Economic Policy Uncertainty and Bank Liquidity Hoarding

Allen N. Berger, Omrane Guedhami, Hugh H. Kim, Xinming Li*

August 2018

Abstract

Using over one million bank-quarter observations, we identify an important channel through which economic policy uncertainty (*EPU*) harms the real economy – bank liquidity hoarding. Our novel comprehensive measure of bank liquidity hoarding (*LH*) takes into account hoarding on the asset-, liability-, and off-balance sheet-sides. We find in response to *EPU*, banks hoard liquidity overall and through all three components. Identification analyses find that these effects are primarily from decreased liquidity supply by banks, rather than demand, suggesting causal effects on the real economy. Our results may help explain prior findings of unfavorable effects of uncertainty on firm and household behavior.

JEL: G21, G18, P16

Keywords: economic policy uncertainty, banks, liquidity hoarding, economic growth

---

* Berger, Guedhami, Kim, and Li are affiliated with the Darla Moore School of Business, University of South Carolina, 1014 Greene St., Columbia, SC 29208. Email: aberger@moore.sc.edu, omrane.guedhami@moore.sc.edu, hugh.kim@moore.sc.edu, and xinming@email.sc.edu, respectively. We appreciate helpful comments from Christa Bouwman, Lucy Chernykh, Jiarui (Jerry) Guo, Xiaonan (Flora) Ma, David Mauer, Raluca Roman, John Sedunov, Yafei Zhang, and seminar participants at the Copenhagen Business School, De Nederlandsche Bank, the Federal Reserve Bank of Kansas City, the Federal Reserve Bank of Richmond – Charlotte Branch, and University of South Carolina. We also thank Raluca Roman for invaluable data help.

1. Introduction

Uncertainty about economic policy can have significant negative consequences for the real economy. Such uncertainty may lead firms to invest less and hire fewer employees and cause households to purchase fewer homes and consumer durables. In this paper, we investigate another channel through which economic policy uncertainty (*EPU*) may harm the real economy – through bank liquidity hoarding. Banks may hoard liquidity both on and off of their balance sheets to protect themselves in less predictable environments. Banks may hold more cash and other liquid assets and supply fewer loans on the asset side of their balance sheets, leaving both firms and households with less liquidity. Banks may also collect more deposits and other liquid liabilities on the liability side of their balance sheets, leaving fewer funds to be intermediated through nonbank financial institutions and markets. Banks might also issue fewer loan commitments, letters of credit, and other financial guarantees off of their balance sheets. This may leave firms and households with less ability to access future funds from both banks and from other nonbank financial institutions and markets that require back-up guarantees. This liquidity hoarding may further reduce firm and household spending, exacerbating the harmful impacts of *EPU* on the real economy.

These different potential harmful effects of *EPU* on the real economy are illustrated in Figure 1. On the left, *EPU* (represented by the symbols of the U.S. Democratic and Republican Parties fighting) adversely affects the real economic agents of firms and households (depicted by the factory and house, respectively), as well as the financial agents of banks and other nonbank financial institutions and markets (represented by the bank and New York Stock Exchange buildings, respectively). Through a number of channels, the real economy (illustrated by the soup lines) is damaged. Arrows show the directions of causation through which these channels operate. When *EPU* rises, firms cut back investment and hiring and households make fewer purchases, both of which directly harm the economy. Banks hoard liquidity on both sides of their balance sheets and off their balance sheets, absorbing liquidity directly from the firms and households, as well as soaking up funds that would otherwise be available for firms and households from other financial institutions and markets. In turn, the firms and households reduce their spending more, further damaging the economy.[1] Nonbank financial institutions and markets may also hoard liquidity in response to uncertainty, with similar effects through firms and households on the real economy, but our focus here is on the banks.

Some of the channels that do not involve banks and other financial agents are investigated in the literature. This literature focuses primarily on the first channel that operates through firm behavior and uses new measures of *EPU* developed by Baker, Bloom, and Davis (BBD, 2016). The research confirms expectations and finds that *EPU* indeed negatively affects corporate behavior. Gulen and Ion (2016) find that U.S. corporate investment declines for an extended period following an increase in *EPU*. *EPU* is also found to reduce venture capital investment (Tian and Ye (2017)), hinder merger and acquisition (M&A) activities (Bonaime, Gulen, and Ion (2017), Nguyen and Phan (2017)), increase risk premiums on stocks (Pastor and Veronesi (2013), Kelly et al. (2016)), and raise corporate debt financing costs (Waisman, Ye, and Zhu (2015)).[2] There is much less analysis of the household channel. Aaberge, Liu, and Zhu (2017) find that Chinese households reduced expenditure and increased savings in the face of abrupt political turmoil following the Tian'anmen Square event.[3] Although it is not always acknowledged, part of the measured effects of the first two channels in the literature could also reflect the indirect effects on firm and household behavior of bank liquidity hoarding as discussed above regarding Figure 1. That is, part of the observed reductions in firm and household spending may be due to bank liquidity hoarding, rather than any direct effects of *EPU*.

To investigate the effects of *EPU* on bank liquidity hoarding, we first need a comprehensive measure of this hoarding that is inclusive of all of the asset, liability and off-balance sheet components described above. We base our new liquidity hoarding measure, *LH*, on the asset-side, liability-side, and off-balance sheet-side components of Berger and Bouwman's (2009) liquidity creation measure, *LC(asset), LC(liab),*

[1] Although not shown in the figure, these effects may be amplified to the extent that banks hoard liquidity from each other in interbank markets, exacerbating the effects of liquidity shocks (e.g., Allen and Gale (2000), Diamond and Rajan (2011), Heider, Hoerova, and Holthausen (2015)).

[2] Waisman, Ye, and Zhu (2015) focus on election uncertainty, but also use BBD's composite *EPU* measure in a robustness check and find that it increases debt financing costs.

[3] Research using other measures of political and policy uncertainty similarly find negative economic consequences (Barro (1991), Julio and Yook (2012), Bhattacharya, Hsu, Tian, and Xu (2017), Jens (2017)). See Bloom (2014) for a general review of the economic effects of political uncertainty.

and LC(off), respectively, which are weighted sums of all bank assets, liabilities, and off-balance sheet activities.[4] *LC(asset)* gives a negative weight to liquid assets, such as cash and securities, and a positive weight to illiquid loans, like commercial loans. Our *LH(asset)* component is measured as -*LC(asset)*, so that increasing cash and securities and reducing commercial loans count positively toward bank liquidity hoarding. *LC(liab)* gives a positive weight to liquid liabilities like transactions accounts. Banks may hoard liquidity by increasing such deposits, so our *LH(liab)* component is *LC(liab)* with a positive sign. *LC(off)* gives positive weights to loan commitments and similar financial guarantees that either fund future bank loans or provide back up to secure financing from nonbank financial institutions and markets. Banks may hoard liquidity by issuing fewer of these guarantees, so our *LH(off)* component is -*LC(off)*. Our total bank liquidity hoarding measure is *LH(total) = LH(asset) + LH(liab) + LH(off)*.

Importantly, we recognize that liquidity hoarding is a supply concept, and the *LH* measures are quantities that result from both supply and demand. Our use of quantities and calling them hoarding follows the literature, but as discussed below, we conduct additional identification analyses to differentiate between supply and demand effects.

There is substantial research on the topic of bank liquidity hoarding and in some cases, how it might be related to uncertainty. Our paper contributes to this research in several dimensions. First, we develop the only comprehensive measure of bank liquidity hoarding (*LH*), that takes into account all bank assets, liablities, and off-balance sheet activities. Theoretical models of bank liquidity hoarding focus on increased holdings of liquid assets, such as cash (e.g., Diamond and Rajan (2011), Acharya, Gromb, and Yorulmazer (2012), Gale and Yorulmazer (2013), Heider, Hoerova, and Holthausen (2015)) or reserve balances (e.g., Acharya and Merrouche (2012)). Another model focuses on reduced lending (e.g., Acharya and Skeie (2011)). Empirical studies of bank liquidity hoarding or management typically study levels or changes in various categories of liquid assets (e.g., Cornett, McNutt, Strahan, and Tehranian (2011), Berrospide (2012), Acharya and Mora (2015)), or prices and quantities of interbank federal funds (Afonso, Kovner, and Schoar (2011)). In contrast to these liquidity hoarding measures that focus on individual asset categories, our

[4] Bank equity is also included in the liability component of bank liquidity creation, but we just label it as the liability component for expositional convenience.

comprehensive *LH* liquidity hoarding measure combines the contributions to liquidity hoarding on the asset side with hoarding through the liability side of the balance sheet and off the balance sheet.

Some empirical research on the effects of uncertainty on banks goes beyond liquid assets. Most of these papers examine the effects of uncertainty about financial conditions during the subprime financial crisis (e.g., Afonso, Kovner, and Schoar (2011), Cornett, McNutt, Strahan, and Tehranian (2011), Berrospide (2012), Acharya and Mora (2015)). Two of these papers also consider the effects on the quantities of loans and/or off-balance sheet loan commitments in addition to liquid assets, although they do not consider these credit categories as liquidity hoarding instruments (e.g., Cornett, McNutt, Strahan, and Tehranian (2011), Acharya and Mora (2015)). Some of these papers also suggest that banks tried to attract more deposits by raising rates in response to the financial crisis, but again do not call this liquidity hoarding (Acharya and Mora (2015), Berrospide (2012)).

Three additional studies look at the effects of types of uncertainty other than the subprime financial crisis on quantities of bank loans, although they also do not classify cutbacks in lending as liquidity hoarding. Gissler, Oldfather, and Ruffino (2016) find that banks that perceive more regulatory uncertainty reduce mortgage loans more severely. Raunig, Scharler, and Sindermann (2017) similarly find reduced loan quantities after four uncertainty events based on Chicago Board Options Exchange (CBOE) volatility index (VXO). One study by Bordo, Duca, and Koch (2016) documents a negative relation between BBD's economic policy uncertainty measures (*EPU*) and bank loan quantities.

A significant identification issue in these papers is that declines in lending quantities do not necessarily imply a causal impact of uncertainty on bank lending. Reduced lending might alternatively be mainly driven by reduced demand for bank loans by firms and households due to uncertainty as illustrated in Figure 1. Bordo, Duca, and Koch (2016) deal with this issue by showing that the reductions in lending are associated with bank characteristics such as capital ratios that are related to bank financial distress. Such distress would likely cause reductions in credit supply by these banks. However, we argue that bank capital ratios and other indicators of bank distress may also cause reductions in demand for credit from these banks, as firms and households value long-term relationships that may be interrupted by bank financial distress or failure.

In our empirical analysis, by contrast, we conduct additional analyses that identify supply effects for liquidity hoarding. We focus on key items in *LH(asset)*, *LH(liab)*, and *LH(off)* – commercial loans, deposits, and off-balance loan commitments, respectively. We show that *EPU* results in higher interest rate spreads on individual commercial term loans, part of liquidity hoarding on the asset side of the balance sheet. We also find higher spreads on commercial revolving lines of credit (a type of loan commitment), part of liquidity hoarding off the balance sheet. Both analyses using DealScan data for loan contract characteristics and control for borrower risks using Compustat data as well as bank risks using Call Report data. The higher spreads suggest that the reductions in supply of credit exceed any reductions in credit demand. We supplement this analysis by examining the relation between *EPU* and responses to the Federal Reserve's Senior Loan Officer Survey, which directly measures credit supply through bank lending standards. Specifically, the Survey provides national statistics each quarter on the percentage of respondent banks that tightened lending standards and increased interest rate spreads on loans and lines of credit, allowing us to further separate supply from demand for credit. Finally, in future drafts, we will examine interest rate spreads on deposits using RateWatch data.

The only other paper on liquidity hoarding that uses interest rate spreads to distinguish between supply and demand effects is Afonso, Kovner, and Schoar (2011), who examine spreads in the interbank federal funds market during the subprime financial crisis. We extend this work to the more general economic policy uncertainty measure (*EPU*), to the more comprehensive measure of bank liquidity hoarding (*LH*), and to identification analyses using loans on the asset side of the balance sheet, deposits on the liability side of the balance sheet, and loan commitments off of the balance sheet.

Our examination of the U.S. banking industry is aided by availability of very detailed data on a large number of commercial banks from Call Reports over a long period of time. Our main analysis includes virtually all U.S. commercial banks quarterly for over 30 years from 1985:Q2 to 2016:Q4, for a total of over 17,000 unique banks and over one million bank-quarter observations. These data are combined with *EPU* data from BBD's website (http://www.policyuncertainty.com/) and liquidity creation data from Christa Bouwman's website (https://sites.google.com/a/tamu.edu/bouwman/data). We augment the dataset with interest rate spreads on over 28,000 individual term loans and revolvers from DealScan and data on the borrowing firms from Compustat, as well as national statistics from the Senior Loan Officer Survey. In future drafts, we will add thousands of observations on deposit spreads from RateWatch

By way of preview, we find that *EPU* results in statistically and economically significantly increased total bank liquidity hoarding, as well as increases in the asset-, liability- and off-balance sheet-side components. Our findings are robust to the use of instrumental variable estimation and placebo tests. The results also hold after controlling for market volatility, across bank size classes, for banks with both high and low equity capital ratios, pre- and post-Basel III capital and liquidity requirements, for banks in markets with both favorable and unfavorable local economic conditions, and for banks in different survival categories. Importantly, we find that asset-side and off-balance sheet-side the liquidity hoarding are driven primarily by reductions in supply rather than demand, based on the analyses of spreads on term loans and revolvers, as well as the Senior Loan Officer Survey data. In future drafts, we will investigate supply versus demand on the liability side using interest rate spreads on deposits using the RateWatch data.

Our findings of negative effects of *EPU* on the supply of banking services have a causal effect in harming the real economy, rather than simply reflecting the effects of the real economy on the banking sector. The supply channel through banks may also help explain some of the prior findings on the negative effects of uncertainty on corporate and household behavior, which did not take into account reductions in credit supply by banks.

The remainder of the paper is organized as follows. Section 2 briefly discusses the key *EPU* and bank liquidity hoarding measures (*LH*), and Section 3 develops our hypotheses about the relations between these two sets of measures. Section 4 describes our main methodology and control variables. Section 5 reports our main empirical results that test our hypothesis about the relations between *EPU* and *LH*, including instrumental variable analysis, and placebo tests. Section 6 provides the analyses that distinguish supply from demand effects. Section 7 presents conclusions, policy implications, and topics for future research. The Appendix presents additional robustness checks of our main findings.

2. Economic policy uncertainty and bank liquidity hoarding measures

2.1 Economic policy uncertainty measure

Table 1 Panel A briefly describes all of the variables used in the main analysis, but in this section we focus only on our key variables of interest. Our most important explanatory variables are measures of *EPU*, which are obtained from BBD's website given above. They are based on textual analysis of newspaper articles and compilation of policy uncertainty related to government spending, inflation risk, and tax code expiration.

