respectively.

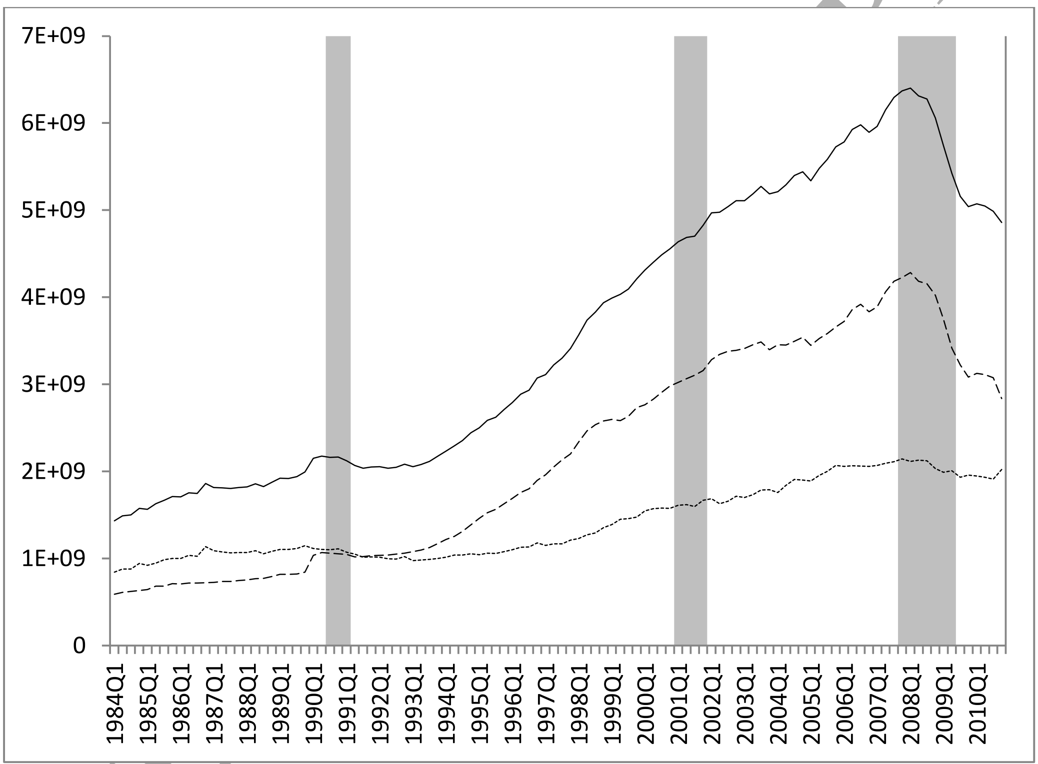

Fig. 1. Bank on- and off-balance sheet liquidity creation.

This figure plots bank liquidity creation variables (in US$) for the U.S. banks. The variables are LC (**solid line**): aggregate bank liquidity creation measure that includes both bank on- and off-balance sheet activities; LC^{ON} (**dotted line**): bank on-balance sheet liquidity creation measure that includes bank on-balance sheet activities; LC^{OFF} (**dashed line**): bank off-balance sheet liquidity creation measure includes bank off-balance sheet activities. The shaded areas are NBER Recession Quarters.

