Bank Management Sentiment and Liquidity Hoarding

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Abstract

We analyze how bank management sentiment affects liquidity hoarding by their banks. Our newly-created sentiment measure captures bank manager emotions based on language in their annual reports (10-Ks). We find that banks with more negative management sentiment hoard additional liquidity, rather than disbursing it to their customers. Our results also suggest how this tendency varies with bank and time period characteristics. Further analysis suggests that our findings incorporate bank volition to some degree, rather than only being driven by customers. Our findings are robust to using clearly exogenous weather conditions as instruments for sentiment. We finally suggest potential policy implications.

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"[T]he only thing we have to fear is fear itself – nameless, unreasoning, unjustified terror…"
President Franklin D. Roosevelt, Inaugural Address (1933)

1. Introduction

The sentiment of economic agents is a powerful force in the economy. Almost a century ago, Keynes (1936) argued that corporate investment and other key economic decisions are greatly influenced by "animal spirits." Researchers today find that the sentiments of different sets of agents have strong effects on many different economic and financial outcomes. Corporate finance researchers find that sentiment or human emotion plays a large role in corporate decision making (e.g., Ben-David, Graham, and Harvey (2013), Graham, Harvey, and Puri (2015), Jiang, Lee, Martin, and Zhou (2019)). Similarly, asset pricing research suggests that investor sentiment causes significant misallocations in financial markets that are not corrected by rational market forces (e.g., Shleifer and Vishny (1997), Baker and Wurgler (2006), Huang, Jiang, Tu, and Zhou (2015)). Researchers in household finance also find that consumer sentiment is impactful. The Index of Consumer Sentiment – compiled from households' responses to the University of Michigan Surveys of Consumers – is a significant predictor of consumer spending and other macroeconomic and financial market outcomes (e.g., Carroll (1992), Carroll, Fuhrer, and Wilcox (1994), Batchelor and Dua (1998), Lemmon and Portniaguina (2006)).

These findings of key economic and financial effects of corporate manager, investor, and consumer sentiment are also consistent with numerous studies of the effects of sentiment in the psychology and behavioral economics literatures (e.g., Rick and Loewenstein (2008), Lerner, Li, Valdesolo, Kassam (2014)). All of this research motivates us to investigate the role of the sentiment of the bank managers. Banks allocate trillions of dollars in assets, liabilities, and off-balance sheet activities, and their actions have substantial effects on the real economy (e.g., see Berger, Molyneux, and Wilson (2020) for a survey). Thus, to the extent that bank management sentiment affects bank behavior, this sentiment may also have significant economic and financial consequences.

We specifically hypothesize that negative bank management sentiment increases liquidity hoarding. Bank liquidity hoarding is a very broad concept involving bank assets, liabilities, and off-balance sheet

activities, and we hypothesize that negative sentiment affects all of these components. Our hypothesis is also motivated by three key strands of the banking literature, each of which tries to explain a problem behavior by banks with rational explanations. In each case, we offer an alternative explanation based on bank management sentiment.

The first strand of this literature concerns procyclicality in the bank lending behavior. The research suggests that banks lower their credit standards and increase on-balance sheet loans and off-balance sheet loan commitments during credit booms, possibly contributing to subsequent financial crises that cost these banks dearly (e.g., Thakor (2005), Acharya and Naqvi (2012), Berger and Bouwman (2017)). The banks then cut credit supply deeply during credit busts. The extant research offers rational explanations for these booms and busts. Under the institutional memory problem, bank loan officers' and/or bank managers' skills and memory deteriorate as the time lapses since they experienced last problem loans (Berger and Udell (2004)). These loan officers or managers approve more credit during booms when skills and memory are atrophied. These skills and memories are restored during busts and the banks reduce credit supply. In contrast to this rational explanation, we offer the possibility of sentiment swings. Bank managers may lower credit standards and lend more during booms because of positive sentiment during these times, and then cut back credit during busts due to negative sentiment.

The second strand of research suggests that banks often make negative net present value loans, sometimes referred to as "zombie lending," that hurts the banks as well as the rest of the economy (e.g., Peek and Rosengren (2005), Caballero, Hoshi, and Kashyap (2008), Acharya, Crosignani, Eisert, and Eufinger (2019)). This behavior is attributed in the literature to rational "evergreening," giving additional credit to existing problem borrowers to prevent or delay disclosure to regulators or markets of losses on prior loans (e.g., Bonfim, Cerqueiro, Degryse, and Ongena (2018)). In contrast, we offer the possibility that positive sentiment causes bank managers to overestimate the likelihood of loan repayment.

Third, other research suggests that banks hoard liquidity in the face of various types of uncertainty. Banks are found to hoard liquidity in response to uncertainty about economic policy (e.g., Berger, Guedhami, Kim, and Li (2020)), regulatory changes (e.g., Gissler, Oldfather, and Ruffino (2016)), and counterparty

risk (e.g., Afonso, Kovner, and Schoar (2011), Heider, Hoerova, and Holthausen (2015)). While these responses to uncertainty may be rational, we offer the alternative explanation that they responses may be irrational overreactions due to negative bank management sentiment.

An additional contribution of this paper is that we develop a novel measure of bank management sentiment based on textual analysis of banking organizations' annual 10-K reports and test its effects on individual bank behavior in the form of liquidity hoarding. Almost all publicly traded banking organizations that file 10-Ks are bank holding companies (BHCs) that own commercial banks, so the sentiment is measured at the BHC level for these organizations and at the bank level for independently-traded banks, but we refer to it as bank management sentiment in all cases for expositional convenience.

Our measure expands on the innovative literature in finance of textual analysis that explores the information content of corporate disclosure documents (e.g., Hwang and Kim (2017), Hanley and Hoberg (2019)). We construct a measure of negative sentiment for the management of individual banks based on the proportion of negative words minus positive words in 10-K reports from 1993:Q4 to 2016:Q4. We obtain 10-Ks files reported by all 837 publicly traded banks and BHCs and derive their tone using Loughran and McDonald (2011)'s dictionary of positive and negative words in a finance context.[1] We use the proportional difference between negative and positive words, consistent with an ancillary finding in our paper that negative and positive words contain roughly equivalent incremental information about bank liquidity hoarding behavior.[2] We also find substantial dispersion of negative management sentiment across banks, suggesting that this sentiment does not merely reflect macro events. As discussed in Section 2, our negative management sentiment measure offers some distinct advantages over the option-based bank CEO optimism indicator dummy employed in some other studies of bank behavior.

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[1] Examples of positive words in a finance context are "assure," "effective," and "rebound," while negative examples are "abnormal," "abrupt," and "controversial."

[2] Many studies in the textual analysis literature focus on the negative words, rather than positive words because negative words are used with more heed and care (e.g., Chen, De, Hu and Hwang (2014)). Our ancillary finding suggests that both negative and positive words suggests that positive words have approximately the same incremental value in our context of bank liquidity hoarding.

We use a comprehensive liquidity hoarding measure and its components developed by Berger, Guedhami, Kim, and Li (2020). It takes into account all balance sheet and off-balance sheet sources and uses of liquid funds, and is inclusive of all liquid and illiquid assets, liabilities, and off-balance sheet activities. This treatment contrasts with narrower measures of liquidity hoarding in the literature, such as specifying liquid assets alone, or including only a limited set of other balance sheet and off-balance sheet elements.[3]

To test our hypothesis, we regress the measures of bank liquidity hoarding on our new measure of negative bank sentiment, along with an extensive set of controls. We control at the macro level for the other major types of sentiment shown in the literature to have strong economic effects – corporate manager, investor, and consumer sentiment. We also include controls for other determinants of bank liquidity hoarding found in prior research – including economic policy uncertainty (EPU) and individual bank financial conditions – as well as borrower and local economy variables.

Importantly, both our dependent and key independent variables are measured at the bank-time level. This contrasts with the aggregate basis employed as in most of the sentiment literature – e.g., corporate sentiment by Jiang, Lee, Martin, and Zhou (2019), investor sentiment by Baker and Wurgler (2006), and consumer sentiment by Lemmon and Portniaguina (2006). Thus, our treatment allows for important cross-sectional differences in both sentiment and liquidity hoarding.

We recognize the possibility that observed bank liquidity hoarding could be driven by the customer demands for and supplies of liquidity as well as bank actions. We deal with this concern by analyzing the determinants of interest rate spreads on bank loans and credit lines using DealScan data, as well as spreads on deposits using RateWatch data. Loans, credit lines, and deposits are key elements of asset, off-balance sheet, and liability liquidity hoarding, respectively. While we cannot precisely separate bank from customer supply and demand effects, the price movements are indicative of whether bank supplies or demands are behind the quantity changes observed in our main results.. Thus, higher credit spreads in response to greater

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[3] See Berger, Guedhami, Kim, and Li (2020, Table 1 Panel B) for a complete list of these other measures.

bank negative sentiment would suggest that the observed cutback in credit quantities incorporates bank volition in withdrawing credit supply at least to some extent, rather than being entirely driven by reduced borrower credit demand. Analogously, higher deposit spreads would suggest that increases in deposit quantities reflect at least in part increases in bank deposit demand, as opposed to being driven only by depositors' supply.

We also acknowledge and deal with potential endogeneity problems. Bank management sentiment may be affected by the bank balance sheet and off-balance sheet activities that are part of our liquidity hoarding measures. There may also be spurious relations between sentiment and liquidity hoarding because of influential omitted variables. We deal with these potential endogeneity issues by using exogenous local weather conditions in the vicinity of bank headquarters to instrument for negative bank management sentiment. Weather conditions make rather ideal instrumental variables for bank sentiment because weather is clearly exogenously determined and has been found to have real effects on human sentiment (e.g., Lerner, Li, Valdesolo, and Kassam (2014)). A potential concern is that these weather conditions may also affect the sentiment of bank customers. Because our sample includes only publicly-traded banking organizations that generally have geographically widespread operations, the local weather conditions in the vicinity of bank headquarters are less likely to affect their customers' demands and supplies for banking services (c.f. Goetzmann, Kim, Kumar, and Wang (2015), Cortés, Duchin, and Sosyura (2016)). In a robustness check, we verify that our results hold in a subsample of only banks that operate in multiple states. To find the best instruments from a large number of weather conditions, we implement the least absolute shrinkage and selection operator (LASSO) of Belloni, Chernozhukov, and Hansen (2011).