The newspaper element *EPU(News)* is based on textual analysis of ten large newspapers.[5] BBD count the number of news articles containing a combination of terms related to *EPU*. These terms are "economic" or "economy;" "uncertain" or "uncertainty;" and one or more of "Congress," "deficit," "Federal Reserve," "legislation," "regulation," or "White House." For example, an article mentioning "economy," "uncertain," and "Federal Reserve" would be included in the count. This is scaled by the total number of articles published by each newspaper. The fraction of *EPU*-related articles for each newspaper is further scaled to have unit variance. The normalized fractions are summed across the ten newspapers. The final index is then adjusted to have a mean of 100 from 1985 to 2009.[6]

Other *EPU* elements are related to specific policy categories. The government spending measure *EPU(Govt.)* is the scaled interquartile range of four-quarter-ahead purchases by federal and state/local government. Inflation-related policy uncertainty *EPU(CPI)* is based on the interquartile range of four-quarter-ahead inflation risk compiled by the Federal Reserve Bank of Philadelphia. The tax measure *EPU(Tax)* draws on temporary federal tax code provisions. It is a weighted sum of the total dollar amount of future federal tax code provisions with higher weights assigned to expiring tax codes in the near future. The composite measure *EPU(Composite)* is the weighted sum of the other measures with a weight of 1/2 for *EPU(News)*, and weights of 1/6 for each of the other measures, *EPU(Govt.), EPU(CPI),* and *EPU(Tax)*.

[5] These are *USA Today*, *Miami Herald*, *Chicago Tribune*, *Washington Post*, *Los Angeles Times*, *Boston Globe*, *San Francisco Chronicle*, *Dallas Morning News*, *Houston Chronicle*, and *Wall Street Journal*.

[6] To validate their computer-generated index, BBD provide several types of checks, including an extensive human audit of newspaper articles.

We examine the composite measure as well as each of the four elements.[7] The *EPU* measures constructed by BBD have a monthly frequency. We follow Gulen and Ion (2016) and take the natural log of the arithmetic average of the BBD indices over the three months of the quarter.

2.2 Bank liquidity hoarding measure

Our comprehensive measure of bank liquidity hoarding *LH(total)*, and its components, *LH(asset)*, *LH(liab)*, and *LH(off)* is based on Berger and Bouwman's (2009) liquidity creation components, *LC(asset)*, *LC(liab)*, and *LC(off)*.[8] Berger and Bouwman (2009) classify all on- and off-balance sheet activities into liquid, semiliquid, and illiquid items. In their measures, illiquid assets and liquid liabilities are assigned positive weights of 1/2, so that transforming \$1 of illiquid commercial loans into \$1 of liquid transactions deposits is counted as \$1 of bank liquidity creation. Similarly, liquid assets and illiquid liabilities are assigned negative weights of -1/2, so that taking \$1 of liquid cash or securities from the public and giving the public \$1 of subordinated debt is counted as \$1 of bank liquidity destruction. Off-balance sheet activities are weighted consistently with the treatments of functionally similar on-balance sheet items. Loan commitments are assigned a positive weight of 1/2 because they provide customers with access to liquid funds almost as easily as transactions deposits. Berger and Bouwman (2009) employ weighted sums of the individual items into asset-side, liability-side, and off-balance sheet-side liquidity creation components, *LC(asset), LC(liab), and LC(off)*, respectively, as well as the overall sum, *LC(total)*.

The focus in this paper is on bank liquidity hoarding, rather than liquidity creation. As discussed above increasing cash and securities and similar liquid assets and reducing commercial loans and similar illiquid assets should count positively toward bank liquidity hoarding, so we measure *LH(asset)* component as -*LC(asset)*, since *LC(asset)* gives positive weights to these items. Increasing liquid liabilities like transactions deposits and decreasing illiquid liabilities like subordinated debt is also liquidity hoarding, so

[7] BBD show that their news-based index exhibits considerable time-series variation, spikes during events that increase policy-related uncertainty, and correlate with other measures of economic uncertainty.

[8] Bai, Krishnamurthy, and Weymuller (2018) offer the Liquidity Mismatch Index (LMI), which measures the illiquidity of banks, as an alternative to Berger and Bouwman's (2009) liquidity creation measure. We focus on the components of Berger and Bouwman's (2009) measure here because they are easily adaptable to measure bank liquidity hoarding, which LMI is not.

our *LH(liab)* component is *+LC(liab)*, consistent with the weights on these items in *LC(liab)*. *LC(off)* is measured by *-LC(off)*, since decreasing loan commitments and similar financial guarantees is a form of liquidity hoarding, and these items are positively weighted in *LC(off)*. Total bank liquidity hoarding is *LH(total) = LH(asset) + LH(liab) + LH(off).e*

We argue that *LH(total)* is much more comprehensive than liquid assets as usually employed in the bank liquidity hoarding literature, as well as loans, off-balance sheet loan commitments, and deposits used in some of the studies, but acknowledged as liquidity hoarding components. We use the *LH(asset)*, *LH(liab)*, and *LH(off)* components to assess the sources of bank liquidity hoarding, as well as to test additional hypotheses about supply versus demand effects. We normalize the *LH* measures by gross total assets (*GTA*) in our regression analyses below so that the measures are comparable across banks, and the regression results are not dominated by the largest banks.[9] Dollar values are also adjusted to real 2016 values using the implicit GDP price deflator.

3. Hypothesis development

As discussed in the introduction, our focus in this paper is to examine how *EPU* may affect bank liquidity hoarding. As shown in Figure 1 above, liquidity hoarding can be affected by both the supplies of liquidity by banks and demands for liquidity by firms, households, and nonbank financial institutions and markets. In this section, we develop hypotheses about these supplies and demands, and these hypotheses are tested in the following sections.

Our first hypothesis is multidimensional, covering *LH(total)* and its three components, *LH(asset)*, *LH(liab)*, and *LH(off)*, and is inclusive of both supply and demand effects. When *EPU* is high, banks may wish to hoard liquidity overall to protect themselves against future potential loan losses, falls in the values of their other assets, or funding difficulties. At the same time, more uncertain firms, households, and nonbank financial institutions and markets also have lower demands for liquidity from banks as they wish to spend and intermediate less. Thus, *LH(total)* may increase due to both supply and demand effects.

[9] Gross total assets (GTA) equals total assets (TA) plus the allocation for loan and lease losses (ALLL), an accounting item for expected losses, and the allocated transfer risk reserve (ATRR), a reserve for certain troubled foreign loans. GTA incorporates all the assets that are included in the bank liquidity creation measures.

These supply and demand effects may occur for all three components of liquidity hoarding. On the asset-side, banks may react to *EPU* by increasing demands for liquid assets, such as cash and securities and and cut their loan supplies, all of which increase *LH(asset)*. Demand may also go in the same direction. There may be reduced demand for bank liquidity on the asset side in reaction to *EPU* because firms and households wish to borrow less for spending and nonbank financial institutions and markets want to intermediate less, also increasing *LH(asset)*.

Turning to the liability side, banks may respond to *EPU* by trying to raise more funds through liquid deposits, such as transactions accounts. Although bank deposit rates are generally sticky during normal times (Hannan and Berger (1991)), banks try to attract more deposits, which increases *LH(liab)*, by raising deposit rates in times of uncertainty as discussed above regarding the financial crisis. Demand for deposits may also go in the same direction. Demand for deposits by the public may increase in times of high uncertainty because deposits serve as safe havens (e.g., Beber, Brandt, and Kavajecz (2006), Gatev and Strahan (2006), Pennacchi (2006)), also increasing *LH(liab)*.

Finally, on the off-balance sheet side, most of the liquidity is in the form of loan commitments and similar financial guarantees. The arguments above about decreased supply and demand for bank loans in the face of high *EPU* apply to these off-balance sheet instruments as well. When *EPU* is high, banks would wish to renew fewer loan commitments, and borrowers would want fewer commitments, both of which increase *LH(off)*. Loan commitments may further decrease in the face of uncertainty, increasing *LH(off)* more, as borrowers draw down their existing commitments out of fear that the banks may not be willing or able to honor them (Ivashina and Scharfstein (2010)).

Thus, our first hypothesis is:

Hypothesis 1: *EPU increases total bank liquidity hoarding, LH(total), and its three components, LH(asset), LH(liab), and LH(off), ceteris paribus.*

Hypothesis 1 is tested in Section 5 by regressing the bank liquidity hoarding variables on the *EPU* measures.

Our remaining hypotheses, ***Hypotheses 2***, ***3***, and ***4***, are contingent on ***Hypothesis 1*** being true, and are about whether bank liquidity hoarding in each component is primarily driven by supply versus demand. This identification is crucial because the channel through which *EPU* affects the real economy through banks depends on supply being relatively important:

Hypothesis 2a: *EPU increases asset-side bank liquidity hoarding, LH(asset), primarily through reduced supply, ceteris paribus.*

Hypothesis 2b: *EPU increases asset-side bank liquidity hoarding, LH(asset), primarily through reduced demand, ceteris paribus.*

Hypothesis 3a: *EPU increases liability-side bank liquidity hoarding, LH(liability), primarily through reduced supply, ceteris paribus.*

Hypothesis 3b: *EPU increases liability-side bank liquidity hoarding, LH(liability), primarily through reduced demand, ceteris paribus.*

Hypothesis 4a: *EPU increases off-balance sheet-side bank liquidity hoarding, LH(off), primarily through reduced supply, ceteris paribus.*

Hypothesis 4b: *EPU increases off-balance sheet-side bank liquidity hoarding, LH(off), primarily through reduced demand, ceteris paribus.*

These hypotheses have real economic implications. To the extent that ***Hypotheses 2a***, ***3a***, and ***4a*** hold – bank supply contractions of asset-side, liability-side, and off-balance sheet-side liquidity dominate demand reductions – the banking sector is a channel through which *EPU* harms the real economy and negatively impacts corporate and household behavior. In contrast, to the extent that ***Hypotheses 2b***, ***3b***, and ***4b*** hold – demand effects dominate supply effects – the effects of *EPU* on the banking sector may primarily reflect rather than cause these adverse outcomes.

In Section 6, we test these hypotheses by investigating the price impacts of *EPU*. We regress commercial term loan interest rate spreads, deposit rate spreads, and commercial loan commitment spreads on *EPU*, controlling as well as possible for other factors. These price movements indicate whether supply versus demand effects dominate. For example, if loan rate spreads increase, this would signal that the supply reduction of loans exceeds the demand reduction. We also examine the effects of *EPU* on responses to the Federal Reserve's Senior Loan Officer Survey (SLOS), which represent supply only.

4. Regression methodology and control variables

4.1 Regression methodology

We estimate regressions of the form:

$$(LH/GTA)_{i,t} = \beta EPU_{t-1} + \delta X_{i,t-1} + \theta W_{i,t-1} + \gamma' Z_{t-1} + \alpha_i + q_t + \epsilon_{i,t}, \quad (1)$$

where *i* indexes a bank, and *t* indicates a calendar quarter. The dependent variable is one of the normalized liquidity hoarding measures, *LH(total)/GTA*, *LH(asset)/GTA*, *LH(liab)/GTA,* or *LH(off)/GTA*, and the key independent variable is one or more of the *EPU* variables, *EPU(Composite*), *EPU(News), EPU(Govt.), EPU(CPI)*, or *EPU(Tax)*. We lag the independent variables to mitigate potential reverse-causality concerns. We include an extensive set of controls to isolate the effects of *EPU.* Our bank controls (*X*) consist of *Ln(GTA), sqr. Ln(GTA)*, and *Capital ratio* to account for differences across bank size and condition. Controls related to local market and corporate demand for investment (*W*) are *HHI, Population, Tobin's Q,* and *Cash flows*. Our controls for political, financial market, and general economic uncertainty (*Z*) include *Election year*, *SD (stock ret.)*, and *GDP dispersion*. Finally, we include bank fixed effects (α) to control for omitted bank characteristics that are invariant over time, and quarter dummies (q) to account for seasonality. We cluster standard errors by bank and year-quarter to account for cross-sectional and serial correlations of error terms.[10]

4.2 Control variables and descriptive statistics

Our key explanatory *EPU* variables and our dependent bank liquidity hoarding variables are

[10] Given that the *EPU* measures are common across all banks and potentially serially correlated, in untabulated analyses, we also adjust standard errors to allow for cross-sectional and temporal dependence based on Driscoll and Kraay's (1998) and Hoechle's (2007) approach. Our results are robust to this adjustment of standard errors.

discussed in Section 2. Here, we briefly discuss the controls and present descriptive statistics on all variables.

We include controls for bank characteristics to account for other bank supply effects and controls for local market economic circumstances to account for demand effects. We obtain bank-specific variables such as asset size and equity ratio from Bank Call Reports. Population is taken from the Federal Reserve Bank of St. Louis. Economic conditions of potential customers, *Tobin's Q and Cash flows*, are computed for Compustat firms in the banks' states to control for the demand for banking services. These variables are averaged for each bank based on the proportion of deposits in each area. Data for bank deposit amount per branch is from the Summary of Deposits by FDIC (from 1994 to 2016) and Bouwman's website (from 1985 until 1993). To control for other types of uncertainty, we include a binary variable for election years (*Election year*), stock market return volatility (*SD(stock ret.)*) and forecast dispersion of real GDP (*GDP dispersion*). All variables used in the main analysis are formally defined in Table 1 Panel A.

Table 1 Panel B reports summary statistics for 1,022,644 bank-quarter observations from 1985:Q2 through 2016:Q4. Total normalized bank liquidity hoarding *LH(total)/GTA* has a mean of 0.125, suggesting that banks hoard liquidity of 12.5% of the gross total assets (GTA) on average. There is a wide dispersion in liquidity hoarding across banks. The standard deviation of *LH (total)/GTA* is 0.183, with the 25th and 75th percentile values at 0.004 and 0.250, respectively. Asset-side liquidity hoarding, *LH (asset)/GTA*, has a mean value of -0.009 with the 25th and 75th percentile values at -0.111 and 0.092, respectively. The mean of *LH(asset)/GTA* is negative because banks often hold more illiquid assets (e.g., commercial loans) than liquid assets (e.g., cash due from other institutions, securities) with positive weights.[11] Mean liability-side liquidity hoarding (*LH(liab)/GTA*) is 0.177. Most banks have more liquid deposits than illiquid liabilities. The mean liquidity hoarding off the balance sheet (*LH(off)/GTA*) is -0.043. The negative sign mostly reflects loan commitments, which are illiquid from the point of view of the banks..

EPU(Composite) has a mean of 4.642 and standard deviation of 0.247. The news-based element *EPU(News*) has a mean value of 4.631. *EPU* related to government spending *EPU(Govt.)*, inflation risk

[11] For example, JPMorgan Chase holds about as much in securities as loans, presumably reflecting its liquidity needs for trading purposes, unexpected deposit withdrawals or loan commitment takedowns, and/or as well as meeting regulatory liquidity requirements (Berger and Bouwman (2016), p. 21, Table 3.1).

EPU(CPI), and tax code expiration *EPU (TAX)* have mean values of 4.560, 4.572, and 3.760, respectively.