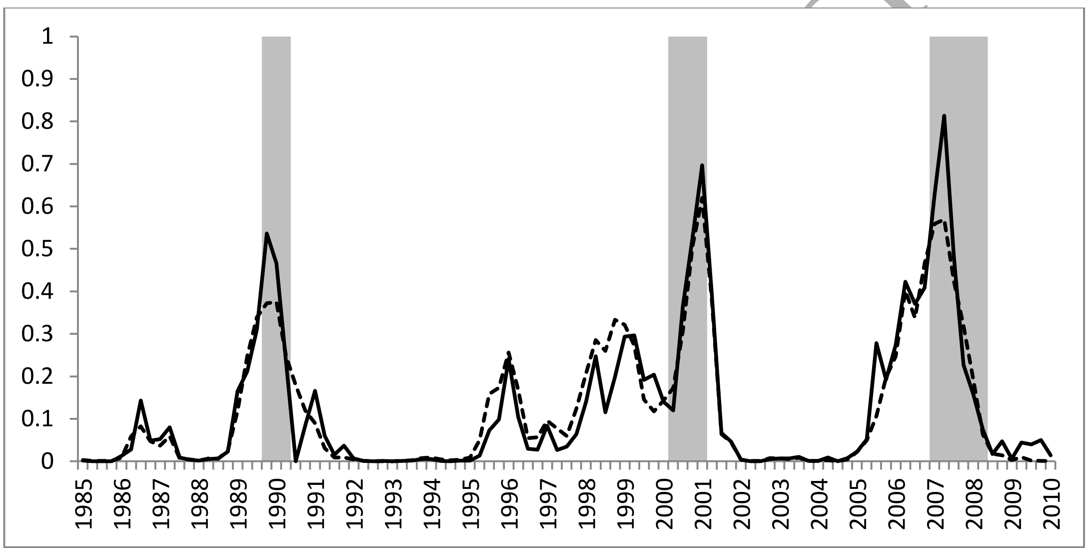

Fig. 2. Estimates of recessions probabilities at four quarters forecast horizon.

This figure plots in-sample estimates of four-quarter-ahead recession probabilities for the 1984:Q1–2010:Q4 sample. The benchmark model (**dotted line**) has one predictor variable: TS(-4); Bank on-balance sheet liquidity creation-augmented benchmark model (**solid line**) has two predictor variables: TS(-4) and ΔLC^{ON}(-4), where (-4) implies a lag of 4 quarters, and TS is the term spread, and ΔLC^{ON} is bank on-balance sheet liquidity creation growth. The shaded areas are NBER Recession Quarters.