We include annual sentiment data from all 837 publicly-traded U.S. banks and BHCs from 1993 to 2016, a total of 7,770 unique annual 10-K files. We employ 57,841 quarterly bank observations from 1993:Q4 to 2016:Q4 for our analysis of the effects of bank sentiment on liquidity hoarding. In these regressions, we use quarterly liquidity hoarding at the bank level and employ the most recent sentiment measure calculated for the BHC on the right hand side. Our analyses for the impact of bank sentiment on loan and credit line pricing are based on over 12,692 individual term loans and revolvers from the DealScan

database, as well as information on the corporate borrowers using Compustat. Our deposit spread analysis employs 394,428 observations from the RateWatch database. Our LASSO instrumental variable technique is based on combinations of 2,090 instrumental variables created from 144 different weather conditions in the vicinity of bank headquarters.

By way of preview, we find statistically and economically significant evidence supporting our hypothesis that banks with more negative manager sentiment hoard more liquidity. The findings are more pronounced for highly capitalized banks and during and especially after the Global Financial Crisis. Our investigations of interest rate spreads using DealScan, Compustat, and RateWatch data find statistically and economically significant higher spreads on loans, credit lines, and deposits, suggesting that our main results incorporate at least to some degree bank supplies and demands, rather than being driven entirely by customer behavior. Our IV results confirm the findings of both the main and spread analyses.

Our findings may also have policy implications. Bank management sentiment may interfere with the credit channel of monetary policy to the extent that the sentiment results in banks hoarding too much or too little of the liquidity provided by central banks. Similarly, sentiment may thwart prudential policy by causing banks to take on more or less risk than intended by bank regulators and supervisiors. As discussed in Section 6, our results may also bear on other policy issues. Such as the separation or integration of commericial and investment banking and countercyclical capital requirements.

The remainder of the paper is organized as follows. Section 2 presents the bank sentiment and liquidity hoarding measures. Section 3 reports our main empirical results of the effects of sentiment on liquidity hoarding, and Section 4 provides the analyses on interest rate spreads. Section 5 presents our analyses using local weather conditions as instruments for bank sentiment that support both the main liquidity hoarding and interest rate spread findings. Section 6 concludes and offers policy implications. The appendices provide additional information.

2. Data and key variables

2.1 Bank sentiment measure derived from textual analysis of annual reports

We construct our bank sentiment measure based on the textual tone of the most recent annual reports (form 10-K) of publicly traded banks and BHCs from 1993:Q4 to 2016:Q4. Using the PERMCO – RSSD identifier link provided by the Federal Reserve Bank of New York, we merge the Call Report information with the CRSP and COMPUSTAT dataset. As discussed above, most publicly-traded banking organizations are BHCs (with available RSSD9364 identifier), but we also include independent public banks (with available RSSD9001 identifier). We obtain 7,770 unique 10-Ks files reported by 837 publicly-traded institutions. We derive their tone using Loughran and McDonald (2011)'s dictionary of positive and negative words. We use the fraction of negative words minus positive words relative to total words in the 10-Ks as our measure of bank sentiment:

$$Negative\ bank\ sentiment = \frac{(Negative\ words - Positive\ words)}{Total\ words} \tag{1}$$

As noted above, an ancillary finding that negative and positive words have approximately equal effects on bank liquidity hoarding (see Appendix D) helps justify the use of the proportional difference in equation (1).

We are aware of two other studies of the effects of bank management sentiment that both employ dummies for option-based bank CEO optimism. Specifically, Bui, Chen, Lin, and Lin (2017) and Shu-Chun, Wei-Da, and Yehning (2018) observe if a bank CEO postpones exercising stock options that are more than 100% in the money at least twice during their tenure, and classify the CEO as optimistic from the time of the first delay. This measure originates in the corporate finance literature (e.g., Malmendier and Tate (2005); Campbell, Gallmeyer, Johnson, Rutherford, and Stanley (2011)).

We prefer our text-based measure of negative bank management sentiment to the CEO optimism dummy for studying the effects of sentiment on bank liquidity hoarding for several reasons. First, our text-based measure may be more representative of bank management as a whole because the 10-K is produced

and vetted by the management team, rather than only representing the thoughts of the CEO. Second, our measure is continuous, rather than a dummy. Thus, our measure allows for the possibility that stronger sentiment may have greater economic or financial effects. Finally, the exercise or non-exercise of financial options in the CEO's company stock is likely influenced by the CEO's personal wealth position, diversification motives, and risk aversion in addition to sentiment. In contrast, the 10-K is a professional document without direct links to the managers' financial conditions, and so may more accurately reflect sentiment.

Figure 1 shows the trends of individual banks' negative sentiment over time, normalized at the start of the sample period.[4] The figure clearly shows substantial heterogeneity across banks over time, suggesting that sentiment revealed in banks' annual reports have significant bank-specific determinants, and do not merely reflect macro events. *Negative bank sentiment* is widely dispersed during the 2008-2009 Global Financial Crisis period, implying that the market-level turmoil did not drive all banks' sentiment with same magnitude.

2.2 Bank liquidity hoarding measures

Our key dependent variables measure total bank liquidity hoarding *LH(total)* and its asset, liability, and off-balance sheet components, *LH(asset)*, *LH(liab)*, and *LH(off)*. These measures are developed by Berger, Guedhami, Kim, and Li (2020), who adapted them from Berger and Bouwman's (2009) liquidity creation measures. The liquidity hoarding measures include all the sources of liquid funds as well as their uses. Table 1 presents a detailed definition of the liquidity hoarding measures.[5]

Total liquidity hoarding, *LH(total)*, is the sum of asset-side, liability-side, and off-balance sheet-side components, *LH(asset) + LH(liab) + LH(off)*. *LH(asset)* = (+1/2) × liquid assets + (-1/2) × illiquid assets. Acquiring liquid assets, such as cash and securities, make the bank more liquid, as securities can usually be easily sold for cash. As well, procuring fewer illiquid assets, such as commercial and industrial

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[4] For this figure, we include 116 banks in existence at least 10 years since the starting year (1993) of our sample.
[5] Table 1 excludes items classified as semiliquid by Berger and Bouwman (2009), which are generally neutral that neither create nor hoard liquidity.

(C&I) loans, can also free up cash. The magnitudes of 1/2 mean that making $1 fewer C&I loans and storing the funds as $1 of cash increases bank liquidity hoarding by $1. Similarly, *LH(liab)* = (+1/2) × liquid liabilities because banks can also raise cash by issuing more liquid liabilities like transaction deposits. *LH(off)* = (-1/2) × illiquid guarantees + (+1/2) × liquid derivatives.[6] Illiquid guarantees, such as loan commitments, can be withdrawn quickly and drain cash, and liquid derivatives, measured by their gross fair values and can be sold to raise cash. In our empirical analyses, the *LH* measures are normalized by gross total assets (GTA) to be comparable across banks and avoid dominance by the largest banks.[7]

Notably, one of the two studies of bank CEO optimism noted above, Shu-Chun, Wei-Da, and Yehning (2018), examines this optimism's effects on bank liquidity creation. The authors find that banks with optimistic CEOs create more liquidity for the public per dollar of GTA than banks with non-optimistic CEOs. It is important to distinguish between bank liquidity hoarding and liquidity creation, both of which are key bank financial concepts with rich histories in terms of theoretical and empirical research.[8] Bank liquidity hoarding refers to liquidity held by the bank, while bank liquidity creation is liquidity supplied to the public by the bank. In terms of formulas, *LH(asset)* and *LH(off)* are direct opposites from the liquidity creation components *LC(asset)* and *LC(off)* and are measured as *-LC(asset)* and *-LC(off)*, respectively, using data from Bouwman's website (https://sites.google.com/a/tamu.edu/bouwman/data). However, *LH(liab)* gives the same positive sign to liquid liabilities as *LC(liab)*, instead of the opposite sign. This is because liquid liabilities like transactions deposits help the bank hoard liquidity by providing the bank with a source of liquid funds, while also creating liquidity for the public.

Table 2 Panel A reports summary statistics for the 57,841 bank-quarter observations from 1993:Q4 through 2016:Q4. Total bank liquidity hoarding normalized by GTA, *LH(total)/GTA* has a mean of 0.074, suggesting that banks hoard liquidity of 7.4% of GTA on average. The liquidity hoarding measure has a

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[6] In Berger and Bouwman (2009), "net participations acquired" is labeled as liquid guarantees. For expositional convenience, we include "net participation sold," its arithmetic inverse, as an item of illiquid guarantees.

[7] Gross total assets (*GTA*) equals total assets (*TA*) plus the allocation for loan and lease losses (*ALLL*), which accounts for expected losses, and the allocated transfer risk reserve (*ATRR*), a reserve for certain troubled foreign loans. *GTA* incorporates the full value of all the assets that are included in the bank liquidity hoarding measures.

[8] Bank liquidity hoarding research is summarized in Berger, Guedhami, Kim, and Li (2020)), while Berger and Bouwman (2016) review bank liquidity creation research.

wide dispersion across banks with the 25th and 75th percentile values at -0.050 and 0.193, respectively. Asset-side liquidity hoarding, *LH(asset)/GTA*, has a mean value of -0.080 with the 25th and 75th percentile values at -0.183 and 0.013, respectively. The negative mean value of *LH(asset)/GTA* occurs because banks often hold more illiquid assets (e.g., commercial loans) with negative weights than liquid assets (e.g., cash and due from other institutions, securities) with positive weights. Mean liability-side liquidity hoarding (*LH(liab)/GTA*) is 0.239. The mean liquidity hoarding off the balance sheet (*LH(off)/GTA*) is -0.084. The negative sign mostly reflects loan commitments, which are illiquid from banks' point of view.

2.3 Descriptions and summary statistics for the control variables

We obtain bank-specific variables (e.g., asset size and equity ratio) and local market conditions (e.g., populations) from Call Reports and the Federal Reserve Bank of St. Louis, respectively. We compute the economic conditions of banks' potential customers (*Tobin's Q,* and *Cash flows*) based on information from Compustat. Potential customer firms of banks are those in the banks' states of operation. We take the weighted average of these variables for each bank based on the proportion of a bank's deposits in each area (MSA or county). We obtain bank deposit amounts per branch from the Summary of Deposits by FDIC (from 1994 to 2016) and Bouwman's website (from 1985 to 1993). Appendix A presents more detailed definitions of all variables used in the analysis.