Turning to the controls, the average size of banks (*GTA*) is \$1.133 billion.[12] The distribution of bank size is highly right-skewed with the median value of *GTA* being \$116 million. Thus, most banks are quite small, but sizes range up to over \$2 trillion. The average capital ratio (*Capital ratio*) is 0.070. The average Herfindahl-Hirschman index (*HHI*) based on bank deposits is 0.083. The average *Tobin's Q* of firms in the banks' states is 2.082, comparable to the average of the full CRSP/Compustat universe (e.g., Bertrand and Schoar (2003)). The percentiles of *Cash flows* (25th percentile = 0.000 and 75th percentile = 0.022) suggest that *Cash flows* has a wide dispersion across companies in different states where banks are operating. Not surprisingly, about one-quarter of our sample covers U.S. presidential election years. The average standard deviation of aggregate stock market returns is 0.009. On average, GDP forecast dispersion is 42.7% over the sample period.[13]

Table 1 Panel C provides summary statistics of bank liquidity hoarding dependent variables by bank size class. The *EPU* measures have only a time dimension and so have essentially no variation by bank size. Following Kashyap and Stein (2000), we categorize banks into small, medium, and large classes based on the 95th and 99th percentile cutoff values of GTA. The 95th and 99th percentile values of GTA correspond to \$1.3 billion and \$11.0 billion, respectively. The small size class roughly corresponds to the usual research definition of community banks, those with up to \$1 billion in assets (e.g., DeYoung, Hunter, and Udell (2004)). The size cutoff between medium and large banks is close to an alternative upper limit sometimes used for community banks, \$10 billion in assets (Whalen (2013), Lux and Greene (2015)). Large banks hoard less liquidity per dollar of assets (*LH(total)/GTA*) than small banks, with roughly half of the difference due to *LH(off)/GTA*. The mean *LH(off)/GTA* decreases in bank size class, implying that large banks extend proportionately more credit off the balance sheet than small banks.

Figure 2 shows the temporal patterns of the liquidity hoarding ratios for the nation as a whole as well as *EPU(Composite)* over our sample period. The figure shows *LH(total)/GTA* as the sum of liquidity

[12] Note that *GTA* shown in Table 1 is measured in thousands of real 2016 dollars.

[13] We do not include the GDP growth rate as a control in the baseline analysis because it is one potential outcome of liquidity creation (Berger and Sedunov (2017)). However, the inclusion of this variable as a control in untabulated results does not change our findings.

hoarding for the banking industry at each point in time divided by the sum of *GTA* for the industry at that time, and similarly for the components. They represent the industry, rather than the averages of the ratios, which would be dominated by the small banks. The data show that *EPU(Composite)* generally declined over time, shot up during the recent financial crisis, and stayed high for a time as policymakers figured out their responses. These aggregate data also appear to suggest that the total bank liquidity hoarding ratio, *LH(total)*, and *EPU(Composite)* are moving in tandem over time, consistent with banks' hoarding more liquidity in response to an increase in *EPU*.

Table 1 Panel D presents correlations of the key variables. The composite policy uncertainty (*EPU(Composite)*) is positively related to all liquidity hoarding measures, and all are significant at the 1% level. Most of the *EPU* elements tell similar stories. These findings are consistent with *EPU* increasing total, asset-side, liability-side, and off-balance sheet-side liquidity hoarding. We next turn to our multivariate regression setting to test the hypotheses.

5. The effects of *EPU* on bank liquidity hoarding

We present our tests of *Hypothesis 1* about the effects of *EPU* on total bank liquidity hoarding and all of its components. This is followed by tests of *Hypotheses 2–4* about the dominance of supply vs. demand effects in each liquidity hoarding component. We also discuss results of instrumental variable estimation, placebo tests, and additional robustness checks.

5.1 Main regressions of bank liquidity hoarding on *EPU*

Table 2 presents regressions of *LH(total)/GTA* on the *EPU* measures. The coefficient on *EPU(Composite)* in column 1 is positively and statistically significant at the 1% level (coeff. = 0.092, *t*-statistic = 8.89). This suggests that banks' total liquidity hoarding increases in response to *EPU*. Given that the standard deviation of *EPU(Composite)* is 0.183, a one-standard-deviation increase in *EPU(Composite)* leads to an 18% increase in bank liquidity hoarding relative to its average value.

In columns 2–5 of Table 2, we replace the key independent variable *EPU(Composite)* with one of its four elements: *EPU(News)*, *EPU(Govt.)*, *EPU(CPI),* or *EPU(Tax)*. The coefficient estimates on the first two elements are positive and statistically significant at the 1% level. One-standard-deviation increases in *EPU(News)* and *EPU(Govt.)* are estimated to result in 18% and 23% increases in bank liquidity hoarding, respectively, relative to average *LH(total)*. In contrast, the uncertainty from inflation (*EPU(CPI)*) and tax code expiration (*EPU(Tax)*) is not related to overall liquidity hoarding. The result suggests that inflation- and tax-related policy uncertainty does not pose a substantial risk for banks to hoard overall liquidity.

In Table 2 column 6, we include all the *EPU* elements in the same regression. The coefficient estimates on *EPU(News)* and *EPU(Govt.)* are of the same sign and similar magnitudes as in columns 2–3. After controlling for all other *EPU* elements, the tax-based measure, the effect of *EPU(Tax)* becomes negative and statistically significant, but remains small in magnitude. This result is consistent with arguments that banks are more highly levered, and thus tax-advantaged relative to their shadow-banking competitors. They may therefore be better positioned to provide liquidity than other financial institutions when tax-related policy uncertainty is high.

Control variable coefficients are generally consistent with expectations. Small banks hoard more liquidity per dollar of assets. Well-capitalized banks hoard less liquidity, consistent with the idea that the bank capital absorbs more risks from borrwers, enabling banks to hoard less liquidity and extend more illiquid loans (Bhattacharya and Thakor (1993), Coval and Thakor (2005), Repullo (2004), Von Thadden (2004)). High competition (inversely measured by *HHI*) reduces bank liquidity hoarding, consistent with the idea that bank competition increases lending (e.g., Braggion et al. (2017)). Banks in states with firms having high cash flows tend to hoard more liquidity, consistent with low credit demand in those states. Political uncertainty (proxied by *Election year*) has essentially no effect after including *EPU* elements in the regressions, and financial market uncertainty has a counterintuitive negative effect of bank liquidity hoarding. High uncertainty about future economic growth (proxied by *GDP dispersion*) is associated with less liquidity hoarding, but with marginal statistical significance. In the interest of brevity, we suppress tabulation of the control variable coefficient estimates in subsequent tables, although they are included in all the regressions.

Table 3 Panels A, B, and C present estimates from regressions of *LH(asset)/GTA*, *LH(liab)/GTA*, and *LH(off)/GTA*, respectively, on the *EPU* measures. In Panel A column 1, the estimated coefficient on

EPU(Composite) is 0.040 (*t-statistic* = 6.40), suggesting that a one-standard-deviation increase in uncertainty is associated with a 4.3% increase in the asset-side liquidity hoarding. In the other columns, coefficient estimates on *EPU(News)* and *EPU(Govt.)* are also positive and statistically significant at the 1% level. The insignificant coefficient estimate on *EPU(CPI)* suggests that asset-side liquidity hoarding is not affected much by inflation-related policy uncertainty. The estimated coefficient on *EPU(Tax)* is -0.007 (*t-statistic* = -5.10), suggesting that policy uncertainty from tax code expiration decrease asset-side liquidity hoarding. As discussed abov, the *EPU(Tax)* result is consistent with the idea that banks are highly leveredwith tax-advantage, and they are better positioned to extend credit than other financial institutions when tax-related policy uncertainty is high.

In Table 3 Panel B, the estimated effect of *EPU(Composite)* on *LH(liab)/GTA* is 0.029 (*t-statistic* = 5.69), suggesting that an increase in *EPU* leads to an increase in liability-side bank liquidity hoarding. The estimated coefficients on *EPU(News)* and *EPU(Govt.)* are positive and statistically significant, 0.032 (*t-statistic* = 5.81) and 0.012 (*t-statistic* = 3.88), respectively. Interestingly, the coefficient on *EPU(CPI)* is negative, although not significant, consistent with the possibility that firms and households prefer hedging against inflation with investments having higher expected returns than deposits. In column 5, the positive coefficient on *EPU(Tax)* is consistent with the arguments that firms and households may demand for more liquid funds to pay unexpected taxes. Alternatively, banks may want to raise more liquidity when *EPU(Tax)* is high because their tax-advantageous status enables them to extend more credit when tax-related economic policy uncertainty is high. The results from Panel B are consistent with the prediction that *EPU* increases liability-side liquidity hoarding.

In Table 3 Panel C, the estimates from regressions of *LH(off)/GTA* on *EPU(Composite)* and all its elements are positive and statistically significant, except for *EPU(Tax)*, which is insignificant. These results are consistent with arguments above that both demand and supply of loan commitments decline and banks can hoard more liquidity in reaction to *EPU*.

To help readers to better understand how *EPU* affects individual items of liquid assets and liabilities in the on- and off-balance sheet, Appendix Table A2 presents coefficient estimates from regressions of selected bank balance sheet and off-balance sheet categories on the composite *EPU* measure and controls.

The result shows that banks increase cash and government security holdings in response to an increase in *EPU*. At the same time, they decrease loans and loan commitments. They also increase liquidity hoarding through increased deposits. This item-by-item analysis confirms our main findings.

Overall, the regression analysis results support the *Hypothesis 1* that *EPU* increases total bank liquidity hoarding, *LH(total)* and its three components, *LH(asset)*, *LH(liab)*, and *LH(off)*.

5.2 Instrumental variable analysis and placebo tests

We are concerned about potential endogeneity of *EPU*. Although we saturate our regressions with an extensive set of controls, bias may arise from omitted explanatory variables. For example, indicators of general economic uncertainty other than those for which we control could drive both *EPU* and bank liquidity hoarding. Similarly, a significant increase in bank liquidity hoarding could create uncertainty among regulators and politicians regarding how to respond, increasing *EPU*.

To address these potential endogeneity concerns, we follow Gulen and Ion (2016) and implement an instrumental variable approach using the U.S. Senate polarization index of McCarty, Poole, and Rosenthal (1997) as an instrument for *EPU(Composite)*. It is unlikely that U.S. Senate polarization would directly affect bank liquidity hoarding other than through its impact on policy uncertainty, satisfying the exclusion restriction. The first-stage regression in column 1 of Table 4 Panel A shows the expected positive and significant effect of Senate polarization on *EPU(Composite)*, suggesting that the relevance condition of our instrument is satisfied.[14] In the second-stage regressions in columns 2–5, we regress the liquidity hoarding measures on the instrumented *EPU* measure, $\widehat{EPU}(Composite)$, and the controls. The *t*-statistics are based on bootstrapped standard errors to mitigate biases from errors in the estimated independent variables. The coefficients all have the same signs and significance with comparable magnitudes as our main results that *EPU* increases banks liquidity hoarding.

To rule out the possibility of spurious correlations between *EPU* and bank liquidity hoarding measures, we perform placebo tests in Table 4 Panel B. We replace the true *EPU(Composite)* measure with

[14] In our first-stage regression, the F-statistic for the instrumental variable is 28.68, which is well above the weak instrument criteria (Stock and Yogo (2005)).

$\widetilde{EPU}$*(Composite)* randomly drawn from the sample distribution of *EPU(Composite)*. We estimate regression coefficients with 100 different random samples of $\widetilde{EPU}$*(Composite)* and report the average coefficient estimates on $\widetilde{EPU}$*(Composite)*. We find that $\widetilde{EPU}$*(Composite)* is neither statistically nor economically significantly related to any components of bank liquidity hoarding, further supporting our hypotheses.

5.3 Additional robustness checks

In the Appendix, we report an extensive set of additional robustness checks that we briefly summarize here. We find the impact of *EPU* on bank liquidity hoarding holds after controlling for implied volatility of equity options (VIX), across bank size classes, for banks with both high and low equity capital ratios, pre- and post-Basel III capital and liquidity requirements, for banks in markets with both favorable and unfavorable local economic conditions, and for banks in different survival categories. To ensure that our main evidence is not driven by bank-specific policies, we also control for *EPU* measures of monetary policy and financial regulation. The results still show that *EPU* leads to an increase in the bank liquidity hoarding.

Taken together, our results provide robust evidence that *EPU* hampers the key function of banks in providing liquidity for the public. However, the picture is not complete without an analysis of the extent to which these findings reflect bank supply versus demand effects, which we turn to next.

6. The effects of *EPU* on supply versus demand

In this section, we test *Hypotheses 2-4* regarding whether supply versus demand effects dominate the increases in bank liquidity hoarding from *EPU* established in the evidence supporting *Hypothesis 1* in Section 4. The extent to which our findings primarily reflect supply versus demand for banking services is key to distinguishing whether our findings reflect causal effects on the real economy. Returning to Figure 1, if the observed positive effects of *EPU* on liquidity hoarding primarily reflect reduced demand for banking services rather than supply, then the effects on bank liquidity hoarding would have little impact on the real economy. Moreover, this would suggest that banks play almost no role in explaining the prior research findings that policy uncertainty negatively influences corporate and household behavior. In contrast, to the extent that bank supply effects dominate the demand effects, our findings may reflect important effects of *EPU* on the real economy through the banking sector, and may help explain some of the findings in the literature.

To investigate supply versus demand effects, we first focus our attention on asset-side and off-balance sheet-side liquidity hoarding through specific loan and loan commitment categories. Specificly, we examine supply versus demand channels at the *intensive margin* using interest rate spreads on term loans and revolving lines of credits[15] from Loan Pricing Corporation's (LPC's) DealScan database, representing on- and off-balance sheet credits, respectively. We also evaluate on an aggregate basis the effects of *EPU* on the net tightening of credit standards using the the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices (SLOS). For liability-side liquidity hoarding, we will investigate the supply versus demand effects using deposit rates from *RateWatch* in future drafts of the paper.

In the first analysis at the *intensive margin*, interest rate spreads should rise if the decrease in supply of credit dominates the reduction in demand, and *vice versa* if the reduction in demand dominates, controlling for credit risk of borrowers. We estimate regressions of the form:

$$Spread_{i,j,t} = \rho EPU_{t-1} + \omega' X_{i,t-1} + \pi V_{j,t-1} + \vartheta' K_{i,j,t} + \alpha_i + q_t + \epsilon_{i,t}, \tag{2}$$

where i indexes a bank, j indexes a borrower for a credit contract, and t indicates a calendar quarter. The dependent variable (*Spread*) is the borrowing spread plus annual fee (if any) the borrower pays in basis points over LIBOR, obtained from DealScan.[16] We match the data with borrowers' accounting information from Compustat and bank characteristics from Bank Call Reports, since spreads should crucially depend on the risk of the borrowing firm and the condition of the supplying bank.[17] We include only the lead bank because it is the main decision maker on credit terms.[18]

---

[15] Term loans refer to loans of fixed amounts with fixed maturities. Revolvers refer to credits for which the borrower may draw down and repay any amount up to a fixed maximum as often as desired until maturity.

[16] DealScan dataset includes borrower firms' identities, credit spreads over LIBOR, credit amount, credit types, lenders' names and lenders' roles in the credit contract.

[17] We use the DealScan-Compustat link file available from WRDS for matching with Compustat before year 2012. Thanks to Raluca Roman for sharing her manually matched DealScan-Compustat links data from 2013 to 2014. We further extend the matched DealScan-Compustat links from 2015 to 2016. Based on bank names, locations, and other bank characteristics, we manually merge the DealScan with Bank Call Report.