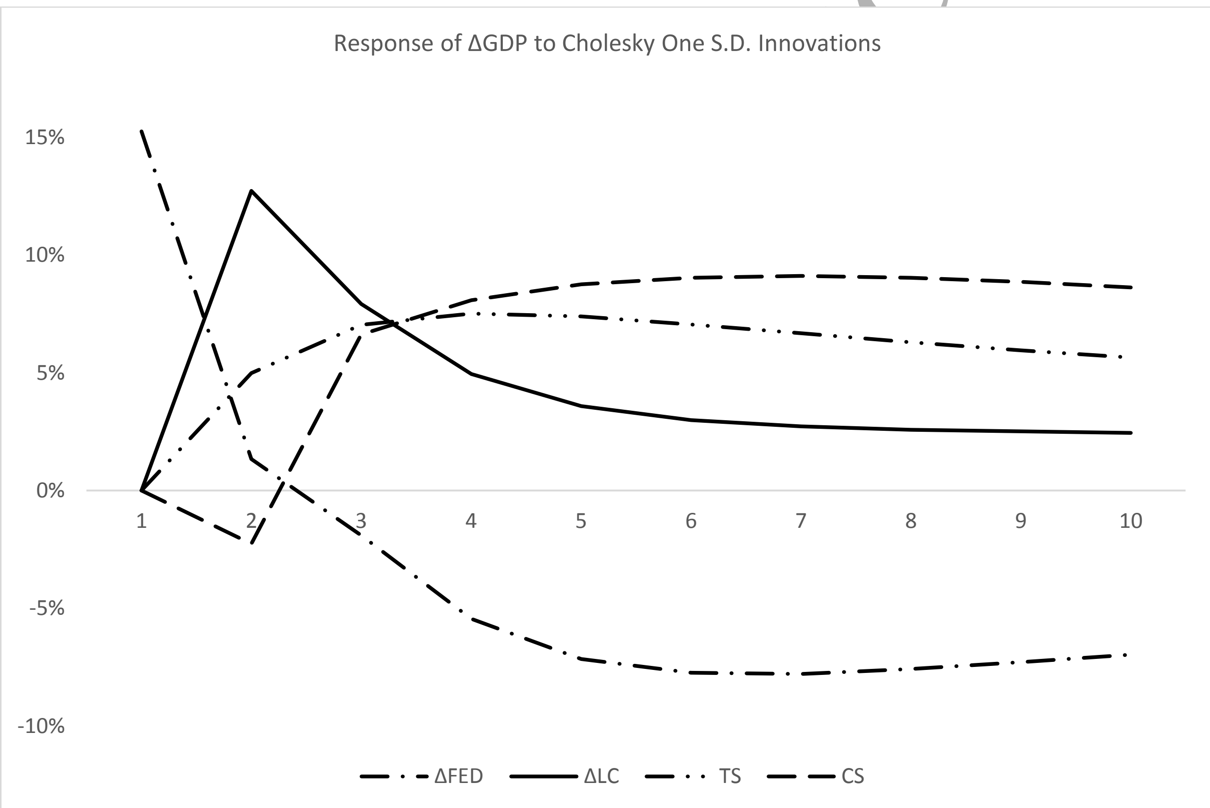

Fig. 3. Robustness: dynamic responses of real GDP to bank liquidity creation shocks.

This figure shows impulse responses of ΔGDP to ΔFED, TS, CS, and ΔLC Cholesky shocks for the VAR(1) model with the following endogenous variables: ΔFED, ΔGDP, ΔLC, TS, CS, ΔILR, RET, and VOL. Response functions are plotted for 10 quarters. Responses are shown as a % of the mean ΔGDP of 0.69% per quarter. Quarterly data from 1984:Q1 to 2010:Q4.

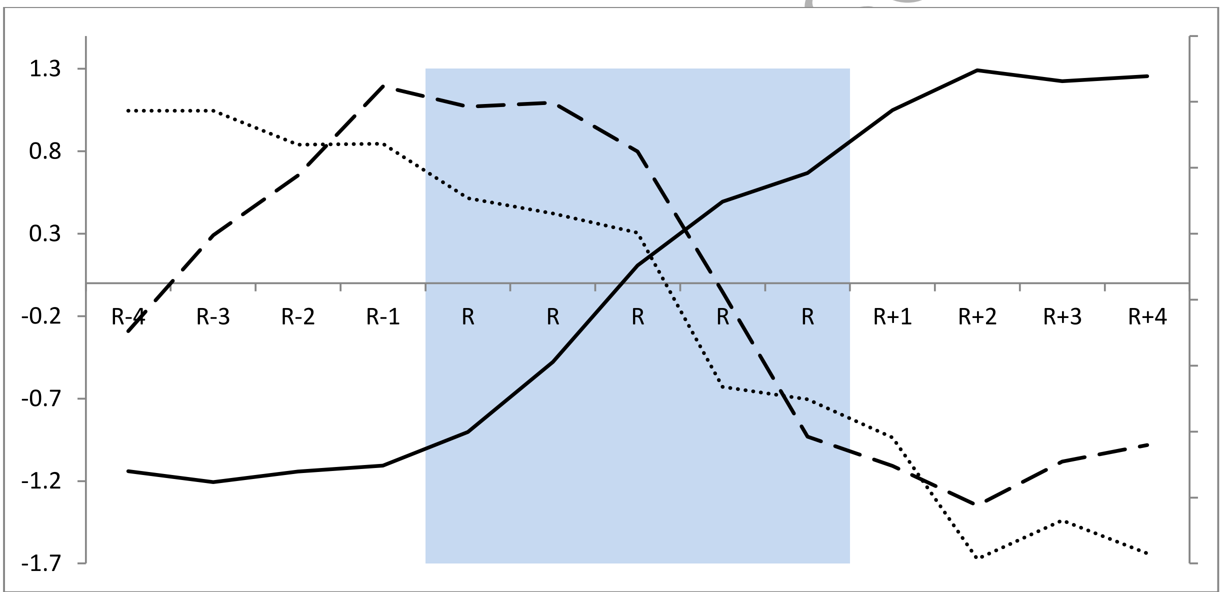

Fig. 4. An event study: Treasury term structure, bank liquidity creation around recessions.

This figure shows the dynamics of bank liquidity creation around recessions. For the 1984:Q1–2010:Q4 quarterly sample, there were three recessions and the average recessions lasted for approximately 4.7 quarters. We plot aggregated TS (**solid line**), LC^{ON}(**dotted line**), and LC^{OFF}(**dashed line**) for thirteen quarters, starting from four quarters before the first NBER recessions quarter (the "event"). Since TS is in % and $LC^{ON}$and $LC^{OFF}$are in $ trillion, we plot standardized values for ease of comparison. The shaded areas are NBER Recession Quarters (R).