Table 2 Panel A also shows summary statistics for the control variables. The median size of banks *Ln(GTA)* is 13.53, or corresponding to $752 million.[9] *Capital ratio* has a mean of 0.078 and most banks have capital ratios between 0.06 and 0.09. *Earnings*, as measured by return on assets (ROA) is distributed around 0.011 (median) with average value of 0.01. The average value of bank competition measure, Herfindahl–Hirschman Index (*HHI*) based on bank deposits, is 0.108. The *Tobin's Q* of firms in the states where a bank has operation is an average value of 2.419, similar to the average value for firms in the full CRSP/Compustat universe (e.g., Bertrand and Schoar (2003)). *Cash flows* is widely dispersed across firms in different locations with 25th percentile at -0.014 and 75th percentile at 0.017. The average corporate

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[9] All dollar amounts in Table 2 are measured in real 2016 dollars.

sentiment index (*Corporate sentiment*) is -0.072 with standard deviation of 1.043. The percentiles of the investor sentiment measure (*Investor sentiment*) show there is wide variation in investor sentiment; the 25th percentile number of *Investor sentiment* is -0.077 and the 75th percentile number is 0.567. The average index of consumer sentiment by University of Michigan (*Consumer sentiment*) is 88.713 during the sample period. The average values for TED spread and EPU are 0.514 and 4.570, respectively.

Table 2 Panel B present Pearson correlation matrix among *Negative bank sentiment* and macro-level controls including the other sentiment measures.Not surprisingly, negative bank sentiment is inversely correlated with economic growth (GDP growth). The *Negative bank sentiment* is also associated with other macro-level sentiment measures including *Corporate, Investor and Consumer sentiment*, as well as *EPU*. To control for potential confounding effects of these sentiment measures on bank liquidity hoarding, we include all these macro-level variables in our regression specifications.

3. Regression analysis of the impact of bank sentiment on liquidity hoarding

To test our hypothesis, we estimate regressions of the form:

$$(LH/GTA)_{i,t} = \beta Negative\ bank\ sentiment_{i,t-1} + \delta'X_{i,t-1} + \theta'W_{i,t-1} + \nu S_{t-1} + \gamma'Z_{t-1} + \alpha_i \quad (2)$$
$$+ q_t + \epsilon_{i,t},$$

where *i* and *t* index a bank and a calendar quarter, respectively. The dependent variable is one of the normalized liquidity hoarding measures: *LH(total)/GTA*, *LH(asset)/GTA*, *LH(liab)/GTA,* or *LH(off)/GTA*. The key independent variable is the *Negative bank sentiment*, measured from the most recent bank annual report. To mitigate potential reverse-causality concerns, we lag the independent variables. Our bank control variables (*X*) include *Ln(GTA), Sqr.Ln(GTA)*, *Capital ratio,* and *Earnings* to account for bank size, leverage and earnings. We also control for the local market and corporate demand for investment (*W*): bank competition (*HHI),* local market size (*Population),* local firms' average value (*Tobin's Q),* their cash flows (*Cash flows*) and economic growth (*GDP growth*). We include market-level sentiment measures (*S*) of corporate manager sentiment (*Corporate sentiment)* by Jiang, Lee, Martin, and Zhou (2019), investor sentiment (*Investor sentiment*) by Baker and Wurgler (2006), and the index of consumer sentiment by

University of Michigan (*Consumer sentiment*).[10] Controls for other macro conditions (*Z*) include *TED spread* and economic policy uncertainty (*EPU*). 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 at the bank and year-quarter level to account for correlations of error terms.

3.1 Main regressions of bank liquidity hoarding on bank sentiment

Table 3 Panel A presents coefficient estimates from regressions of *LH(total)/GTA*) on *Negative bank sentiment* and the controls. In column (1), we control for bank characteristics and bank and seasonal fixed effects and observe the estimated coefficient on *Negative bank sentiment* is positive and statistically significant at 1% level. In column (2), we additionally control for local market-level variables and continue to find a positive and statistically significant result. This result suggests that the impact of *Negative bank sentiment* on bank liquidity hoarding is not driven by local market characteristics, such as corporate demand for cash or investment opportunities. In column (3), we include well-known sentiment measures affecting corporate managers (*Corporate sentiment*), investors (*Investor sentiment*), and consumers (*Consumer sentiment*) as well as other macro variables (*GDP growth*, *TED spread*, and *EPU*) along with seasonal fixed effects. The coefficient on *Negative bank sentiment* is still positively and statistically significant at the 1% level. This result suggests that bank sentiment has an incremental impact on their liquidity hoarding behavior beyond corporate, investor, and consumer sentiment and other macro variables.

The results in Panel A, Table 3 strongly support our hypothesis. The economic significance of the estimates is also sizable. In our preferred full specification (column 3), a one-standard-deviation increase in *Negative bank sentiment* leads to a 1.7 percentage point increase in *LH(total)/GTA*.[11]

Table 3 Panel B presents coefficients estimates from regressions of bank liquidity hoarding

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[10] The corporate manager sentiment data is only avaliable during 2003-2014. To avoid contracting the sample period, we create a dummy variable to indicate whether manager sentiment information is avaliable or not and replace the missing values with the avearge values of available information. In regression models, we include the manager sentiment measure along with this dummy variable.

[11] This is calculated as the coefficient (3.453)×standard deviation of bank sentiment (0.005) =1.7%.

components, *LH(asset)/GTA*, *LH(liab)/GTA*, and *LH(off)/GTA*, on *Negative bank sentiment* using the full preferred specification with all the controls. The estimated coefficients on *Negative bank sentiment* are all positive and statistically significant except for in the case of assets, suggesting that an increase in the *Negative bank sentiment* leads to an increase in most of the components of bank liquidity hoarding. In Appendix B, we further investigate the lack of statistical significance for the effects on *LH(asset)/GTA*, and find that this appears to be due to a weak effect on loans. The response of cash holdings to negative sentiment is strong and highly significant, but the effect on loans is not statistically significant. In terms of economic significance, a one-standard-deviation increase in *Negative bank sentiment* is associated with a 1.4 percentage increase in *LH(liab)/GTA* and a 0.2 percentage increase in *LH(off)/GTA*, suggesting that the strongest effects may be on the liability side.

Collectively, the Table 3 results support our hypothesis – *Negative bank sentiment* increases bank liquidity hoarding.

3.2 Effects of bank sentiment by bank capital and time period

We next analyze whether our findings differ by bank capital ratios and time periods. In Table 4 Panel A, we regress *LH(total)/GTA* and its components on *Negative bank sentiment* and its interaction term with *High capital ratio*, a dummy equal to one if lagged *Capital ratio* is greater than its 75th percentile for that point in time and zero otherwise.[12] We also include all of the controls and fixed effects from full specification in column (3) of Table 3 Panel A.

We recognize that banks with high capital ratios differ in numerous ways from other banks, making the interaction effect difficult to predict. High capital is likely to be associated with better bank health and reduced likelihood of interventions or restrictions imposed by government supervisors. As a result, liquidity hoarding may be less sensitive to bank sentiment, as the management of these healthy, less encumbered banks need to worry less about the market and supervisory dangers of liquidity shortfalls. However, a high capital ratio may also be associated with more conservative or prudentially concerned managers that hold

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[12] All analysis results are robust to using 90% capital ratio as a cutoff for the *High capital ratio* variable.

more capital to protect the bank's franchise value or their own employment. More conservative or prudent managers may respond more than other managers to negative sentiment because of a greater fear of illiquidity problems. It is an empirical question as to which of these effects may dominate.

In the first column of Table 4 Panel A, the interaction term is positive and highly statistically significant, suggesting that the impact of *Negative bank sentiment* on total liquidity hoarding is greater when a bank's *Capital ratio* is high. This is consistent with the prudent manager prediction, but we refrain from drawing strong causal conclusions because other factors that may affect the results are excluded from the specification. In terms of the economic significance, the result in column (1) (coeff. = 3.302, *t*-statistic = 6.49) suggests that a one-standard-deviation increase in *Negative bank sentiment* for high capital banks is associated with an additional 0.8 percentage increase in the *LH(total)/GTA* compared to low capital banks. This interaction term coefficient also exceeds the linear term coefficient on *Negative bank sentiment*, suggesting that the effects of sentiment on high-capital banks are more than double those on other banks. The interaction terms in columns (2)-(4) are also all positive and statistically significant, suggesting that high-capital banks increase all the components of liquidity hoarding – i.e., the asset-, liability-, and off-balance sheet-sides – more than other banks in response to negative management sentiment.

In Table 4 Panel B, we test whether the effects of negative sentiment vary across key time periods for *LH(total)/GTA* and its components. Specifically, we examine the differences in the effects of bank sentiment on liquidity hoarding among the pre-crisis, Global Financial Crisis, and post-crisis time periods. Thus, following Berger and Bouwman's (2013) crisis definition, we interact *Negative bank sentiment* with *Global Financial Crisis*, a dummy for the period 2007:Q3-2009:Q4, and *Post crisis*, a dummy from 2010:Q1-2016:Q4, leaving the pre-crisis period 1993:Q4-2007:Q1 as the omitted base case. As above for the tests of the effects of capital, we also include these time dummies and all of the controls and fixed effects from full specification of the model.

Similar to the interactions with the *High capital ratio*, it is difficult to predict *ex ante* the effects of the interactions of *Negative bank sentiment* with *Global Financial Crisis* and *Post crisis* because several external forces acted on banks during these two periods. During these periods, market forces and

government policies in some cases assisted banks with their liquidity hoarding, potentially easing banks' concerns about their liquidity and mitigating the effects of bank-specific negative sentiment on liquidity hoarding. During the crisis, deposits flowed into banks from those seeking safe havens (e.g., Acharya and Mora (2015)), and government authorities provided liquidity as well (e.g., the Federal Reserves' discount window, Term Auction Facilities (TAF), and expansive conventional and unconventional monetary policies, the Troubled Asset Relief Program (TARP), and other bailouts).[13] The Federal Reserve also encouraged bank liquidity hoarding through paying interest on bank reserves. During the post-crisis period, expansionary conventional and unconventional monetary policy and interest on reserves continued to help increase bank liquidity hoarding. During this period, the phasing in of the Basel III liquidity requirements also encouraged bank liquidity hoarding.