[18] We identify a lead bank of each credit contract based on its designated role. We denote a lender as a lead bank when the lender role is described as "Administrative Agent," "Agent," "Arranger," "Lead arranger," "Lead bank,"

We control for bank characteristics (*X*), bank fixed effects (α), and quarter dummies (q) as in equation (1). We also control in equation (2) for borrower characteristics (*V*), including firm size (*Ln(ME)*), book-to-market ratio (*BE_ME*), leverage (*Leverage*), tangible asset ratio (*Tangible*), cash ratio (*Cash*), Altman (1968) Z-score (*Z_score*), and credit rating (*Credit rating*). To further control for loan risk, we include credit contract variables (*K*), including credit amount (*Credit size*), maturity (*Ln(Maturity)*), collateral (*Secured*), and covenants (*Covnt. index*). All variables are formally defined in Table 5.

In the second analysis, we focus on the responses to four SLOS questions about banks' treatment of their commercial and industrial (C&I) loan and credit line customers.[19] The survey asks respondent banks quarterly whether their credit standards to large and middle-market firms and to small firms changed, as well as the spreads on these credits. We cannot separate the on-balance sheet loans from the off-balance sheet credit lines because the survey questions combine these. We use simple correlations in this analysis, rather than regressions because we have access only to aggregate time series on these responses, so we are unable to control for borrower and loan risk. The data for these correlations start in 1990:Q2, rather than 1985:Q2 because earlier data from the Survey are not publicly available. Because of these limitations, we view this as secondary evidence.

Table 5 Panels A1 and A2 show definitions and summary statistics, respectively, for the variables used in the supply versus demand analyses based on DealScan data. This sample includes 28,200 observations at the facility-bank level from 1985:Q2 through 2016:Q4.[20] There are 438 unique lead lenders and 5,866 borrowing firms. Panels B1 and B2 show definitions and summary statistics, respectively, for the variables used in the analyses based on selected responses to the SLOS from 1990:Q2 to 2016:Q4. There are 107 quarterly observations.

Table 6 Panel A columns 1–5 report the results of estimating the interest rates spread equation (2) for term loans, and columns 6–10 report results for revolvers. For both term loans and revolvers, we report a

"Lead manager," or "book-runner." When multiple banks are identified as lead banks in the above way, we choose the bank with the largest assets as the lead lender.

[19] C&I loans in the SLOS analysis are loans to firms that are not secured by real estate. The commercial loans in our DealScan analysis include both C&I and commercial real estate (CRE) loans.

[20] We find similar results when we follow Qian and Strahan (2007) and begin the sample period in 1994 to account for DealScan's improved coverage of lending to companies outside the U.S.

number of different specifications with different groups of control variables. In all cases, the effect of *EPU(Composite)* is positive and statistically and economically significant, implying that supply effects dominate demand effects in the contractions in bank credit. The results with full specifications (columns 5 and 10) imply that a one-standard-deviation increase in *EPU(Composite)* leads to an increase in spread of about 13.90 basis points for term loans and 17.97 basis points for revolvers. The estimated coefficients on control variables are generally consistent with expectations that risky borrowers are charged high interest rates.[21] In an untabulated instrumental variable analysis, we also find consistent positive effects of *EPU* on spreads, supporting the dominance of the supply effect over the demand effect.

Table 6 Panel B replicates the analysis by replacing the *EPU(Composite)* with its elements. The results still hold except for CPI- and tax-related policy uncertainty for on-balance sheet loans. Spreads for off-balance sheet revolvers are increasing in all *EPU* elements.

Table 7 shows the correlations between the *EPU* measures and the net percentages of SLOS bank respondents reporting tightening credit standards and increasing spreads on C&I credit to large and medium firms and to small firms. The net percentages are the differences at each point in time between tightening and loosening standards or increasing or decreasing spreads. The net tightening variables may be viewed as pure measures of loan supply, since they refer to lending standards only. The net spread increases reflect whether supply or demand factors dominate, analogous to our prior analysis of individual loan spreads.

These correlations strongly suggest that *EPU* is associated with reduced supplies of credit to firms of both sizes. For *EPU(Composite)*, *EPU(News)*, and *EPU(CPI),* the correlations are large and positive in all cases, and statistically significant in all but one case. The effects of *EPU(Govt.)* are not significant and the effects of *EPU(Tax)* are negative and mostly statistically significant, consistent with much of our earlier analysis that finds that *EPU(Tax)* results are somewhat different.

The results in this section suggest that our main findings of positive effects of *EPU* on asset-side and off-balance sheet-side liquidity hoarding primarily reflect reductions in credit supply, rather than demand, consistent with ***Hypotheses 2a*** and ***4a***. Although we do not rule out demand effects, our results suggest that

[21] In an additional untabulated analysis, we also use fees for undrawn credits as a dependent variable. Consistent with the results in Table 6, these fees increase with *EPU*.

supply effects dominate demand effects in determining the impact of *EPU* on bank liquidity hoarding. These supply findings suggest that the effects of *EPU* on asset-side and off-balance sheet-side liquidity hoarding may cause harm to the real economy and could help explain part of the findings in the literature that uncertainty adversely affects corporate and consumer behavior.

7. Conclusions, policy implications, and topics for future research

An exciting new research agenda explores the implications of policy uncertainty, and finds adverse effects on corporate and household behavior. Much of this literature employs innovative measures of economic policy uncertainty (*EPU*) provided by Baker, Bloom, and Davis (2016). We extend this literature by investigating another important potential channel through which *EPU* may affect the real economy – by increasing bank liquidity hoarding. We specifically examine the effects of *EPU* on bank total liquidity hoarding and its three components – asset-side, liability-side, and off-balance sheet-side bank liquidity hoarding– testing different hypotheses about these effects. For our purpose, we build both a comprehensive measure of bank liquidity hoarding and components which incorporate asset-, liability-, and off-balance sheet-side activities based on Berger and Bouwman's (2009) bank liquidity creation components.

Our empirical analysis covers over one million U.S. bank-quarter observations on over 17,000 banks for more than a 30-year period from 1985:Q2 to 2016:Q4, and yields economically and statistically significant results that support our hypotheses. *EPU* increases bank liquidity hoarding on the asset-, liability-, and off-balance sheet-sides, resulting in increased total liquidity hoarding. Findings suggest *EPU* likely hampers banks' abilities to perform their key function of intermediating liquid funds for productive purposes. This may be an important channel through which *EPU* affects the real economy. Findings are robust to the use of instrumental variables and many robustness checks.

We further investigate the extent to which our findings are driven by bank supply versus demand effects. Only supply effects would imply causation from *EPU* to the real economy running through the impact on bank liquidity hoarding. Our results using interest rate spreads for term loans and revolvers from DealScan, as well as responses to the Federal Reserve's Senior Loan Officer Survey, suggest that reduced bank supply primarily explains our findings, and thus harms the real economy. These findings also suggest that this channel through banks may help explain part of the negative effects of economic policy uncertainty on corporate and household behavior in the literature. Future drafts will include a supply-versus-demand analysis of deposits using the RateWatch data.

The findings have important policy implications. First, they suggest that policymakers might take into account the adverse consequences of leaving the public uncertain of their actions, which may harm the real economy through effects on firms, households, banks, and other nonbank financial institutions and markets. Second, they suggest that policymakers may consider promulgating policies that ensure that banks can continue to provide more liquidity during times of uncertainty.

Our findings also suggest potential topics for future research. Clearly, more research on the relations among *EPU*, liquidity hoarding, and the real economy are in order. While there is some research of uncertainty on households, to our knowledge there is no research yet on the effects of the *EPU* measure on the economy through direct effects on households shown in Figure 1. We also suggest that future research consider the effects of *EPU* on nonbank financial institutions and markets, which may also have significant real economic implications.

References

Aaberge, Rolf, Kai Liu, and Yu Zhu, 2017, Political Uncertainty and Household Savings, *Journal of Comparative Economics* 45, 154–170.

Acharya, Viral V., Denis Gromb, and Tanju Yorulmazer, 2012, Imperfect Competition In the Interbank Market for Liquidity As A Rationale For Central Banking, *American Economic Journal: Macroeconomics* 4, 184-217.

Acharya, Viral V., and Nada Mora, 2015, A Crisis of Banks as Liquidity Providers, *The Journal of Finance* 70, 1-43.

Acharya, Viral V., and David Skeie, 2011, A Model of Liquidity Hoarding and Term Premia in Inter-Bank Markets, *Journal of Monetary Economics* 58, 436-447.

Acharya, Viral V., and Ouarda Merrouche. 2012, Precautionary Hoarding of Liquidity and Interbank Markets: Evidence from the Subprime Crisis, *Review of Finance* 17, 107-160.

Afonso, Gara, Anna Kovner, and Antoinette Schoar, 2011, Stressed, not Frozen: The Federal Funds Market in the Financial Crisis, *The Journal of Finance* 66, 1109-1139.

Allen, Franklin, and Douglas Gale, 2000, Financial Contagion. *Journal of Political Economy*, 1-33.

Altman, Edward, 1968, Financial Ratios, Discriminant Analysis and the Prediction of Corporate Bankruptcy, *Journal of Finance* 23, 589–609.

Bai, Jennie, Arvind Krishnamurthy, and Charles-Henri Weymuller, 2018, Measuring Liquidity Mismatch in the Banking Sector, *Journal of Finance* 73, 51–93.

Baker, Scott R., Nicholas Bloom, and Steven J. Davis, 2016, Measuring Economic Policy Uncertainty, *Quarterly Journal of Economics* 131, 1593–1636.

Barro, Robert J., 1991, Economic Growth in a Cross Section of Countries, *Quarterly Journal of Economics* 106, 407–443.

Beber, Alessandro, Michael W. Brandt, and Kenneth A. Kavajecz, 2006, Intermarket and Intramarket Ordeflow: Sector Rotation and Flights. Working paper.

Berger, Allen N., and Christa H.S. Bouwman, 2009, Bank Liquidity Creation, *Review of Financial Studies* 22, 3779–3837.

Berger, Allen N., and Christa H.S. Bouwman, 2016, *Bank Liquidity Creation and Financial Crises*, Elsevier – North Holland.

Berger, Allen N., and John Sedunov, 2017, Bank Liquidity Creation and Real Economic Output, *Journal of Banking & Finance* 81, 1-19.

Berrospide, Jose, 2012, Liquidity Hoarding and the Financial Crisis: an Empirical Evaluation,Working Paper.

Bertrand, Marianne, and Antoinette Schoar, 2003, Managing with Style: The Effect of Managers on Firm Policies, *Quarterly Journal of Economics* 118, 1169–1208.

Bhattacharya, Sudipto, and Anjan V. Thakor, 1993, Contemporary Banking Theory, *Journal of Financial Intermediation* 3, 2-50.

Bhattacharya, Utpal, Po-Hsuan Hsu, Xuan Tian, and Yan Xu, 2017, What Affects Innovation More: Policy or Policy Uncertainty?, *Journal of Financial and Quantitative Analysis* 52, 1869–1901.

Bloom, Nicholas, 2014, Fluctuations in Uncertainty, *Journal of Economic Perspectives* 28, 153–176.

Blundell, Richard, and Stephen Bond, 1998, Initial Conditions and Moment Restrictions in Dynamic Panel Data Models, *Journal of Econometrics* 87,115–143.

Bonaime, Alice, Huseyin Gulen, and Mihai Ion, 2017, Does Policy Uncertainty Affect Mergers and Acquisitions?, *Journal of Financial Economics,* forthcoming.

Bordo, Michael D., John V. Duca, and Christoffer Koch, 2016, Economic Policy Uncertainty and the Credit Channel: Aggregate and Bank Level U.S. Evidence over Several Decades, *Journal of Financial Stability* 26, 90–106.

Braggion, Fabio, Narly Dwarkasing, and Lyndon Moore, 2017, Nothing Special About Banks: Competition and Bank Lending in Britain, 1885–1925, *The Review of Financial Studies* 30, 3502-3537.

Cornett, Marcia Millon, Jamie John McNutt, Philip E. Strahan, and Hassan Tehranian, 2011, Liquidity Risk Management and Credit Supply in the Financial Crisis, *Journal of Financial Economics*101, 297-312.

Coval, Joshua D., and Anjan V. Thakor, 2005, Financial Intermediation as a Beliefs-Bridge between Optimists and Pessimists, *Journal of Financial Economics* 75, 535-569.

DeYoung, Robert, William C. Hunter, and Gregory F. Udell, 2004, The Past, Present, and Probable Future for Community Banks, *Journal of Financial Services Research* 25, 85–133.

Diamond, Douglas W., and Raghuram G. Rajan, 2011, Fear of Fire Sales, Illiquidity Seeking, and Credit Freezes, *The Quarterly Journal of Economics* 126, 557-591.

Driscoll, John, and Aart Kraay, 1998, Consistent Covariance Matrix Estimation with Spatially Dependent Panel Data, *Review of Economics and Statistics* 80, 549–560.

Fungáčová, Zuzana, Laurent Weill, and Mingming Zhou, Bank Capital, Liquidity Creation and Deposit Insurance, *Journal of Financial Services Research* 51, 97-123.

Gale, Douglas, and Tanju Yorulmazer, 2013, Liquidity Hoarding, *Theoretical Economics* 8, 291-324.

Gatev, Evan, and Philip E. Strahan, 2006, Banks' Advantage in Hedging Liquidity Risk: Theory and Evidence from the Commercial Paper Market, *Journal of Finance* 61, 867–892.

Gissler, Stefan, Jeremy Oldfather, and Doriana Ruffino, 2016, Lending on Hold: Regulatory Uncertainty and Bank Lending Standards, *Journal of Monetary Economics* 81, 89-101.

Gulen, Huseyin, and Mihai Ion, 2016, Policy Uncertainty and Corporate Investment, *Review of Financial Studies* 29, 523–564.

Hannan, Timothy H., and Allen N. Berger, 1991, The Rigidity of Prices: Evidence from the Banking Industry, *American Economic Review* 81, 938–945.

Heider, Florian, Marie Hoerova, and Cornelia Holthausen, 2015, Liquidity Hoarding and Interbank Market Rates: The Role of Counterparty Risk, *Journal of Financial Economics* 118, 336-354.

Hoechle, Daniel, 2007, Robust Standard Errors for Panel Regressions with Cross-sectional Dependence, *The Stata Journal* 7, 281–312.

Horváth, Roman, Jakub Seidler, and Laurent Weill, 2014, Bank Capital and Liquidity Creation: Granger-Causality Evidence, *Journal of Financial Services Research* 45, 341-361.

Ivashina, Victoria, and David Scharfstein, 2010, Bank Lending During the Financial Crisis of 2008, *Journal of Financial Economics* 97, 319-338.

Jens, Candace E., 2017, Political Uncertainty and Investment: Causal Evidence from U.S. Gubernatorial Elections, *Journal of Financial Economics* 124, 563–579.

Julio, Brandon, and Youngsuk Yook, 2012, Policy Uncertainty and Corporate Investment Cycle, *Journal of Finance* 67, 45–83.

Kashyap, Anil K., and Jeremy C. Stein, 2000, What Do a Million Observations on Banks Say about the Transmission of Monetary Policy?, *American Economic Review* 90, 407-428.

Kelly, Bryan, Ľuboš Pástor, and Pietro Veronesi, 2016, The Price of Political Uncertainty: Theory and Evidence from the Option Market, *The Journal of Finance* 71, 2417-2480.