However, other market forces and government policies in some cases made bank liquidity hoarding more difficult during these two periods, potentially amplifying bank managers' concerns about their banks' liquidity and intensifying the effects of negative bank sentiment on liquidity hoarding. In the crisis period, many business customers drew down their loan commitments (e.g., Ivashina and Scharfstein (2010)), reducing banks' liquidity hoarding.[14] The sometimes frozen and frosty conditions in interbank and syndicated loan markets also created difficulties for some banks in hoarding liquidity. In the post-crisis period, additional regulation and supervision from the implementation of the 2010 Dodd-Frank Act and the phasing in of the Basel III capital requirements could have also increased bank managers' concerns and increased the effects of negative management sentiment on liquidity hoarding.

We again look to the empirical results to resolve these issues. The findings in Table 4 Panel B suggest slightly stronger effects of negative bank sentiment during the crisis period for total liquidity

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[13] The Federal Reserve widely opened its liquidity facilities through its expanded discount window (DW) and Term Auction Facilities (TAF), pumping almost $4 trillion in liquidity into the banks (e.g., Berger, Black, Bouwman, and Dlugosz (2017)). The Federal Reserve expanded its balance sheet as well through both conventional monetary policy and unconventional quantitative easing. The U.S. Treasury, Federal Reserve, FDIC, Federal Home Loan Banks, and other agencies provided hundreds of billions more in liquidity through the Troubled Asset Relief Program (TARP) and other bailouts (see the survey in Berger and Roman (2020)).

[14] Drawing down $1 of loan commitments decreases loan commitments by $1, increases loans by $1, and decreases cash by $1. Since loan commitments and loans have -1/2 weights and cash has a +1/2 weight, bank liquidity hoarding goes down by -$0.50.

hoarding stemming primarily from off-balance sheet liquidity hoarding. The data show much stronger effects of negative sentiment on liquidity hoarding during the post-crisis period, with the exception of the liability side. In terms of economic significance, a one-standard-deviation increase in *Negative bank sentiment* is associated with additional 1.7 percentage and 5.6 percentage increases in *LH(total)/GTA* during the crisis and post-crisis periods compared to the pre-crisis period.

Our findings of strong impacts of negative bank sentiment on bank liquidity hoarding during the post-crisis period in Table 4 Panel B is consistent with our findings in Table 4 Panel A. The tougher regulation and supervision after the crisis may have encouraged bank managers to be more cautious and prudent, so they hoarded more liquidity in response to negative sentiment during the post-crisis period.

3.3 Additional analyses and robustness checks

To better understand the mechanisms behind the main findings, we next regress selected bank balance sheet and off-balance sheet items that make up much of the bank liquidity hoarding measure on *Negative bank sentiment*, and again include all the controls and fixed effects in the regressions. The findings are shown in Appendix B. We find that when *Negative bank sentiment* increases, banks increase cash holdings, and the results are highly statistically significant. They also decrease loans and loan commitments, although the effects through loans are not statistically significant. When bank managers have more negative sentiment, their banks also hoard more liquidity through increased deposits. This item-by-item analysis reinforces our main findings and suggests that several mechanisms are at work in explaining the findings.

While we control for many macro variables, our estimates might be biased by the inadvertent omission of some key macro variables. In Appendix C, we include year-quarter time fixed effects to rule out the possibility that our findings are driven by unobservable macro variables affecting both bank sentiment and liquidity hoarding. The estimated coefficient on *Negative bank sentiment* is still positive and statistically significant at 5% level, although somewhat smaller in magnitude, suggesting that our findings are robust to confounding effects of unobservable macro-level conditions. This additional result suggests that the impact of *Negative bank sentiment* is not merely reflecting other market-level sentiments, but it

signifies that *Negative bank sentiment* is indeed an important determinant of the bank liquidity hoarding.

Many studies in the textual analysis literature focus on the negative words only, arguing that negative words are used with more heed and care than positive words (e.g., Chen, De, Hu and Hwang (2014)). To address this issue, we include the ratios of negative words and positive words to total words separately in Appendix D. The estimated coefficients on negative words and positive words are positive and negative, respectively, and reasonably close in magnitude, justifying our combined treatment in our *Negative bank sentiment* measure.

We further test if negative bank management sentiment is a concern for banks of different sizes. Columns (1) and (2) of Table 5 report coefficient estimates on *Negative bank sentiment* for small and large banks, respectively, divided based on median GTA for each year. The results suggest that our main findings hold with positive and statistically significant coefficients for both small and large banks.

A key policy issue in the U.S. since the 1930s is whether BHCs should be allowed to combine commercial and investment banking in the same corporate organization. After the systemic risk consequences of the 2008 bankruptcy of stand-alone investment bank Lehman Brothers, authorities encouraged other large investment banks, including Goldman Sachs and Morgan Stanley, to join BHCs with commercial banks to help reduce risks. Currently, many argue to the contrary that that such combinations increase risks. Thus, a key issue here is whether the combined institutions are more or less swayed by management sentiment as stand-alone commercial banks. In column (3) of Table 5, we estimate the main regression for banks and BHCs with commercial banks only, while column (4) reports results for BHCs with both commercial and investment banks. The coefficient estimates on *Negative bank sentiment* are positive and statistically significant for both sets, but the findings are several times stronger for the combined institutions. While policymakers have many other systemic risk and other considerations in their policy choices about the structure of the industry, our findings here suggesting that the combined firms' bank liquidity hoarding decisions may be more influenced by managerial emotions may be an additional consideration.

A potential econometric concern with our analyses is that in some cases we may be using "stale"

sentiment information. Our baseline result is based on annual sentiment measure from the most recent annual reports, which may not always be so recent. In column (5) of Table 5, we reestimate the main regression equation (2) excluding the "stale" observations whose *Negative bank sentiment* is measured more than one quarter prior to the quarter of the liquidity hoarding dependent variable. The results continue to be positive and statistically significant.

Another potential concern is that the *Negative bank sentiment* measure may be confounded by the writing quality of the financial report. In column (6) of Table 5, we reestimate our regression by additionally controlling for the readability of the 10-K. We use the Gunning-Fog-Index to measure the readability of 10-Ks (Li (2008)). The coefficient estimate is still positive and statistically significant with similar magnitude to our baseline result, suggesting that this potential concern does not drive our findings.

4. The effects of *Negative Bank Sentiment* on interest rate spreads: Evidence from pricing of loans, credit lines, and deposits

So far, we find that *Negative bank sentiment* is associated with increased bank liquidity hoarding. However, we acknowledge that this result could be driven by both banks' supply and demand choices and customers' supplies and demands for the items that comprise bank liquidity hoarding. We want to ensure that our findings do not simply reflect customer choices. To do so, we measure the effects of *Negative bank sentiment* on interest rate spreads for loans, credit lines, and deposits, which are important asset-side, off-balance sheet-side, and liability-side liquidity hoarding elements. We see if these spreads move in the directions of bank supply and demand choices versus those of their customer counterparties. If they move in the directions of bank choices, this would be evidence that our main findings on bank liquidity hoarding quantities reflect bank choices in reducing credit supply or increasing deposit demand at least to some extent, rather than being entirely driven by customer choices.

For the pricing of loans and credit lines, we employ credit spreads from Loan Pricing Corporation's (LPC's) DealScan database on commercial term loans and revolving lines of credit, representing on- and

off-balance sheet credits, respectively. [15] We link the DealScan data with borrowers' accounting information from Compustat and bank characteristics from Bank Call Reports because the credit risk of borrowing firms and the characteristics of lending banks are crucial determinants of credit spreads.[16] We include only the lead bank in our analyses because it is the main decision maker on credit terms.[17]

We acknowledge the difficulty with using DealScan data that most of the loans are at least partially syndicated, so that only parts of the credits are usually retained by the lead bank. Thus, some of the supply of credit is by other banks and other syndicate members. However, the lead bank generally retains significant portions of these loans, and DealScan has the benefit of reporting detailed pricing and contract terms on the loans, and being able to match it to Compustat data on the firms. Thus, we believe that the benefits of using these data outweigh any estimation noise introduced by the syndication.

We estimate regressions of the form:

$$Credit\ spread_{i,j,t} = \rho Bank\ Sentiment_{i,t-1} + \pi^{'} V_{j,t-1} + \vartheta^{'} K_{i,j,t} + X_{i,t-1} + W_{i,t-1} + Z_{t-1} \tag{3}$$

$$+\alpha_i + q_t + \epsilon_{i,j,t},$$

where $i, j,$ and t index a bank, a borrower, and a calendar quarter, respectively. The dependent variable (*Credit spread*) is the borrowing credit spread plus annual fee (if any) the borrower pays in percentage over LIBOR, obtained from DealScan. [18] We include bank fixed effects (α) to control for omitted bank characteristics that are invariant over time; quarter dummies (q) to account for seasonality; and borrower characteristics (V) to account for credit risk, 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*),

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[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] 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.

[17] 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," "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.

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

and credit rating (*Credit rating*).[19] To further control for loan risk, we add credit contract variables (*K*), including credit amount (*Credit size*), maturity (*Ln(Maturity)*), collateral (*Secured*), and covenants (*Covnt. index*). In addition, we control for bank-level characteristics (*X*), local market and corporate demand variables (*W*), and macro-level sentiment and market condition measures (*Z*) as in equation (2). All variables are described in Appendix E.

Table 6 Panel A presents the summary statistics of these variables by term loans and revolvers. The final sample is at the loan facility-bank level including 266 lead banks and 5,199 borrowing firms from 1993:Q4 through 2016:Q4. There are 12,893 observations for term loans and 36,507 for revolvers.

Table 7 columns (1)–(2) report the estimated impact of *Negative bank sentiment* on the *Credit spread* in equation (3) for term loans and columns (3)-(4) report comparable information for revolvers. For both credit types we follow the convention in the research literature of first excluding the other credit contract terms and then including them with the other controls. The inclusion of these terms is because credit spreads usually depend on the other terms that affect loan risk, such as collateral pledged. The exclusion is because to some extent all the other credit terms are determined endogenously with the spreads. In all regression specifications, the estimated coefficients on *Negative bank sentiment* are positive, consistent with the direction of our hypothesized reductions in bank supply in response to negative bank management sentiment, rather than reduced demand for credit. Thus, our main findings of reduced credit likely reflect at least in part bank volition in reducing credit supply, rather than simply the effects of customer credit demand.

We next check the direction of the effects of *Negative bank sentiment* on deposit spreads to see if our finding of increased liability-side liquidity hoarding reflects at least in part increases in banks' demands for deposits. We use the following specification:

$$Deposit\ Spread_{i,t} = gBank\ Sentiment_{i,t-1} + l'X_{i,t-1} + m'W_{i,t-1} + n'Z_{t-1} + \alpha_i + q_t + \epsilon_{i,j,t} \qquad (4)$$

where *i* and *t* indicates a bank and a calendar quarter, respectively. The dependent variable is a *Deposit*

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[19] For the missing credit rating information in CRSP dataset, we create a dummy variable to indicate whether a borrower has a credit rating information or not. We replace the missing values with the avearge values of available information and include this dummy variable in the regression.

spread for checking accounts, savings accounts, or money market accounts relative to the three-month T-bill rate. The key independent variable is *Negative bank sentiment*. We lag the independent variables to alleviate potential reverse-causality concerns and include the same set of controls with equation (2). Unlike the credit-spread analysis in Table 7, we include only bank and macro variables because depositor details are not available.

We obtain deposit spread information from the RateWatch database. The bottom part of Table 6 provides summary statistics for the deposit spreads. The RateWatch data start in 1998. The data contain 605 unique banks and 394,428 observations at the bank-deposit product-calendar quarter level from 1998:Q1 to 2016:Q4.

Table 8 reports the findings. The coefficient estimates on *Negative bank sentiment* are all positively and statistically significant for the checking accounts, savings accounts and money market accounts. These results are consistent with our main findings of increased liability-side liquidity hoarding reflecting at least to some degree increases in banks' demands for deposits.

5. Endogeneity of bank sentiment and instrumental variable analysis

There is a potential endogeneity concern regarding *Negative bank sentiment*. Omitted explanatory variables affecting both bank sentiment and liquidity hoarding may bias our OLS estimates. For example, banks may observe latent indicators of future economic conditions, which may drive both *Negative bank sentiment* and their liquidity hoarding.

To address this concern, we use local weather conditions in the vicinity of bank headquarters as instrument variables for banks' sentiment. Weather conditions are appealing instruments for bank sentiment because weather is exogenously determined, and it is shown to have real effects on human sentiment (e.g., Lerner, Li, Valdesolo, and Kassam (2014)). We posit that the local weather conditions near bank headquarters influence the sentiment of bank officials writing annual reports, which then affects their liquidity hoarding decisions.[20] Our identification strategy is to estimate the impact of weather-driven

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[20] For studies showing that weather conditions affect decision-making by investors and managers, see, e.g.,

sentiment on banks' behavior, so our empirical analysis estimates the local average treatment effect (LATE) of the banks whose sentiment is sensitive to changes in the exogenous weather conditions.

From the National Oceanic and Atmospheric Administration (NOAA)'s Climate Database, we obtain a broad set of weather information, including cloud coverage, one-hour or six-hour precipitation, air temperature, dew point temperature, wind speed, wind direction, and sea level pressure at the day-hour-weather station level. We select weather conditions only during local working hours 8:00AM – 5:00PM for the working days of a week.

The large set of weather conditions poses a challenge. Using many weather conditions as instruments carries the risk of overfitting the first-stage regressions. Hand-picking some of the instruments raises data-mining concerns.

To overcome the overfitting and data-mining problems, we implement the least absolute shrinkage and selection operator (LASSO) to select the best instrumentals, following Belloni, Chernozhukov, and Hansen (2011) and Gilchrist and Sands (2016). The LASSO method offers a principled procedure for selecting instruments and provides well-performing results compared to other robustness procedures for instrumental variables (Belloni, Chen, Chernozhukov, and Hansen (2012)).

For LASSO, we consider 144 seasonally-adjusted weather conditions on weekdays (i.e., Tuesday only, Tuesday to Thursday, or Monday to Friday) during working hours with one- or two-quarter lags adjusted by prior one-, two-, or three-year' average weather condition in the same quarter of the year.[21] We choose one- or two-quarter lags of weather conditions based on the assumption that the annual report 10-K is prepared mainly in the last quarter of fiscal year and it takes about two or three months for the completed 10-K files to be prepared and updated to the SEC EDGAR system.[22] We create dummies for each of the

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Hirshleifer and Shumway (2003), Bassi, Colacito, and Fulghieri (2013), Goetzmann, Kim, Kumar, and Wang (2015), Cortés, Duchin, and Sosyura (2016).

[21] To account for seasonal variation of weather conditions, we construct seasonally adjusted weather conditions for cloud coverage, one-hour or six-hour precipitation, air temperature, dew point temperature, wind speed, wind direction, and pressure using Tuseday only, Tuseday to Thursday, or Monday to Friday working hours information and lagging one or two quarters.

[22] For example, Apple Inc. has fiscal year 2018 ending in September 29, 2018. The 2018 annual report was filed to the SEC EDGAR system on November 5, 2018. We posit that the annual report was mainly prepared during June – October, 2019.

144 local weather conditions to account for potential nonlinear relations between sentiment and weather conditions (Gilchrist and Sands (2016)). Specifically, we create cloud coverage dummies in 1 okta bins for each of the cloud coverage variables, where an okta is a measure of cloud cover ranging from 0 (completely clear sky) to 8 (completely overcast). Similarly, temperature dummies are in 5-degree celsius bins, sea level pressure dummies are in 5 hectopascals bins, where hectopascals are international units of barometric pressure that are increasing in this pressure, and one-hour or six-hour precipitation are in 20 millimeters bins. The selection of bin width is based on the previous literature (Gilchrist and Sands (2016)) and the computational concern. In total, we include 2,090 dummy variables indicating different levels of local weather conditions of bank headquarters in our LASSO selection model.

The first LASSO-chosen instrument is the seasonally-adjusted cloud coverage dummy indicating a -3 to -2 oktas difference between the current and preceding 3-year's average from Monday to Friday working hours with one-quarter lags. When we choose two instrumental variables, LASSO additionally chooses the cloud coverage dummy indicating the same difference (-3 to -2 oktas) between the current and previous three-years average from Monday to Friday with two-quarter lag. When choosing three instrumental variables, LASSO additionally selects the sea level pressure dummy for the 0 to 5 hectopascals difference between the current and previous three-years average from Tuesday to Thursday with two-quarter lags as the best instrumental variables for the bank sentiment measure. The choice of cloud coverage is largely consistent with prior studies in the literature (e.g., Goetzmann, Kim, Kumar, Wang (2014), Chhaochharia, Kim, Korniotis, Kumar (2019)). In total, we consider these three instrumental variables for the bank sentiment.

Table 9 Panel A reports the first-stage regressions of the *Negative bank sentiment* on the LASSO-chosen instrument variables. The coefficients on the instrumental variables based on seasonally-adjusted weather conditions are all statistically significant at 1% level, and the *F*-stats are all well above the conventional threshold for the weak instrumental variables (Stock and Yogo (2005)). We use all three

instrumental variables for implementing the two-stage least squares analysis.[23]

In the second-stage regressions in Table 9 Panel B, we regress the liquidity hoarding measures on the instrumented *Negative bank sentiment* measure and the controls. The *t*-statistics are based on bootstrapped standard errors to mitigate biases from errors in the estimated independent variables. The estimated coefficients on the instrumented *Negative bank sentiment* all have the same positive signs as our main results in Table 3, and all are statistically significant. The estimated coefficients on *Negative bank sentiment* in the 2nd-stage regressions are greater in magnitude than the baseline OLS regressions because we are estimating the local average treatment effect (LATE) for bankers who are more sensitive to the weather conditions.[24] Regarding the economic magnitude, a one-standard-deviation increase in the *Negative bank sentiment* leads to a 12.14 percentage point increase in (*LH(total)/GTA*).

In Table 9 Panel C, we report the coefficient estimates from the 2nd stage regressions of credit and deposit spreads on the instrumented *Negative bank sentiment* measure and other controls. The estimated coefficients on the *Negative bank sentiment* are all positive and statistically significant. These results are consistent with those in Tables 7 and 8, again suggesting that our main results reflect at least in part the supplies and demands of the banks, rather than just the choices of their customers.

A potential concern for the validity of the instrumental variable analysis is that the weather conditions near bank headquarters would also affect their customers (Chhaochharia, Kim, Korniotis, and Kumar (2019)). This concern is somewhat mitigated in our empirical setting because our sample of publicly-traded banks and BHCs often have extensive geographic footprints beyond the headquarters where the weather is measured. Nonetheless, to further address this concern, we restrict our sample to BHCs operating in multiple states. The IV analysis results presented in Appendix F confirm the impact of negative bank sentiment on liquidity hoarding with similar statistical significance and economic magnitudes.

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[23] Results with only one or two instrumental variables are qualitatively and quantitatively similar.

[24] In other words, the IV analysis estimates the impact of bank sentiment on liquidity hoarding for the "emotionally sensitive" banks. Because the identification strategy is based on weather-driven sentiment, banks who are more emotionally sensitive would be likely to be affected by these exogenous shocks. And their tendency to change their liquidity hoarding due to sentiment would be greater than other banks whose sentiments are less dependent on weather conditions. The increased magnitude of estimated local average treatment effects is not uncommon in financial economics research (see, Jiang (2017))

6. Conclusions and policy implications

We develop a new measure of bank management sentiment for individual institutions over time based on textual analysis of banks' annual reports (form 10-K), and test its effects on bank liquidity hoarding. Our empirical analysis finds that negative bank management sentiment increases bank liquidity hoarding, controlling for a large set of bank- and market-level characteristics. Additional analyses suggest that the effects occur on both sides of the balance sheet and off the balance sheet, that the findings reflect at least to some degree bank supply and demand choices as opposed to their customers' choices, and that the results are highly robust to an advanced instrumental variable approach. The sentiment-driven liquidity hoarding behavior is more pronounced for banks with high capital ratios and during and especially after the Global Financial Crisis. The findings are also more pronounced for BHCs with investment banks than organizations with only commercial banks.