Lei, Adrian CH, and Zhuoyun Song, 2013, Liquidity Creation and Bank Capital Structure in China. *Global Finance Journal* 24, 188-202.

Lux, Marshall, and Robert Greene, 2015, The State and Fate of Community Banking, M-RCBG Associate Working Paper 37.

McCarty, Nolan M., Keith T. Poole, and Howard Rosenthal, 1997, Income Redistribution and the Realignment of American Politics. Washington DC: AEI Press.

Nickell, Stephen, 1981, Biases in Dynamic Panel Models with Fixed Effects, *Econometrica* 49(6), 1417–1426.

Nguyen, Nam H., and Hieu V. Phan, 2017, Policy Uncertainty and Mergers and Acquisitions, *Journal of Financial and Quantitative Analysis* 52, 613–644.

Pastor, Lubos, and Pietro Veronesi, 2013, Political Uncertainty and Risk Premia, *Journal of Financial Economics* 110, 520–545.

Pennacchi, George, 2006, Deposit Insurance, Bank Regulation, and Financial System Risks, *Journal of Monetary Economics* 53, 1–30.

Qian, Jun, and Philip Strahan, 2007, How Laws and Institutions Shape Financial Contracts: The Case of Bank Loans, *Journal of Finance* 62, 2803–2834.

Raunig, Burkhard, Johann Scharler, and Friedrich Sindermann, 2017, Do Banks Lend Less in Uncertain Times?, *Economica* 84, 682-711.

Repullo, Rafael, 2004, Capital Requirements, Market Power, and Risk-Taking in Banking, *Journal of Financial Intermediation* 13, 156-182.

Stock, James, and Motohiro Yogo, 2005, Testing for Weak Instruments in Linear IV Regression, In: Andrews D.W.K. (Ed.) Identification and Inference for Econometric Models. New York: Cambridge University Press, 80–108.

Tian, Xuan, and Kailei Ye, 2017, How Does Policy Uncertainty Affect Venture Capital?, Working paper. DOI: 10.2139/ssrn.2910075

Von Thadden, Ernst-Ludwig, 2004, Asymmetric Information, Bank Lending and Implicit Contracts: The Winner's Curse, *Finance Research Letters* 1, 11-23.

Waisman, Maya, Pengfei Ye, and Yun Zhu, 2015, The Effect of Political Uncertainty on the Cost of Corporate Debt, *Journal of Financial Stability* 16, 106–117.

Whalen, Gary, 2013, Investigating the Relationship between Supervisory Change and Community Bank Failure in a Competing Risk Framework, Working paper. https://ssrn.com/abstract=2225418.

Figure 1: How economic policy uncertainty can affect the real economy

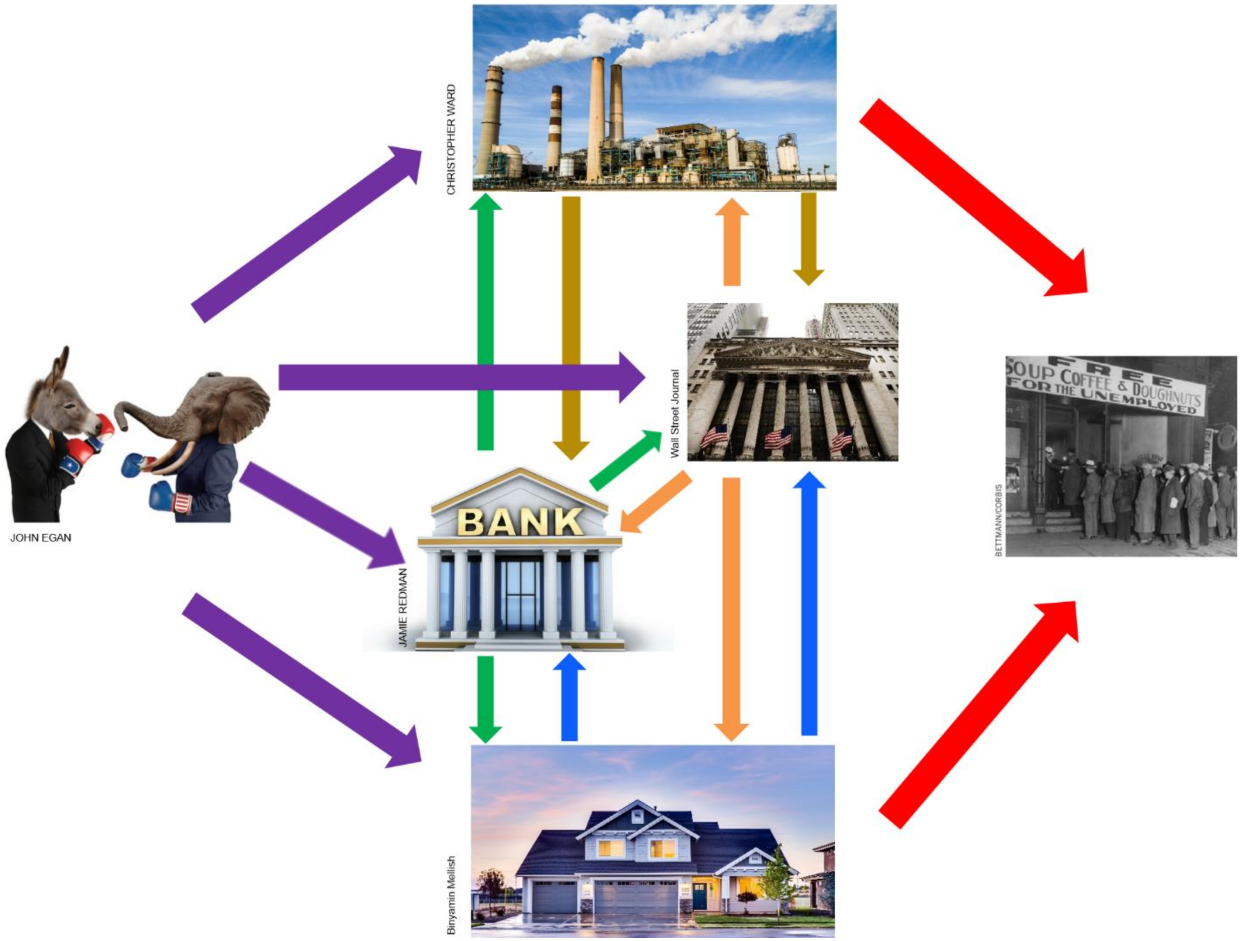
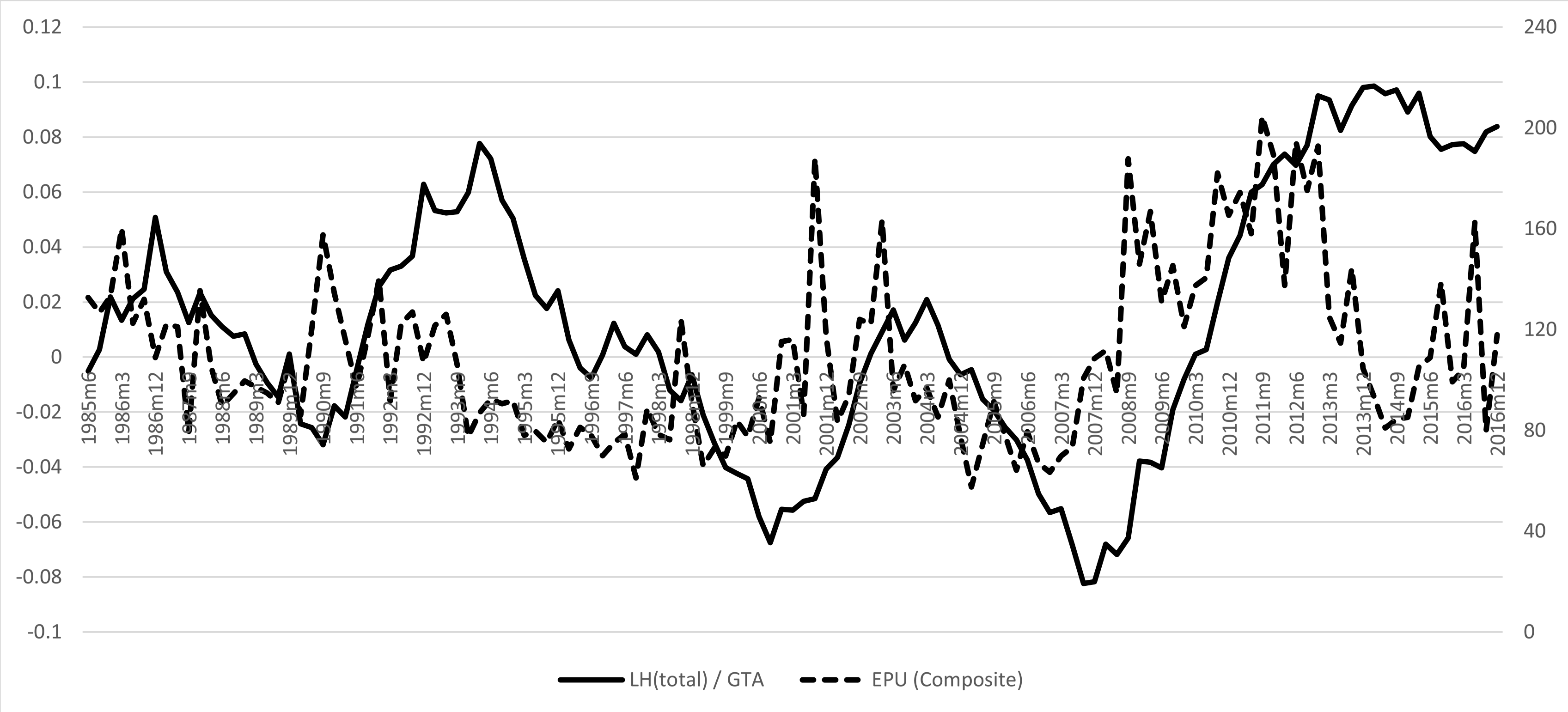


Figure 1 shows how economic policy uncertainty (*EPU*) can affect the real economy through both real economic agents and financial agents. *EPU* is represented by the symbols of the U.S. Democratic and Republican Parties fighting. The real economic agents of firms and households are depicted by the images of the factory and house, respectively. Banks are represented by the bank office building, and other financial agents such as nonbank financial institutions and markets are represented by the New York Stock Exchange. The real economy is illustrated by the soup lines. Arrows show directions of causation.

Figure 2: Patterns of bank liquidity hoarding and economic policy uncertainty (1985:Q2 – 2016:Q4)



This figure shows the temporal patterns of the liquidity hoarding ratios for the nation as a whole as well as *EPU(Composite)* over our sample period from 1985:Q2 to 2016:Q4. *LH(total)/GTA* is defined as the sum of liquidity hoarding for the banking industry at each point in time divided by the sum of *GTA* for the industry at that time. Sources: authors' calculation, bank liquidity hoarding data is based on liquidity creation data from Bowman's website (https://sites.google.com/a/tamu.edu/bouwman/data) and *EPU* data is from Baker, Bloom, and Davis' website (http://www.policyuncertainty.com).

Table 1: Description and summary statistics for the main analysis

This table presents definitions of variables and summary statistics for the sample of U.S. banks and policy uncertainty measures. The sample includes 17,164 banks from 1985:Q2 through 2016:Q4. The observations are on a bank-calendar-quarter level. Panel A describes variables definitions. Panel B presents descriptive statistics for the whole sample and Panel C provides descriptive statistics by bank size. Banks are categorized into size classes based on gross total assets (GTA). Panel D presents Pearson correlation coefficients across dependent variables and key independent variables. All dollar values are adjusted to real 2016 values using the implicit GDP price deflator. All control variables except macro variables are winsorized at 1% level.

Panel A: Description of variables

Variable	Description
Dependent variables	
LH(total) / GTA	A bank's total bank liquidity hoarding measure including on- and off-balance sheet activities normalized by the GTA of a bank. For a more detailed definition, see Berger and Bouwman (2009).
LH(asset) / GTA	A bank's bank liquidity hoarding measure including only asset-side activities normalized by the total asset size of a bank. For a more detailed definition, see Berger and Bouwman (2009).
LH(liab) / GTA	A bank's bank liquidity hoarding measure including only liability-side activities normalized by the total asset size of a bank. For a more detailed definition, see Berger and Bouwman (2009).
LH(off) / GTA	A bank's bank liquidity hoarding measure including only off-balance sheet activities normalized by the total asset size of a bank. For a more detailed definition, see to Berger and Bouwman (2009).
Key independent variables	
EPU(Composite)	The natural log of the arithmetic average of the overall policy uncertainty measure developed by Baker, Bloom, and Davis (BBD 2016) over the three months of calendar quarter *t*.
EPU(News)	The natural log of the arithmetic average of the news-based element of the policy uncertainty measure developed by BBD over the three months of calendar quarter *t*.
EPU(Govt.)	The natural log of the arithmetic average of the government spending element of the policy uncertainty measure developed by BBD over the three months of calendar quarter *t*.
EPU(CPI)	The natural log of the arithmetic average of the inflation element of the policy uncertainty measure developed by BBD over the three months of calendar quarter *t*.
EPU(Tax)	The natural log of the arithmetic average of the tax-code element of the policy uncertainty measure developed by BBD over the three months of calendar quarter *t*.
Control variables	
Ln(GTA)	The natural log of the GTA of a bank defined as the total asset + allowance for loan and lease losses + allocated transfer risk reserve (a reserve for certain foreign loans) in $1000.
Capital ratio	The total equity capital as a proportion of GTA for each bank.

Table 1 (continued)

HHI	A bank-level competition level calculated as a weighted average of the Herfindahl-Hirschman index in all areas (MSA or counties if not included in MSA) in which a bank has a business. For each bank, the proportion of deposits in each area is used as weights.
Population	A bank-level population index calculated as the natural log of a weighted average of the population (in millions) in all areas in which a bank has a business. For each bank, the proportion of deposits in each area is used as weights.
Tobin's Q	A state-level cross-sectional average of normalized Tobin's Q defined as a firm-level Tobin's Q in quarter *t* normalized by a lagged total asset of each firm in the Compustat data whose headquarters is located in a corresponding state. Tobin's Q is defined as the market value of assets divided by the book value of assets (Compustat Item 6). A firm's market value of assets equals the book value of assets plus the market value of common stock less the sum of the book value of common stock (Compustat Item 60) and balance sheet deferred taxes (Compustat Item 74).
Cash flows	A state-level cross-sectional average of operating cash flows for each firm in quarter *t* divided by a lagged total asset of each firm in the Compustat data whose headquarters is located in a corresponding state. Cash flow is calculated as the sum of earnings before extraordinary items (Compustat Item 18) and depreciation (Compustat Item 14).
Election year	A binary variable equal to one if the calendar year is a presidential election year and zero otherwise.
SD (stock ret.)	The standard deviation of daily value-weighted stock market returns from WRDS in quarter *t.*
GDP dispersion	Forecast dispersion of real GDP defined as 75th percentile minus 25th percentile scaled by the absolute value of 75th percentile of expected real GDP growth in the next quarter from the Survey of Professional Forecasters of the Federal Reserve Bank of Philadelphia.
Instrumental variable	
Senate polarization	An instrumental variable for economic policy uncertainty (*EPU*). A measure of partisan polarization tracking legislators' ideological positions based on McCarty, Poole, and Rosenthal (1997).