Our findings have some potential policy implications. First, our main results suggest that negative bank sentiment may interfere with the effective operations of some policies. For example, expansionary monetary policy may be thwarted by negative bank sentiment that causes more of the additional liquidity injected by the central bank to be hoarded by banks. Timely implementation of prudential policies could be impeded by an exuberant sentiment of bank managers who take on excessive risks.

Second, as discussed above, we find that BHCs with investment banks may be much more swayed by management sentiment in their bank liquidity hoarding decisions than commercial banking organizations without investment banks. Investigation of the full consequences of this finding is beyond the scope of this paper, but such consequences might help inform policymakers considering these banking powers.

Third, on a more speculative note, policymakers may be able to influence the effects of negative bank sentiment on bank liquidity hoarding behavior. Some of our analyses suggest that higher bank capital and harsher regulatory and supervisory treatment may increase the effects of negative bank sentiment on liquidity hoarding. Thus, subject to the Lucas critique that changes in policy may alter the underlying model, policymakers may be able to encourage more bank liquidity hoarding during a boom by requiring higher

capital and other strict regulation and supervision. Such policies might be reversed during a bust. A consequence is that countercyclical capital requirements may be more effective than previously thought.

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Figure 1: The pattern of individual *Negative bank sentiment* over time (1993:Q4 – 2016:Q4)
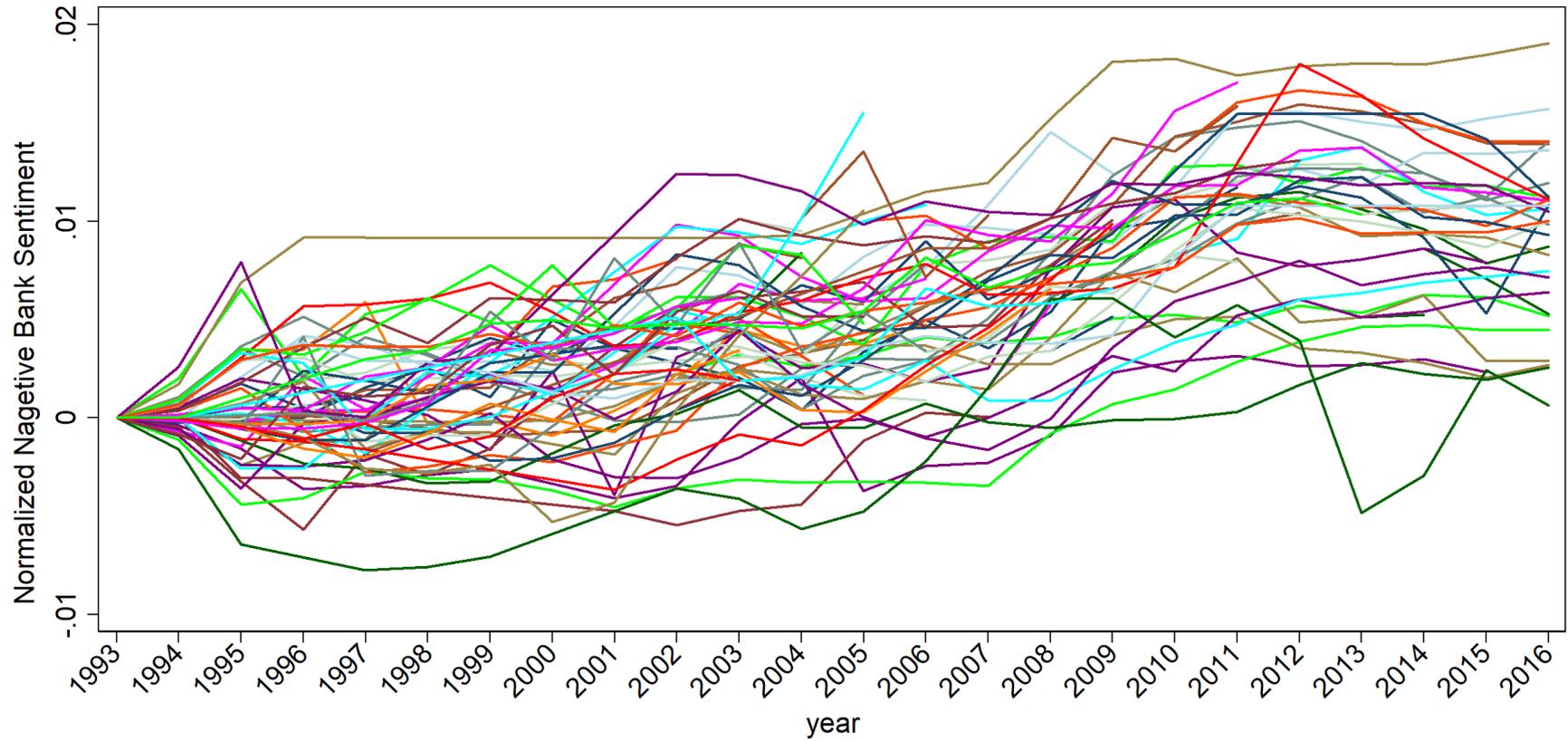
This figure shows the individual *Negative bank sentiment* trajectory measured by the ratio of negative words minus the ratio of positive words normalized to the first observation of each bank over our sample period from 1993:Q4 to 2016:Q4. 116 unique banks existing in year 1993 with at least 10 years' bank sentiment measure are included in this figure.

Table 1: Measures of bank liquidity hoarding

This table shows how the bank liquidity hoarding measures are constructed from the dollar values of balance sheet and off-balance sheet activities. Weights of +1/2 are assigned to items contributing to bank liquidity hoarding, and weights of (-1/2) are assigned to items reducing such hoarding. Total bank liquidity hoarding, *LH(total) = LH(asset) + LH(liab) + LH(off)*, where *LH(asset)* = (+1/2) × liquid assets + (-1/2) × illiquid assets; *LH(liab)* = (+1/2) × liquid liabilities; and *LH(off)* = (-1/2) × illiquid guarantees + (+1/2) × liquid derivatives. These liquidity hoarding measures are developed by Berger, Guedhami, Kim, and Li (2019), who adapted them from Berger and Bouwman's (2009) liquidity creation measures.

LH(asset)		*LH(liab)*	*LH(off)*	
Liquid assets (weight = + 1/2)	**Illiquid assets (weight = - 1/2)**	**Liquid liabilities (weight = + 1/2)**	**Illiquid guarantees (weight = - 1/2)**	**Liquid derivatives (weight= + 1/2)**
Cash and due from other institutions	Commercial real estate loans (CRE)	Transactions deposits	Unused commitments	Interest rate derivatives
All securities (regardless of maturity)	Loans to finance agricultural production	Savings deposits	Net standby letters of credit	Foreign exchange derivatives
Trading assets	Commercial and industrial loans (C&I)	Overnight federal funds purchased	Commercial and similar letters of credit	Equity and commodity derivatives
Fed funds sold	Other loans and lease financing receivables	Trading liabilities	Net participations sold	
	Other real estate owned (OREO)		All other off-balance sheet liabilities	
	Customers' liability on bankers' acceptances			
	Investment in unconsolidated subsidiaries			
	Intangible assets			
	Premises			
	Other assets			
LH(total) = LH(asset) + LH(liab) + LH(off)				

Table 2: Summary statistics and a correlation matrix

This table presents summary statistics for the variables used in the main analysis. The sample includes 2,965 banks (57,841 bank-quarter observations) from 1993:Q4 through 2016:Q4. The observations are on a bank-calendar quarter level. 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% and 99% level.

Panel A: Summary statistics

	N	Mean	StDev	25th Pctl	Median	75th Pctl
Dependent variables						
LH(total)/GTA	57841	0.074	0.177	-0.050	0.070	0.193
LH(asset)/GTA	57841	-0.080	0.139	-0.183	-0.083	0.013
LH(liab)/GTA	57841	0.239	0.070	0.193	0.237	0.285
LH(off)/GTA	57841	-0.084	0.052	-0.110	-0.073	-0.047
Key independent variable						
Negative bank sentiment	57841	0.007	0.005	0.004	0.007	0.011
Control variables						
Ln(GTA)	57841	13.615	1.474	12.497	13.526	14.643
Capital ratio	57841	0.078	0.029	0.057	0.071	0.092
Earnings	57841	0.010	0.020	0.008	0.011	0.015
HHI	57841	0.108	0.118	0.034	0.091	0.135
Population	57841	1.962	0.872	1.498	2.012	2.516
Tobin's Q	57841	2.419	1.007	1.808	2.152	2.653
Cash flows	57841	-0.002	0.030	-0.014	0.004	0.017
GDP growth	57841	2.664	2.492	1.400	2.900	4.000
Corporate sentiment	27807	-0.072	1.043	-0.297	0.212	0.609
Investor sentiment	57841	0.262	0.631	-0.077	0.193	0.567
Consumer sentiment	57841	88.713	12.372	82.433	90.733	94.900
TED spread	57841	0.514	0.359	0.250	0.476	0.616
EPU	57841	4.570	0.272	4.333	4.509	4.734

Panel B: Perason correlation matrix between *Negative bank sentiment* and macro-level controls including corporate-, investor-, and consumer-sentiment measures

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
(1) Negative bank sentiment	1.000						
(2) GDP growth	-0.248***	1.000					
(3) Corporate sentiment	0.111***	-0.299***	1.000				
(4) Investor sentiment	-0.474***	0.547***	-0.112***	1.000			
(5) Consumer sentiment	-0.329***	0.034***	0.599***	0.373***	1.000		
(6) TED spread	-0.130***	-0.281***	0.453***	-0.074***	0.053***	1.000	
(7) EPU	0.445***	-0.472***	-0.205***	-0.693***	-0.296***	-0.054***	1.000

Table 3: The effects of bank sentiment on bank liquidity hoarding

This table presents coefficient estimates from regressions of the bank liquidity hoarding on the *Negative bank sentiment* and controls. For the dependent variables, we consider total bank liquidity hoarding (*LH(total)*) in Panel A as well as its component (*LH(asset)*, *LH(liab)*, and *LH(off)*) normalized by the gross total asset (*GTA*) in Panel B. The sample includes 2,965 banks (57,841 bank-quarter observations) from 1993:Q4 through 2016:Q4. All variables are described in Tables 1 and Appendix A. Coefficients on constant terms are omitted for brevity. *t*-statistics are reported in parentheses and are based on standard errors clustered at a publicly-traded bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Regressions of bank total liquidity hoarding (*LH(total)/GTA*) on *Negative bank sentiment*