Panel B: Summary statistics for the sample

	N	Mean	StDev	25th Percentile	Median	75th Percentile
Dependent variables						
LH(total) / GTA	1,022,644	0.125	0.183	0.004	0.132	0.250
LH(asset) / GTA	1,022,644	-0.009	0.147	-0.111	-0.009	0.092
LH (liab) / GTA	1,022,644	0.177	0.068	0.129	0.172	0.221
LH (off) / GTA	1,022,644	-0.043	0.040	-0.061	-0.033	-0.013
Key independent variables						
EPU(Composite)	1,022,644	4.642	0.247	4.463	4.636	4.809
EPU(News)	1,022,644	4.631	0.277	4.427	4.586	4.828
EPU(Govt.)	1,022,644	4.560	0.451	4.164	4.544	4.882
EPU(CPI)	1,022,644	4.572	0.293	4.402	4.556	4.807
EPU(Tax)	1,022,644	3.760	1.614	2.602	2.821	4.871
Control variables						
GTA	1,022,644	1,133,312	22,900,000	61,440	116,168	250,467
Capital ratio	1,022,644	0.070	0.030	0.049	0.064	0.086
HHI	1,022,644	0.083	0.099	0.019	0.053	0.119
Population	1,022,644	1.776	0.888	1.182	1.693	2.469
Tobin's Q	1,022,644	2.087	0.844	1.625	1.876	2.272
Cash flows	1,022,644	0.008	0.024	0.000	0.013	0.022
Election year	1,022,644	0.242	0.429	0.000	0.000	0.000
SD (stock ret.)	1,022,644	0.009	0.005	0.006	0.008	0.010
GDP dispersion	1,022,644	0.427	0.454	0.240	0.304	0.437
Additional variables						
Senate polarization	975,206	0.717	0.107	0.611	0.732	0.796
β_{EPU}	131,361	-0.020	0.022	-0.028	-0.015	-0.007

Panel C: Descriptive statistics for bank liquidity hoarding dependent variables by bank size class

	Small banks (GTA<95th percentile ($1.3 billion))			Medium banks (95th percentile ($1.3 billion) ≤$GTA$ <99th percentile ($11.0 billion))			Large banks (99th percentile ($11.0 billion) ≤$GTA$)		
	N	Mean	StDev	N	Mean	StDev	N	Mean	StDev
LH (total) / GTA	971,511	0.130	0.182	40,906	0.044	0.184	10,227	-0.023	0.175
LH (asset) / GTA	971,511	-0.006	0.147	40,906	-0.072	0.132	10,227	-0.056	0.125
LH (liab) / GTA	971,511	0.175	0.067	40,906	0.212	0.074	10,227	0.190	0.083
LH (off) / GTA	971,511	-0.040	0.036	40,906	-0.097	0.054	10,227	-0.158	0.058

Panel D: Correlation matrix for key variables

	LH(total) / GTA	*LH(asset) / GTA*	*LH(liab) / GTA*	*LH(off) / GTA*	*EPU(Composite)*	*EPU(News)*	*EPU(Govt.)*	*EPU(CPI)*	*EPU(Tax)*
LH (total) / GTA	1.000								
LH (asset) / GTA	0.927***	1.000							
LH (liab) / GTA	0.377***	0.058***	1.000						
LH (off) / GTA	0.529***	0.472***	-0.189***	1.000					
EPU(Composite)	**0.068*****	**0.025*****	**0.058*****	**0.117*****	**1.000**				
EPU(News)	-0.000	-0.031***	0.056***	0.020***	0.874***	1.000			
EPU(Govt.)	0.275***	0.244***	0.056***	0.269***	0.584***	0.272***	1.000		
EPU(CPI)	0.111***	0.106***	-0.041***	0.185***	0.454***	0.096***	0.504***	1.000	
EPU(Tax)	-0.257***	-0.296***	0.059***	-0.190***	0.353***	0.321***	-0.210***	-0.034***	1.000

Correlations with *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 2: The effects of *EPU* on bank total liquidity hoarding

This table presents coefficient estimates from regressions of the total bank liquidity hoarding normalized by the gross total assets (*LH(total) / GTA*) on the economic policy uncertainty measures and controls. The sample includes 17,164 banks from 1985:Q2 through 2016:Q4. All variables are described in Table 1. Coefficients on constant terms are omitted. *t*-statistics are reported in parentheses and are based on standard errors clustered at a bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1)	(2)	(3)	(4)	(5)	(6)
EPU(Composite)	**0.092*** **					
	(8.89)					
EPU(News)		**0.081*** **				**0.053*** **
		(7.02)				**(3.96)**
EPU(Govt.)			**0.063*** **			**0.057*** **
			(8.59)			**(7.77)**
EPU(CPI)				**0.011**		**-0.012**
				(1.18)		**(-1.33)**
EPU(Tax)					**-0.001**	**-0.008*** **
					(-0.50)	**(-4.20)**
Ln(GTA)	-0.095***	-0.097***	-0.087***	-0.095***	-0.095***	-0.082***
	(-12.57)	(-12.74)	(-11.33)	(-12.25)	(-12.16)	(-10.79)
Sqr. Ln(GTA)	0.001***	0.001***	0.001***	0.001***	0.001***	0.001***
	(4.45)	(4.53)	(4.40)	(4.59)	(4.61)	(4.36)
Capital ratio	-0.966***	-1.029***	-0.733***	-0.971***	-0.967***	-0.647***
	(-11.84)	(-12.13)	(-9.24)	(-10.46)	(-9.95)	(-8.66)
HHI	-0.077***	-0.079***	-0.081***	-0.098***	-0.099***	-0.070***
	(-6.00)	(-6.52)	(-6.59)	(-7.30)	(-7.49)	(-6.51)
Population	-0.006	-0.011	0.025*	0.003	0.005	0.036***
	(-0.44)	(-0.89)	(1.81)	(0.24)	(0.34)	(2.71)
Tobin's Q	0.001	0.001	-0.000	-0.002	-0.002	0.002
	(0.44)	(0.72)	(-0.22)	(-1.31)	(-1.30)	(1.47)
Cash flows	0.135***	0.142***	0.076*	0.136***	0.134***	0.091**
	(3.18)	(3.11)	(1.83)	(2.80)	(2.76)	(2.20)
Election year	0.007	0.006	0.009*	0.007	0.007	0.010*
	(1.20)	(0.97)	(1.68)	(0.90)	(0.92)	(1.95)
SD (stock ret.)	-3.134***	-3.763***	-1.581**	-2.061**	-2.062**	-2.709***
	(-3.53)	(-3.89)	(-1.99)	(-2.23)	(-2.19)	(-3.01)
GDP dispersion	-0.014*	-0.010	-0.016**	-0.005	-0.003	-0.017**
	(-1.66)	(-1.15)	(-2.53)	(-0.73)	(-0.46)	(-2.07)
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.724	0.722	0.728	0.712	0.712	0.733
Number of obs.	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644

Table 3: The effects of *EPU* on components of the bank liquidity hoarding

This table presents coefficient estimates from regressions of components of liquidity hoarding measures on elements of economic policy uncertainty measures. The sample includes 17,164 banks from 1985:Q2 through 2016:Q4. *Controls* include *Ln(GTA)*, *Sqr. Ln(GTA)*, *Capital ratio*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *Election year*, *SD (stock ret.), GDP dispersion*. Coefficients on *Controls* are omitted for brevity. Panels A–C present coefficients estimates from regressions of asset-side liquidity hoarding (*LH(asset)/GTA*), liability-side liquidity hoarding (*LC(liab.)/GTA*), and off-balance sheet liquidity hoarding (*LH(off)/GTA*), respectively. All variables are described in Table 1. *t*-statistics are reported in parenthesis and are based on standard errors clustered at a bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: The effects of *EPU* on asset-side liquidity hoarding (*LH (asset)/GTA*)

	Dep. = *LH(asset) / GTA*					
	(1)	(2)	(3)	(4)	(5)	(6)
EPU(Composite)	**0.040*** **					
	(6.40)					
EPU(News)		**0.037*** **				**0.028*** **
		(5.79)				**(3.59)**
EPU(Govt.)			**0.036*** **			**0.036*** **
			(7.51)			**(7.65)**
EPU(CPI)				**0.005**		**-0.001**
				(0.96)		**(-0.19)**
EPU(Tax)					**-0.007*** **	**-0.012*** **
					(-5.10)	**(-9.95)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644

Panel B: The effects of *EPU* on liability-side liquidity hoarding (*LH(liab)/GTA*)

	Dep. = *LH(liab) / GTA*					
	(1)	(2)	(3)	(4)	(5)	(6)
EPU(Composite)	**0.029*****					
	(5.69)					
EPU(News)		**0.032*****				**0.021*****
		(5.81)				**(2.88)**
EPU(Govt.)			**0.012*****			**0.008***
			(3.88)			**(1.81)**
EPU(CPI)				**-0.009**		**-0.020*****
				(-1.61)		**(-2.77)**
EPU(Tax)					**0.006*****	**0.005*****
					(3.67)	**(2.96)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644

Panel C: The effects of *EPU* on off balance sheet liquidity hoarding (*LH(off)/GTA*)

	Dep. = *LH(off) / GTA*					
	(1)	(2)	(3)	(4)	(5)	(6)
EPU(Composite)	**0.022*****					
	(13.57)					
EPU(News)		**0.012*****				**0.004****
		(5.08)				**(2.22)**
EPU(Govt.)			**0.015*****			**0.013*****
			(14.42)			**(9.90)**
EPU(CPI)				**0.014*****		**0.009*****
				(6.20)		**(3.83)**
EPU(Tax)					**0.000**	**-0.002*****
					(0.49)	**(-5.88)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644

Table 4: Instrumental variable analysis and placebo tests

This table presents coefficient estimates from instrumental variable analysis (Panel A) and placebo tests (Panel B). The instrumental variable analysis is based on the two-stage least-squares regressions approach with the U.S. Senate polarization measure as an instrumental variable for the overall policy uncertainty (*EPU(Composite)*). The sample period for the Senate polarization is from 1985:Q2 to 2015:Q1. The placebo test is based on random samples of *EPU(Composite)* drawn from the sample distribution of *EPU(Composite)*. We present an average coefficient estimate on *EPU(Composite)* based on 100 random samples of *EPU(Composite)*. *Controls* include *Ln(GTA)*, *Sqr. Ln(GTA)*, *Capital ratio*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *Election year*, *SD (stock ret.), GDP dispersion*. Coefficients on *Controls* are omitted for brevity. All variables are described in Table 1. *t*-statistics are reported in parenthesis and are based on bootstrap standard errors clustered at a quarter level (Panel A) or sample standard errors of the estimated coefficients (Panel B). Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Instrumental variable analysis

	First Stage	Second Stage			
	(1) *EPU (Composite)*	(2) *LH (total)/GTA*	(3) *LH (asset)/GTA*	(4) *LH (liab.)/GTA*	(5) *LH (off)/GTA*
$\widehat{\boldsymbol{EPU}}(\boldsymbol{Composite})$		**0.096*****	**0.027*****	**0.035*****	**0.035*****
		(6.13)	**(3.12)**	**(4.51)**	**(12.34)**
Senate polarization	**4.208*****				
	(5.36)				
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	-	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.485	0.251	0.205	0.088	0.213
Number of obs.	119	975,206	975,206	975,206	975,206

Panel B: Placebo tests

	(1) *LH(total) / GTA*	(2) *LH(asset) / GTA*	(3) *LH(liab) / GTA*	(4) *LH(off) / GTA*
$\widehat{\boldsymbol{EPU}}$***(Composite)***	**0.002**	**0.001**	**0.000**	**0.001**
	(0.22)	**(0.23)**	**(0.06)**	**(0.30)**
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes
Number of obs.	1,022,644	1,022,644	1,022,644	1,022,644

Table 5 : Description of variables and summary statistics for the samples used in supply versus demand analyses

This table presents definitions of variables and summary statistics for the variables used in supply versus demand analyses. Panels A1 and A2 show the definitions and summary statistics, respectively, for the variables used in the supply versus demand analyses based on DealScan data. The observations are at the facility-bank level from 1985:Q2 through 2016:Q4. Panels B1 and B2 show the definitions and summary statistics, respectively, for the variables used in the analyses based on selected responses to the Federal Reserve's Senior Loan Officer Survey from 1990:Q2 to 2016:Q4. The data for these correlations start in 1990:Q2, rather than 1985:Q2 because earlier data from the Survey are not publicly available.

Panel A1: Description of variables for the samples used in supply versus demand analyses for DealScan data, 1985:Q2 to 2016:Q4.

Variable	Description
Bank loan variables	
Spread	The all-in spread drawn defined as the borrowing spread and annual fee (if any) the borrower pays in basis points over LIBOR or LIBOR equivalent for each dollar drawn down.
Credit size	Loaned amount scaled by the borrower's total asset.
Ln(Maturity)	The natural log of the loan maturity (in months) from the loan facility's issue date.
Secured	A binary variable equal to one if a facility is secured by collateral and zero otherwise.
Covnt. Index	Covenant intentensity index based on Bradley and Roberts (2015), which is defined as the sum of all covenants embeded in the loan (i.e., two or more restricted accounting ratios, secured loans, dividend restriction, asset sweep, debt sweep, equity sweep).
Term loans	A binary variable equal to one if a credit contract belongs to the following credit types in the LPC DealScan data: Term Loan, Term Loan A, Term Loan B, Term Loan C, Term Loan D, Term Loan E, Term Loan F, Term Loan G, Term Loan H, Term Loan I, or Delay Draw Term Loan, and zero otherwise.
Revolvers	A binary variable equal to one if a credit contract belongs to the following credit types in the LPC DealScan data: Revolver/Line < 1 Yr or Revolver/Line ≥ 1 Yr, and zero otherwise.
Borrower variables	
Ln(ME)	The natural log of the market value of a firm defined as the number of outstanding shares (in 1,000) multiplied by the market price per share.
BE_ME	The book value of equity defined as the total stockholder's equity plus deferred taxes and investment tax credit minus preferred stock value divided by the market value of a firm.
Leverage	Total debt (short-term debt + long-term debt) divided by total assets.
Tangible	Net Property, Plant, and Equipment divided by the total assets.
Cash	Cash and short-term investment divided by the total asset.
Z_score	(3.3×pre-tax income + sales + 1.4×retained earnings + 1.2×(current assets – current liability)) / book assets (Altman (1968)).
Credit rating	A credit rating score ranging from zero (for C or below) to 20 (for AAA) with an increment of one for each rating category based on an issuer's long-term S&P credit rating.

Panel A2: Summary statistics for the variables used in supply versus demand analyses for DealScan data, 1985:Q2 to 2016:Q4.

	N	Mean	StDev	25th Percentile	Median	75th Percentile
Bank loan variables						
Spread	28,202	187.362	120.103	100.000	175.000	255.000
Credit size	28,202	0.221	0.225	0.070	0.150	0.290
Ln(Maturity)	27,434	3.821	0.548	3.611	4.111	4.111
Secured	28,202	0.321	0.467	0.000	0.000	1.000
Covnt. Index	28,202	1.810	2.053	0.000	1.000	4.000
Term loans	28,202	0.292	0.455	0.000	0.000	1.000
Borrower variables						
Ln(ME)	28,202	13.435	2.009	11.980	13.498	14.873
BE_ME	28,202	0.768	1.200	0.272	0.485	0.820
Leverage	28,202	0.282	0.215	0.116	0.256	0.403
Tangible	28,202	0.324	0.239	0.127	0.263	0.484
Cash	28,202	0.088	0.113	0.015	0.043	0.116
Z_score	28,202	1.647	1.239	0.814	1.607	2.413
Credit rating	14,222	10.292	3.161	8.000	10.000	12.000

Panel B1: Description of variables for the samples used in supply versus demand analyses for selected responses to the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices, 1990:Q2 to 2016:Q4.

Net tightened standards for C&I loans or credit lines to large and medium firms	Net percentage of domestic respondents reporting tightened standards for C&I loans or credit lines on large and medium firms from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices from 1990:Q2 to 2016:Q4.
Net tightened standards for C&I loans or credit lines to small firms	Net percentage of domestic respondents reporting tightened standards for C&I loans or credit lines on small firms from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices from 1990:Q2 to 2016:Q4.
Net increased interest rates spread on loans to large and medium firms	Net percentage of domestic respondents reporting increased spreads of loan rates over banks' cost of funds on large and medium firms from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices from 1990:Q2 to 2016:Q4.
Net increased interest rates spread on loans to small firms	Net percentage of domestic reporting increased spreads of loan rates over banks' cost of funds on small firms from the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices from 1990:Q2 to 2016:Q4.

Panel B2: Summary statistics for the samples used in supply versus demand analysis for selected responses to the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices, 1990:Q2 to 2016:Q4.

	N	Mean	StDev	25th Percentile	Median	75th Percentile
Net tightened standards for C&I loans or credit lines to large and medium firms	107	5.942	22.871	-8.800	-0.900	14.000
Net tightened standards for C&I loans or credit lines to small firms	107	5.467	19.593	-7.000	-1.800	9.400
Net increased interest rates spread on loans to large and medium firms	107	-10.440	42.921	-46.100	-28.800	27.100
Net increased interest rates spread on loans to small firms	107	-8.130	33.442	-32.700	-16.700	14.000

Table 6: The effects of *EPU* on spreads: Supply versus demand effects on credit supply at the *intensive margin*

This table presents coefficient estimates from regressions of the interest rate spreads on the economic policy uncertainty measures and controls. Panel A reports the effects of *EPU(Composite)* on interest rate spreads and Panel B replicates Panel A by replacing the *EPU(Composite)* with each element of *EPU*. The sample includes 438 lead lender banks and 5,866 borrowing firms from 1985:Q2 through 2016:Q4. *Controls* include *Ln(GTA)*, *Sqr. Ln(GTA)*, *Capital ratio*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *Election year*, *SD (stock ret.), GDP dispersion*. All variables are described in Tables 1 and 5. *t*-statistics are reported in parentheses and are based on standard errors clustered at a bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: The effects of *EPU (Composite)* on interest rate spreads

	Term loans (On-balance sheet)					*Revolvers (Off-balance sheet)*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EPU(Composite)	**90.041*** **	**76.092*** **	**107.466*** **	**58.681*** **	**56.282*** **	**93.276*** **	**67.828*** **	**100.739*** **	**70.976*** **	**72.759*** **
	(4.66)	**(6.39)**	**(6.09)**	**(3.99)**	**(4.21)**	**(7.49)**	**(6.57)**	**(9.30)**	**(6.29)**	**(7.30)**
Ln (ME)			-73.064***	-71.149***	-89.059***			-60.309***	-60.010***	-53.207***
			(-3.78)	(-4.20)	(-7.25)			(-13.05)	(-13.20)	(-8.15)
Sqr. Ln(ME)			2.192***	2.055***	2.687***			1.906***	1.790***	1.839***
			(3.22)	(3.45)	(6.03)			(11.70)	(11.43)	(9.00)
BE_ME			-1.001	-3.201*	-2.581			-0.757	-2.376**	1.753
			(-0.57)	(-1.96)	(-1.37)			(-0.55)	(-2.02)	(1.38)
Leverage			-9.394	-6.800	-15.452			15.032**	19.445**	20.780***
			(-0.68)	(-0.49)	(-1.13)			(2.22)	(2.52)	(3.36)
Tangible			0.012	2.780	11.507**			-19.669***	-18.452***	-16.330***
			(0.00)	(0.45)	(2.13)			(-4.05)	(-3.19)	(-3.09)
Cash			47.067*	41.314*	44.353**			4.188	3.610	-15.195***
			(1.87)	(1.89)	(2.27)			(0.45)	(0.59)	(-2.76)
Z_score			-9.045***	-7.853***	-6.791***			-6.675***	-6.526***	-6.094***
			(-3.80)	(-3.66)	(-3.56)			(-10.50)	(-7.98)	(-8.51)
Credit rating			-19.213***	-18.945***	-14.944***			-18.855***	-17.445***	-15.070***
			(-11.21)	(-10.01)	(-7.24)			(-22.71)	(-15.82)	(-12.62)

Table 6 (continued)

Panel A (continued)

	Term loans (On-balance sheet)					*Revolvers (Off-balance sheet)*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Credit size					0.292					-11.792***
					(0.14)					(-7.16)
Ln(Maturity)					-3.102					-20.456***
					(-0.53)					(-5.40)
Secured					78.061***					25.446***
					(12.88)					(6.51)
Covnt. index					-1.272					5.108***
					(-0.94)					(5.00)
Controls	NO	YES	NO	YES	YES	NO	YES	NO	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.088	0.102	0.347	0.376	0.431	0.197	0.214	0.563	0.582	0.621
Number of obs.	8231	8231	4228	4228	4147	19,971	19,971	9994	9994	9721

Table 6 (continued)

Panel B: The effects of *EPU* elements on the interest rate spreads

	Term loans (On-balance sheet)					*Revolvers (Off-balance sheet)*				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
EPU(News)	**41.294*****				**35.451****	**43.971*****				**21.220****
	(2.97)				**(2.07)**	**(5.94)**				**(2.06)**
EPU(Govt.)		**40.538*****			**35.403*****		**49.678*****			**39.209*****
		(5.26)			**(3.90)**		**(6.40)**			**(4.74)**
EPU(CPI)			**8.624**		**13.613**			**27.347*****		**8.079**
			(0.71)		**(1.09)**			**(2.97)**		**(1.01)**
EPU(Tax)				**-1.826**	**-7.309*****				**7.094*****	**2.209**
				(-0.83)	**(-2.72)**				**(2.71)**	**(1.47)**
Borrower controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Loan controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Controls	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Seasonal FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Adj. R-squared	0.429	0.432	0.424	0.424	0.436	0.609	0.621	0.604	0.607	0.624
Number of obs.	4147	4147	4147	4147	4147	9721	9721	9721	9721	9721

Table 7: Correlations of *EPU* measures with selected responses to the Federal Reserve's Senior Loan Officer Opinion Survey on Bank Lending Practices

This table presents the correlations between the *EPU* measures and the net percentages of respondents that reported tightening credit standards and increasing spreads to the two size classes of firms. Commercial and industrial (C&I) loans are those made to a firm that are not secured by real estate. The sample period is from 1990:Q2 to 2016:Q4. The data start in 1990:Q2, rather than 1985:Q2 as in previous analyses because earlier data from the Survey are not publicly available. All variables are described in Tables 1 and 5. Correlations with *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively.

	Net tightened standards for C&I loans or credit lines to large and medium firms	*Net tightened standards for C&I loans or credit lines to small firms*	*Net increased interest rates spread on loans to large and medium firms*	*Net increased interest rates spread on loans to small firms*
EPU(Composite)	**0.191****	**0.225****	**0.195****	**0.192****
EPU(News)	0.320***	0.311***	0.296***	0.261***
EPU(Govt.)	-0.083	-0.048	-0.009	0.050
EPU(CPI)	0.158	0.219**	0.233**	0.281***
EPU(Tax)	-0.194**	-0.098	-0.199**	-0.193**

Appendix: Additional robustness checks

To rule out alternative explanations of our findings, we undertake several additional analyses. Definition and summary statistics for additional variables used in this section are provided in Table A1.

A.1 Does *EPU* affect bank liquidity hoarding above and beyond market uncertainty?

A potential concern is that our findings may reflect the effects of other sources of uncertainty, such as market uncertainty. To address this concern, we follow prior research (e.g., Gulen and Ion (2016), Bonaime, Gulen, and Ion (2017)) and control for market uncertainty using the CBOE's *VIX* index. Table A2 reports coefficients from regressions of bank total liquidity hoarding (*LH(total)/GTA*) and its three components on *EPU(Composite)*, all including *VIX* as an additional control. For these regressions, the sample size is reduced to 794,137 observations because *VIX* is unavailable prior to 1990. The coefficients on *EPU(Composite)* are close to those in Tables 2 and 3 and remain highly statistically significant, and *VIX* itself has relatively little to no effect on bank liquidity hoarding.

A.2 The effects of *EPU* on bank liquidity hoarding by bank size class

Table A3 Panel A shows the effects of *EPU(Composite)* on *LH(total)/GTA* and its three components by bank size class. All coefficients are statistically significant at the 1% level and of the same signs as in our main results. Columns 1–3 show that the effects of *EPU(Composite)* on *LH(total)/GTA* are negative and are greater in magnitude (i.e., more negative) for medium and large banks. Columns 4–6 show that the effects of *EPU(Composite)* on *LH(asset)/GTA* are negative and similar in magnitude across size classes. The remaining columns suggest that larger banks appear to react more to uncertainty in terms of liability-side and off-balance sheet-side liquidity hoarding than small banks, and medium banks also have more reaction in terms of off-balance sheet liquidity hoarding than small banks.

The results for the *EPU* elements are reported in Panels B–E. The results for *EPU(News)* and *EPU(Govt.)* show that all coefficients have the same sign and significance across size classes. The impact of *EPU(CPI)* again shows negative, statistically significant effects for *LH(total)/GTA* and *LH(off)/GTA* for all bank sizes, and has insignificant effects across size classes for *LH(asset)/GTA* and *LH(liab)/GTA*. The effects of *EPU(Tax)* are the only ones with statistically significant coefficients of opposing signs across size classes. The effects of *EPU(Tax)* on *LH(total)/GTA* are positive and significant for small banks and negative and significant for large banks, driven mostly by the effects on *LH(asset)/GTA*.

Our results in Table A3 are consistent for all size classes, with some minor variations for *EPU(CPI)* and *EPU(Tax)*. Our findings of consistent results across size classes are robust to a different size class grouping, categorizing banks into five size classes based on a $10-billion cutoff for large banks and quartile values for the smaller banks (not shown for brevity).

A.3 The effects by bank capital, pre- and post-Basel III, and by local market economic conditions

Table A4 examines the effects of *EPU(Composite)* on *LH(total)/GTA* by bank capital, for pre- and post-Basel III, and by local economic conditions. Columns 1–2 report coefficient estimates from regressions of *LH(total)/GTA* on *EPU(Composite)* and other controls for banks above and below the median capital ratio. The literature often finds that bank capital affects liquidity hoarding (e.g., Berger and Bouwman (2009), Lei and Song (2013), Horvath, Seidler, and Weill (2014), Fungáčová, Weill, and Zhou (2017)), so we check whether the effects of *EPU* differ by bank capital ratio. The results are similar for the two groups, suggesting that the effects of *EPU* are robust to differences in bank capital. We also allow for the possibility that our results might be driven by bank actions to comply with the Basel III capital and liquidity regulations. Columns 3 and 4 present regression coefficients for the pre-Basel III period through 2013 when the Basel Committee announced the new capital and liquidity requirements, and the post-Basel III period after 2013, respectively. Basel III capital requirements are more stringent than existed previously, and the new liquidity ratios, Liquidity Coverage Ratio (LCR) and Net Stable Funding Ratio (NSFR), are correlated with liquidity creation (Berger and Bouwman (2016, p. 63, Figure 6.1)). The coefficient on *EPU(Composite)* is positive and statistically and economically significant for both time periods, and actually decreases in the post-Basel III period, suggesting the results are not driven by Basel III requirements. Columns 5 and 6 report regression results for banks in states with favorable and unfavorable local economic conditions, based on being above or below the median state Coincident Index. The results hold in both favorable and unfavorable economic conditions.

A.4 The effects of *EPU* on bank liquidity hoarding by bank survival categories

Table A5 presents coefficient estimates from regressions by bank survival categories to determine if the results may be driven by banks that enter and exit the sample. A bank is categorized as *Surviving* if it exists throughout the sample, as *Exiting* if it existed at the beginning of the sample but subsequently exited, as *Entering* if it did not exist at the beginning of the sample, but later joined. All other banks (e.g., ones that entered late and exited early) are categorized as *Other*. The coefficients on *EPU(Composite)* all have the same sign as in our main results and all are statistically significant at the 1% level.

A.5 Other robustness checks

We conduct additional robustness checks, but do not tabulate them for brevity. To address a concern that our model does not account for persistence of bank liquidity hoarding over time, we add a lagged dependent variable as an additional independent variable. Notably, OLS estimates with bank fixed effects are biased in this setting because the lagged dependent variables and the fixed effects are correlated by construction (Nickell (1981)). We implement the system GMM approach (Blundell and Bond (1998)) to resolve this issue. Our main results still hold: the coefficient estimates on *EPU(Composite)* are negative and statistically significant.

Baker, Bloom, and Davis also recently updated their website to report categorical *EPU* measures. To ensure that our main evidence is not driven by bank-specific policies, we include *EPU* measures of monetary policy and financial regulation as additional controls. The results continue to show that *EPU* leads to an increase in the bank liquidity hoarding.

Our extensive robustness checks confirm our main findings regarding the effects of *EPU* on bank liquidity creation, and give us confidence in our conclusions.

Table A1: Description of variables and summary statistics for the sample of additional robustness checks

This table presents definitions of variables and summary statistics for robustness checks. Panel A describes variables definitions. Panel B presents descriptive statistics.

Panel A: Description of variables for the additional robustness checks

Variable	Description
Cash/GTA	The ratio of cash and balances due from other depository institutions to gross total asset for each bank.
Securities/GTA	The ratio of securities to gorss total asset for each bank.
Loans/GTA	The ratio of total loans to gross total asset for each bank.
Loan cmt./GTA	The ratio of loan commitments to gross total asset for each bank.
Deposits/GTA	The ratio of deposits to gross total asset for each bank.
VIX	Implied volatility conveyed by S&P 500 stock index option prices from 1990 to 2016 obtained from the Federal Reserve Bank of St. Louis.
Size class	Size categories of banks into *small, medium,* and *large banks* with cutoff values of 95th percentile ($1.3 billion) and 99th percentile ($11.0 billion) of gross total assets (Kashyap and Stein (2000)).
Pre-/post-Basel III	Pre-Basel III and post-Basel III belong to sample periods through 2013 when the Basel Committee announced the new liquidity requirements, and after 2013, respectively.
Coincident Index	Bank level weighted average of the Coincident Index with the proportion of deposits in each state as weights. The Coincident Index is from the Federal Reserve Bank of Philadelphia's measure of the state-level economic conditions.
Survival categories (Surviving/Exiting/ Entering/Others)	A bank is categorized into *Surviving banks* if it exists throughout the whole sample period. A bank is categorized into *Exiting banks* if it exists at the beginning of the sample but subsequently exits the sample. A bank is categorized into *Entering banks* if it does not exist at the beginning of the sample but subsequently enters the sample. All other banks are categorized into *Other banks*.