	(1) LH(total)/GTA	(2) LH(total)/GTA	(3) LH(total)/GTA
Negative bank sentiment	5.190***	5.234***	3.453***
	(4.86)	(5.03)	(4.53)
Ln(GTA)	-0.045***	-0.043***	-0.040***
	(-4.40)	(-4.23)	(-4.54)
Sqr.Ln(GTA)	0.000	0.000	0.000
	(0.57)	(0.42)	(0.90)
Capital ratio	-0.555***	-0.551***	-0.495***
	(-4.55)	(-4.57)	(-4.77)
Earnings	0.123*	0.120**	0.056
	(1.98)	(2.04)	(1.21)
HHI		-0.003	-0.002
		(-0.16)	(-0.11)
Population		-0.018*	-0.012
		(-1.82)	(-1.19)
Tobin's Q		0.003	0.004***
		(1.10)	(2.95)
Cash flows		0.155***	0.090*
		(2.74)	(1.91)
GDP growth			0.003**
			(2.32)
Corporate sentiment			0.007**
			(2.02)
Investor sentiment			-0.014***
			(-2.97)
Consumer sentiment			0.000
			(1.12)
TED spread			-0.049***
			(-4.76)
EPU			0.076***
			(5.07)
Bank FE	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes
Adj. R-squared	0.805	0.806	0.829
Number of obs.	57841	57841	57841

Panel B: Regressions of bank liquidity hoarding components on *Negative bank sentiment*

	(1) *LH(asset)/GTA*	(2) *LH(liab)/GTA*	(3) *LH(off)/GTA*
Negative bank sentiment	0.285	2.797***	0.433**
	(0.70)	(4.93)	(2.21)
Ln(GTA)	-0.037***	0.000	-0.003
	(-6.19)	(0.01)	(-1.14)
Sqr.Ln(GTA)	0.000	0.000	-0.000
	(0.94)	(0.88)	(-0.57)
Capital ratio	-0.625***	0.203***	-0.075*
	(-9.25)	(2.68)	(-1.86)
Earnings	-0.008	0.173***	-0.105***
	(-0.28)	(3.98)	(-4.78)
HHI	-0.008	0.015**	-0.008***
	(-0.78)	(2.07)	(-2.73)
Population	-0.017*	0.011*	-0.007**
	(-1.76)	(1.85)	(-2.15)
Tobin's Q	0.002**	0.002**	0.000
	(2.18)	(2.47)	(0.23)
Cash flows	0.052*	0.004	0.034***
	(1.78)	(0.16)	(2.85)
GDP growth	0.002***	0.000	0.001***
	(2.73)	(0.70)	(2.63)
Corporate sentiment	-0.000	0.007***	0.000
	(-0.19)	(3.16)	(0.16)
Investor sentiment	-0.005**	-0.008***	-0.001
	(-2.42)	(-3.05)	(-1.39)
Consumer sentiment	0.000	0.000***	-0.000***
	(0.95)	(2.63)	(-3.04)
TED spread	-0.018***	-0.030***	-0.001
	(-3.42)	(-6.12)	(-0.28)
EPU	0.039***	0.021***	0.017***
	(4.78)	(2.68)	(5.17)
Bank FE	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes
Adj. R-squared	0.844	0.766	0.802
Number of obs.	57841	57841	57841

Table 4: The effects of bank sentiment by bank capital and time period

This table presents coefficient estimates from regressions of the bank liquidity hoarding on the *Negative bank sentiment* and controls including an interaction terms between the *Negative bank sentiment* and *High capital ratio* or *Global Financial Crisis*. *High capital ratio* is a binary variable equal to one if *Capital ratio* is greater than its 75th percentile, otherwise equals to zero. *Global Financial Crisis* is a binary variable equal to one if a sample period is between 2007:Q3 and 2009:Q4, or zero otherwise. *Post crisis* is defined as a binary variable equal to one if a sample period is after 2009:Q4 or zero otherwise. The dependent variables include total bank liquidity hoarding (*LH(total)*) and its components (*LH(asset)*, *LH(liab)*, and *LH(off)*) normalized by the gross total assets (*GTA*). The sample includes 2,965 banks (57,841 bank-quarter observations) from 1993:Q4 through 2016:Q4. All variables are described in Tables 1. Coefficients on constant terms are omitted for brevity. *t*-statistics are reported in parentheses and are based on standard errors clustered at a publicly-traded bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: Bank capital ratio and the impact of bank sentiment on liquidity hoarding

	(1) LH(total)/GTA	(2) LH(asset) / GTA	(3) LH(liab) / GTA	(4) LH(off) / GTA
Negative bank sentiment × High capital ratio	3.302***	1.117***	1.848***	0.345**
	(6.49)	(3.62)	(6.87)	(2.56)
Negative bank sentiment	2.417***	0.017	2.109***	0.352*
	(3.38)	(0.04)	(3.91)	(1.84)
High capital ratio	-0.010***	-0.011***	0.005***	-0.004***
	(-3.72)	(-5.26)	(3.72)	(-4.69)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.832	0.845	0.772	0.803
Number of obs.	57841	57841	57841	57841

Panel B: *Global Financial Crisis* and the impact of bank sentiment on liquidity hoarding

	(1) LH(total)/GTA	(2) LH(asset) / GTA	(3) LH(liab) / GTA	(4) LH(off) / GTA
Negative bank sentiment × Global Financial Crisis	1.801*	0.922	-0.115	1.102**
	(1.83)	(1.04)	(-0.20)	(2.07)
Negative bank sentiment × Post crisis	4.066***	2.571**	-0.075	1.606***
	(2.95)	(2.52)	(-0.11)	(3.76)
Negative bank sentiment	-0.091	-0.645	0.984**	-0.410
	(-0.13)	(-1.14)	(2.25)	(-1.33)
Global Financial Crisis	-0.026**	-0.033***	0.013	-0.007
	(-2.43)	(-3.71)	(1.47)	(-1.27)
Post crisis	0.036	-0.021	0.064***	-0.006
	(1.59)	(-1.45)	(5.01)	(-1.01)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.839	0.846	0.791	0.805
Number of obs.	57841	57841	57841	57841

Table 5: Robustness checks

This table presents coefficient estimates from regressions of the bank liquidity hoarding on the *Negative bank sentiment* with various robustness checks. The dependent variable is the total bank liquidity hoarding (*LH(total)*) normalized by the gross total asset (*GTA*). The sample period is from 1993:Q4 to 2016:Q4. The model specification is the same as the main regression. Columns (1) and (2) include small and large banks, respectively. The small (large) banks are defined as those with below (above) the median gross total asset for each year. Column (3) includes organizations with commercial banking only, which column (5) shows results for BHCs without both commercial and investment banks. Column (5) includes observations whose *Negative bank sentiment* is measured within one quarter before the liquidity hoarding. Column (6) additionally controls for the readability (Gunning-Fog-Index) of annual reports (10-K). Coefficients on constant terms are omitted for brevity. *t*-statistics are reported in parentheses and are based on standard errors clustered at a publicly-traded bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

			Dep. = *LH(total)/GTA*			
	(1) Small banks (GTA<median)	(2) Large banks (GTA>median)	(3) Commercial banking only	(4) Commercial and investment banks	(5) No stale sentiment measures	(6) Controlling for readability of 10-K
Negative bank sentiment	2.731***	3.514***	1.408**	4.741***	3.200***	3.430***
	(3.62)	(4.40)	(2.11)	(4.45)	(3.72)	(4.46)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.864	0.818	0.894	0.833	0.826	0.829
Number of obs.	28922	28919	22847	35827	26838	57841

Table 6: Summary statistics for the samples used in bank supply and demand choices versus customer choices analyses

This table presents summary statistics for the variables used in bank supply/demand choice versus customer choice analyses. The variables in Panel A are at the loan type-loan facility-bank level from 1993:Q4 through 2016:Q4. The variables in Panel B are at bank-deposit product-calendar quarter level from 1998:Q1 to 2016:Q4.

	Term Loan						Revolvers					
	N	Mean	StDev	25th Percentile	Median	75th	N	Mean	StDev	25th	Median	75th
Bank loan variables												
Credit spread	12893	2.196	1.164	1.500	2.000	2.750	36507	1.432	0.970	0.625	1.250	2.000
Credit size	12893	18.955	1.499	18.133	19.114	19.975	36507	19.442	1.347	18.644	19.519	20.367
Covnt. Index	12893	2.824	2.223	1.000	3.000	5.000	36507	1.894	1.947	0.000	1.000	4.000
Secured	12893	0.517	0.500	0.000	1.000	1.000	36507	0.317	0.465	0.000	0.000	1.000
Ln(Maturity)	12692	4.021	0.447	3.932	4.111	4.290	35810	3.915	0.401	3.714	4.111	4.111
Borrower variables												
Ln(ME)	12893	13.930	1.685	12.866	14.041	15.132	36507	14.283	1.745	13.155	14.310	15.477
BE_ME	12893	0.692	1.134	0.244	0.432	0.732	36507	0.649	0.916	0.274	0.456	0.743
Leverage	12893	0.336	0.220	0.180	0.312	0.472	36507	0.271	0.191	0.134	0.254	0.376
Tangible	12893	0.291	0.222	0.107	0.235	0.438	36507	0.334	0.246	0.132	0.269	0.509
Cash	12893	0.080	0.106	0.014	0.041	0.101	36507	0.078	0.100	0.013	0.038	0.103
Z_score	12893	1.494	1.184	0.714	1.431	2.177	36507	1.775	1.182	0.929	1.707	2.475
Credit rating	7838	9.282	2.391	8.000	9.000	11.000	22553	11.022	2.927	9.000	11.000	13.000

Panel B	N	Mean	StDev	25th Percentile	Median	75th Percentile
Bank deposit variables						
Checking accounts deposit spreads	23027	-1.230	1.618	-2.496	-0.281	-0.003
Savings accounts deposit spreads	110014	-0.380	1.061	-0.220	-0.000	0.061
Money market accounts deposit spreads	265387	-0.279	1.002	-0.200	0.030	0.143