Panel B: Summary statistics for the additional robustness checks

	N	Mean	StDev	25th Percentile	Median	75th Percentile
Cash/GTA	1,022,644	0.064	0.052	0.032	0.048	0.076
Securities/GTA	1,022,644	0.263	0.151	0.150	0.246	0.359
Loans/GTA	1,022,644	0.583	0.151	0.486	0.599	0.692
Loan cmt./GTA	1,022,644	0.079	0.075	0.023	0.061	0.114
Deposits/GTA	1,022,644	0.851	0.061	0.825	0.867	0.894
VIX	794,137	19.552	7.118	14.080	17.840	22.840
Coincident Index	1,022,644	118.116	24.362	97.780	117.908	134.126
Surviving	1,022,644	0.388	0.487	0.000	0.000	1.000
Exiting	1,022,644	0.382	0.486	0.000	0.000	1.000
Entering	1,022,644	0.108	0.310	0.000	0.000	0.000
Others	1,022,644	0.122	0.327	0.000	0.000	0.000

Table A2: The effects of *EPU* on selected bank balance sheet and off-balance sheet categories

This table presents coefficient estimates from regressions of selected bank balance sheet and off-balance sheet categories on the the composite economic policy uncertainty (*EPU*) measure and controls. The sample includes 17,164 banks from 1985:Q2 through 2016:Q4. *Controls* include *Ln(GTA)*, *Sqr. Ln(GTA)*, *Capital ratio*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *Election year*, *SD (stock ret.), GDP dispersion*. All variables are described in Table 1. *t*-statistics are reported in parentheses and are based on standard errors clustered at a bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1) *Cash/ GTA*	(2) *Securities/ GTA*	(3) *Loans/ GTA*	(4) *Loan cmt./ GTA*	(5) *Deposits/ GTA*
EPU(Composite)	**0.050*****	**0.009**	**-0.068*****	**-0.045*****	**0.024*****
	(13.486)	**(1.285)**	**(-12.068)**	**(-13.657)**	**(8.971)**
Ln(GTA)	-0.008***	-0.048***	0.083***	0.026***	-0.021***
	(-3.434)	(-9.750)	(12.891)	(7.425)	(-6.054)
Sqr. Ln(GTA)	-0.000*	0.001***	-0.002***	-0.000	0.000
	(-1.818)	(6.196)	(-6.644)	(-0.427)	(0.985)
Capital ratio	0.024	-0.434***	0.286***	0.463***	-0.849***
	(0.850)	(-9.696)	(4.835)	(17.828)	(-35.450)
HHI	-0.045***	-0.011	0.032***	0.020***	-0.018***
	(-10.033)	(-1.294)	(3.901)	(5.415)	(-5.350)
Population	0.021***	-0.057***	0.060***	0.031***	0.023***
	(3.740)	(-4.493)	(4.838)	(6.576)	(4.945)
Tobin's Q	0.000	-0.000	0.000	0.001	0.001
	(0.861)	(-0.125)	(0.349)	(1.268)	(1.619)
Cash flows	0.009	0.098***	-0.089***	-0.035**	0.035***
	(0.602)	(3.223)	(-3.054)	(-2.005)	(2.865)
Election year	-0.000	0.006	-0.002	0.000	0.001
	(-0.129)	(1.640)	(-0.450)	(0.222)	(0.681)
SD (stock ret.)	-0.453*	-2.246***	2.490***	0.620**	-0.924***
	(-1.724)	(-3.978)	(3.733)	(2.015)	(-3.908)
GDP dispersion	-0.006**	0.006	0.000	0.000	0.000
	(-2.075)	(1.444)	(0.030)	(0.026)	(0.232)
Bank FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.463	0.670	0.690	0.693	0.838
Number of obs.	1,022,644	1,022,644	1,022,644	1,022,644	1,022,644

Table A3: Does *EPU* affect bank liquidity hoarding above and beyond the market volatility (VIX)?

This table replicates Table 2 with a VIX index as an additional control. The sample period is from 1990:Q2 through 2016:Q4. All variables are described in Tables 1 and A1. *Controls* include *Ln(GTA)*, *Sqr. Ln(GTA)*, *Capital ratio*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *Election year*, *SD (stock ret.), GDP dispersion*. Coefficients on *Controls* are omitted for brevity. *t*-statistics are reported in parentheses and are based on standard errors clustered at a bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1) *LH (total) / GTA*	(2) *LH (asset) / GTA*	(3) *LH (liab) / GTA*	(4) *LH (off) / GTA*
EPU(Composite)	**0.101*** **	**0.046*** **	**0.038*** **	**0.017*** **
	(9.02)	**(6.88)**	**(6.89)**	**(11.61)**
VIX	**-0.001***	**-0.000**	**-0.001*** **	**0.000**
	(-1.87)	**(-0.72)**	**(-2.95)**	**(0.06)**
Controls	YES	YES	YES	YES
Bank FE	YES	YES	YES	YES
Seasonal FE	YES	YES	YES	YES
Adj. R-squared	0.771	0.758	0.709	0.736
Number of obs.	794,137	794,137	794,137	794,137

Table A4: The effects of *EPU* on the bank liquidity hoarding by bank size class

This table presents coefficient estimates from regressions of components of liquidity hoarding measures on elements of economic policy uncertainty measure by bank size class. Following Kashyap and Stein (2000), we categorize banks into small, medium, and large classes with cutoff values of 95th percentile ($1.3 billion) and 99th percentile ($11.0 billion) of gross total assets (GTA). Panel A presents coefficient estimates from regressions of *LH(total)/GTA, LH(asset)/GTA, LC(liab.)/GTA,* and *LH(off)/GTA* on *EPU(Composite)*, respectively. Panels B–E replicate Panel A with *EPU(News)*, *EPU(Govt.)*, *EPU(CPI)*, and *EPU(Tax)* as an independent variable, respectively. The sample includes 17,164 banks from 1985:Q2 through 2016:Q4. *Controls* include *Ln(GTA)*, *Sqr. Ln(GTA)*, *Capital ratio*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *Election year*, *SD (stock ret.), GDP dispersion*. Coefficients on *Controls* are omitted for brevity. All variables are described in Tables 1 and A1. *t*-statistics are reported in parenthesis and are based on standard errors clustered at a bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: The effects of *EPU(Composite)* on components of bank liquidity hoarding

	Dep. = *LH(total) / GTA*			Dep. = *LH(asset) / GTA*			Dep. = *LH(liab) / GTA*			Dep. = *LH(off) / GTA*		
	(1) Small bank	(2) Medium bank	(3) Large bank	(4) Small bank	(5) Medium bank	(6) Large bank	(7) Small bank	(8) Medium bank	(9) Large bank	(10) Small bank	(11) Medium bank	(12) Large bank
EPU(Composite)	**0.090*** **	**0.103*** **	**0.106*** **	**0.041*** **	**0.038*** **	**0.040*** **	**0.028*** **	**0.028*** **	**0.035*** **	**0.021*** **	**0.037*** **	**0.031*** **
	(8.85)	**(7.89)**	**(5.54)**	**(6.65)**	**(4.96)**	**(3.31)**	**(5.50)**	**(4.79)**	**(4.38)**	**(13.60)**	**(10.45)**	**(6.86)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227

Panel B: The effects of *EPU(News)* on components of bank liquidity hoarding

	Dep. = *LH(total) / GTA*			Dep. = *LH(asset) / GTA*			Dep. = *LH(liab) / GTA*			Dep. = *LH(off) / GTA*		
	(1) Small bank	(2) Medium bank	(3) Large bank	(4) Small bank	(5) Medium bank	(6) Large bank	(7) Small bank	(8) Medium bank	(9) Large bank	(10) Small bank	(11) Medium bank	(12) Large bank
EPU(News)	**0.080*** **	**0.092*** **	**0.096*** **	**0.038*** **	**0.040*** **	**0.038*** **	**0.031*** **	**0.032*** **	**0.039*** **	**0.011*** **	**0.020*** **	**0.019*** **
	(7.01)	**(7.49)**	**(6.23)**	**(6.00)**	**(6.44)**	**(4.25)**	**(5.65)**	**(5.70)**	**(5.38)**	**(5.11)**	**(5.03)**	**(5.00)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227

Panel C: The effects of *EPU(Govt.)* on components of bank liquidity hoarding

	Dep. = *LH(total) / GTA*			Dep. = *LH(asset) / GTA*			Dep. = *LH(liab) / GTA*			Dep. = *LH(off) / GTA*		
	(1) Small bank	(2) Medium bank	(3) Large bank	(4) Small bank	(5) Medium bank	(6) Large bank	(7) Small bank	(8) Medium bank	(9) Large bank	(10) Small bank	(11) Medium bank	(12) Large bank
EPU(Govt.)	**0.061*****	**0.066*****	**0.053*****	**0.035*****	**0.024*****	**0.017****	**0.012*****	**0.016*****	**0.019*****	**0.015*****	**0.026*****	**0.017*****
	(8.45)	**(7.29)**	**(4.23)**	**(7.46)**	**(4.51)**	**(2.09)**	**(3.91)**	**(4.00)**	**(3.58)**	**(14.17)**	**(11.37)**	**(5.99)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227

Panel D: The effects of *EPU(CPI)* on components of bank liquidity hoarding

	Dep. = *LH(total) / GTA*			Dep. = *LH(asset) / GTA*			Dep. = *LH(liab) / GTA*			Dep. = *LH(off) / GTA*		
	(1) Small bank	(2) Medium bank	(3) Large bank	(4) Small bank	(5) Medium bank	(6) Large bank	(7) Small bank	(8) Medium bank	(9) Large bank	(10) Small bank	(11) Medium bank	(12) Large bank
EPU(CPI)	**0.009**	**0.008**	**-0.005**	**0.005**	**-0.006**	**-0.008**	**-0.009**	**-0.008**	**-0.009**	**0.013*****	**0.022*****	**0.013*****
	(1.07)	**(0.64)**	**(-0.30)**	**(0.87)**	**(-0.91)**	**(-0.91)**	**(-1.61)**	**(-1.41)**	**(-1.63)**	**(6.07)**	**(6.32)**	**(3.89)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227

Panel E: The effects of *EPU(Tax)* on components of bank liquidity hoarding

	Dep. = *LH(total) / GTA*			Dep. = *LH(asset) / GTA*			Dep. = *LH(liab) / GTA*			Dep. = *LH(off) / GTA*		
	(1) Small bank	(2) Medium bank	(3) Large bank	(4) Small bank	(5) Medium bank	(6) Large bank	(7) Small bank	(8) Medium bank	(9) Large bank	(10) Small bank	(11) Medium bank	(12) Large bank
EPU(Tax)	**-0.001**	**0.001**	**0.014*****	**-0.006*****	**-0.002**	**0.009*****	**0.005*****	**0.001**	**0.002**	**0.000**	**0.002****	**0.004*****
	(-0.30)	**(0.50)**	**(2.91)**	**(-4.60)**	**(-1.10)**	**(3.08)**	**(3.55)**	**(0.56)**	**(0.73)**	**(0.64)**	**(2.49)**	**(3.47)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227	971,511	40,906	10,227

Table A5: The effects of *EPU* on bank liquidity hoarding by bank capital, pre- and post-Basel III, and by local market economic conditions

This table presents coefficient estimates from regressions of the total bank liquidity hoarding normalized by the gross total assets (*LH(total)/GTA*) on the economic policy uncertainty measure by bank capital, pre- and post-Basel III, and by local economic conditions. *High* and *Low capital* are differentiated by the median of the capital ratio. Pre-Basel III and post-Basel III belong to sample periods through 2013 when the Basel Committee announced the new liquidity requirements, and after 2013, respectively. *High* and *Low Coincident Index* are differentiated by the median of a weighted average of Coincident Index with state deposits as weight. *Controls* include *Ln(GTA)*, *Sqr. Ln(GTA)*, *Capital ratio*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *Election year*, *SD (stock ret.)*, *GDP dispersion*. All variables are described in Tables 1 and A1. Coefficients on constant terms are omitted for brevity. *t*-statistics are reported in parentheses and are based on standard errors clustered at a bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dep. = *LH(total) / GTA*					
	(1) High Capital	(2) Low Capital	(3) Pre- Basel III	(4) Post- Basel III	(5) High Coincident Index	(6) Low Coincident Index
EPU(Composite)	**0.090*** **	**0.086*** **	**0.094*** **	**0.008** **	**0.079*** **	**0.068*** **
	(9.44)	**(8.45)**	**(9.71)**	**(2.48)**	**(5.29)**	**(4.63)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	511,323	511,321	959,913	62,731	511,257	511,387

Table A6: The effects of *EPU* on bank liquidity hoarding by survival categories

This table presents coefficient estimates from regressions of components of bank liquidity hoarding on *EPU(Composite)* by bank survival categories. A bank is categorized into *Surviving banks* if it exists throughout the whole sample period. A bank is categorized into *Exiting banks* if it exists at the beginning of the sample but subsequently exits the sample. A bank is categorized into *Entering banks* if it does not exist at the beginning of the sample but subsequently enters the sample. All other banks are categorized into *Other banks*. The sample includes 17,164 banks from 1985:Q2 through 2016:Q4. *Controls* include *Ln(GTA)*, *Sqr. Ln(GTA)*, *Capital ratio*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *Election year*, *SD (stock ret.), GDP dispersion*. Coefficients on *Controls* are omitted for brevity. All variables are described in Tables 1 and A1. *t*-statistics are reported in parenthesis and are based on standard errors clustered at a bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dep. = *LH(total) / GTA*				Dep. = *LH(asset) / GTA*			
	(1) Surviving banks	(2) Exiting banks	(3) Entering banks	(4) Other banks	(5) Surviving banks	(6) Exiting banks	(7) Entering banks	(8) Other banks
EPU(Composite)	**0.092*****	**0.080*****	**0.088*****	**0.086*****	**0.043*****	**0.039*****	**0.044*****	**0.036*****
	(8.00)	**(7.21)**	**(6.15)**	**(7.50)**	**(5.80)**	**(5.65)**	**(6.69)**	**(5.42)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	396,965	390,345	110,406	124,928	396,965	390,345	110,406	124,928

	Dep. = *LC(liab.) / GTA*				Dep. = *LH(off) / GTA*			
	(1) Surviving banks	(2) Exiting banks	(3) Entering banks	(4) Other banks	(5) Surviving banks	(6) Exiting banks	(7) Entering banks	(8) Other banks
EPU(Composite)	**0.032*****	**0.018*****	**0.021*****	**0.021*****	**0.017*****	**0.022*****	**0.023*****	**0.029*****
	(6.04)	**(3.01)**	**(2.63)**	**(3.58)**	**(11.35)**	**(9.11)**	**(11.54)**	**(10.80)**
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Number of obs.	396,965	390,345	110,406	124,928	396,965	390,345	110,406	124,928