Table 7: The effects of *Negative bank sentiment* on credit spreads: Banks credit supply versus customers demand effects on credit spreads at the *intensive margin*

This table presents coefficient estimates from regressions of the credit spreads on the *Negative bank sentiment* measure and controls. The sample includes 266 lead banks and 5,199 borrowing firms from 1993:Q4 through 2016:Q4. *Controls* include *Ln(GTA)*, *Sqr.Ln(GTA)*, *Capital ratio*, *Earnings*, *HHI*, *Population*, *Tobin's Q*, *Cash flows*, *GDP growth, ICS, Investor sentiment, TED spread, and EPU*. All variables are described in Appendices A and D. For some observations, the *Credit rating* variable is not available. In such cases, we replace them with the average value of available *Credit rating* and include a dummy variable equal to one when the *Credit rating* variable is available and zero otherwise. The observations are slightly different between columns (1) and (2), and between (3) and (4) due to missing observations for control variables. *t*-statistics are reported in parentheses and are based on standard errors clustered at a year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	Dep. = Credit spread over LIBOR			
	Term loans (On-balance sheet)		Revolvers (Off-balance sheet)	
	(1)	(2)	(3)	(4)
Negative bank sentiment	11.727**	9.760*	10.892***	11.648***
	(2.23)	(1.86)	(3.55)	(3.91)
Ln (ME)	-1.238***	-1.267***	-1.181***	-0.980***
	(-9.28)	(-10.43)	(-21.39)	(-17.79)
Sqr. Ln(ME)	0.036***	0.037***	0.034***	0.031***
	(7.55)	(8.73)	(18.02)	(16.12)
BE_ME	0.002	-0.009	-0.036***	0.007
	(0.09)	(-0.54)	(-3.02)	(0.66)
Leverage	0.068	-0.041	0.306***	0.352***
	(0.83)	(-0.53)	(6.33)	(8.00)
Tangible	0.124*	0.181**	-0.190***	-0.170***
	(1.77)	(2.48)	(-6.72)	(-6.11)
Cash	0.655***	0.623***	0.395***	0.162**
	(4.26)	(4.39)	(5.78)	(2.51)
Z_score	-0.121***	-0.119***	-0.117***	-0.105***
	(-6.65)	(-7.11)	(-15.40)	(-14.32)
Credit rating	0.034	0.032	-0.043**	-0.050***
	(0.79)	(0.81)	(-2.45)	(-2.82)
Credit size		0.005		-0.097***
		(0.29)		(-10.62)
Ln(Maturity)		-0.078**		-0.272***
		(-2.15)		(-10.40)
Secured		0.537***		0.215***
		(14.61)		(8.83)
Covnt. index		0.014		0.055***
		(1.35)		(7.72)
Controls	Yes	Yes	Yes	Yes

Bank FE	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes
Adj. R-squared	0.379	0.423	0.574	0.615
Number of obs.	12893	12692	36507	35810

Table 8: The effects of *Negative bank sentiment* on deposit rate spreads: Banks demand versus customers supply effects on deposit spread at the *intensive margin*

This table presents coefficient estimates from regressions of the deposit interest rate spreads on the *Negative bank sentiment* measure and controls. The sample includes 605 banks and 394,428 deposit products×quarter observations from RateWatch covering the sample period 1998:Q1 through 2016:Q4. *Controls* include *Ln(GTA), Sqr.Ln(GTA), Capital ratio, Earnings, HHI, Population, Tobins' Q, Cash flows, ICS, Investor sentiment, TED spread, and EPU*. All variables are described in Appendices A and D. *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. = Deposit rate over 3 month T-bill		
	(1) *Checking accounts*	(2) *Savings accounts*	(3) *Money market accounts*
Negative bank sentiment	28.891**	57.124***	41.013***
	(2.09)	(5.01)	(4.02)
Controls	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes
Adj. R^2	0.718	0.619	0.545
Number of obs.	23027	110014	265387

Table 9: Instrumental variable analysis with local weather conditions

This table presents coefficient estimates from instrumental variable analysis with local weather conditions near bank headquarters as instrumental variables for bank sentiment. In Panel A, we report the first-stage regression results with various numbers of LASSO-chosen instrumental variables. In Panel B, we report the second-stage regression of *Bank negative sentiment* on liquidity hoarding with the LASSO-chosen weather conditions as instrumental variables for the *Negative bank sentiment*. *Controls* include variables of Column (3) of Table 3. In Panel C, we report the second-stage regression of *Bank negative sentiment* on credit- and deposit-spreads with the LASSO-chosen weather conditions as instrumental variables for the *Negative bank sentiment*. *Controls* include variables of Tables 7 and 8, respectively. Coefficients on *Controls* are omitted for brevity. All variables are described in Appendices A and E. *t*-statistics are reported in parentheses and are based on bootstrap standard errors clustered at a bank level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

Panel A: First stage regression of *Negative bank sentiment* on LASSO-chosen instruments

Set of potential Instruments	Count constraint	LASSO-chosen instrument(s)	Coefficient	*F*-Statistic
2,090 dummy variables created based on seasonally adjusted 144 local weather conditions, which include: 8 weather conditions (cloud coverage, precipitation (1hrs or 6hrs), air temperature, dew point temperature, wind speed, wind direction, pressure) × 3 different coverages of weekdays (8 am – 5 pm on Tuesday only, Tuesday – Thursday, Monday – Friday) × 2 different lags from annual reports filing date (one-, two-quarters) × 3 different de-seasonalizing (one-, two-, and three-years) For each weath condition, a dummy variable is created with equally-spaced bins (refer to Section 6)	Choose 1	Monday-Friday, one-quarter lag, de-seasonalized by previous three years' average cloud coverage with the range of -3 to -2 oktas.	0.0005*** (11.14)	163.21
	Choose 2	Monday-Friday, one-quarter lag, de-seasonalized by previous three years' average cloud coverage with the range between -3 to -2 oktas.	0.0005*** (10.95)	153.96
		Monday-Friday, two-quarter lag, de-seasonalized by previous three years' average cloud coverage with the range between -3 to -2 oktas .	0.0004*** (10.29)	
	Choose 3	Monday-Friday, one-quarter lag, de-seasonalized by previous three years' average cloud coverage with the range between -3 to -2 oktas.	0.0005*** (9.05)	123.27
		Monday-Friday, two-quarter lag, de-seasonalized by previous three years' average cloud coverage with the range between -3 to -2 oktas.	0.0004*** (8.44)	
		Tuesday to Thursday, two-quarter lag, de-seasonalized by previous three years' average sea level pressure with the range between 0 to 5 hectopascals.	0.0012** (10.24)	

Panel B: Second stage regressions of liquidity hoarding measures on *Negative bank sentiment* instrumented by LASSO-chosen instrument variables

	Second Stage			
	(1) *LH(total)/GTA*	(2) *LH(asset)/GTA*	(3) *LH(liab)/GTA*	(4) *LH(off)/GTA*
Negative bank sentiment (IV)	24.273*** (9.19)	5.479** (2.22)	17.145*** (11.88)	1.649** (2.27)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes
Number of obs.	42870	42870	42870	42870

Panel C: Second stage regressions of the price of bank loans and deposits on *Negative bank sentiment* instrumented by LASSO-chosen instrument variables

	Second Stage				
	(1) *Term loans Credit spreads*	(2) *Revolvers Credit spreads*	(3) *Checking accounts Deposit spreads*	(4) *Savings account Deposit spreads*	(5) *Money market accounts Deposit spreads*
Negative bank sentiment (IV)	116.388** (2.15)	36.552* (1.69)	343.420*** (6.92)	523.730*** (9.95)	431.014*** (12.34)
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes
Number of obs.	10425	28728	17838	84859	203763

Appendix A: Descriptions of variables for the impact of bank sentiment on liquidity hoarding

This table presents descriptions of the dependent and key independent variables for the main analysis. The sample includes 2,965 banks (57,841 bank-quarter observations) from 1993:Q4 through 2016:Q4. The observations are on a bank-calendar quarter level. 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% and 99% level.

Variable	Description
Dependent variables	
LH(total)/GTA	A bank's total liquidity hoarding measure including on- and off-balance sheet activities normalized by the gross total assets of a bank: *LH(total) = LH(asset)+LH(liab)+LH(off)*.
LH(asset)/GTA	A bank's liquidity hoarding measure in the asset-side, defined as (+1/2)×all items of liquid assets + (-1/2)×all items of illiquid assets normalized by the gross total assets of a bank. For a more detailed definition of all items belonging to liquid and illiquid assets, see Table 1.
LH(liab)/GTA	A bank's liquidity hoarding measure in the liability-side, defined as (+1/2)×all liquid liabilities normalized by the gross total assets of a bank. For a more detailed definition of all items belonging to liquid liabilities, see Table 1.
LH(off)/GTA	A bank's liquidity hoarding measure in the off-balance sheet-side, defined as (+1/2) × all items of illiquid guarantees + (-1/2) × all items of liquid derivatives normalized by the gross total assets of a bank. For a more detailed definition of all items belonging to liquid derivatives and illiquid guarantees, see Table 1.
Key independent variables	
Negative bank Sentiment	The ratio of the difference between the number of negative words minus positive words to total number of words in a bank's annual reports (form 10-K) based on the Loughran and McDonald (2011) dictionary of sentiment words.
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.
Earnings	Bank return on assets (ROA), measured as the ratio of the annualized net income to *GTA*.
HHI	A bank-level competition level calculated as a weighted average of the Herfindahl–Hirschman index in all areas (Metropolitan Statistical Area (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 (Metropolitan Statistical Area (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.
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 the 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 lagged total assets 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).
GDP growth	Gross domestic product (GDP) is the value of the goods and services produced by the nation's economy less the value of the goods and services used up in production. It is the percent change from the preceding period, seasonally adjusted annual rate.
ICS	The Index of Consumer Sentiment by the University of Michigan
Investor sentiment	Investor sentiment index from Baker and Wurgler (2006)
Corporate sentiment	Corporate manager sentiment index from Jiang, Lee, Martin, and Zhou (2019)
TED Spread	Difference (in percentage) between three-month Treasury bill and three-month LIBOR based on US dollars
EPU (Economic Policy Uncertainty)	The natural log of the arithmetic average of the overall economic policy uncertainty measure developed by Baker, Bloom, and Davis (BBD 2016) over the three months of calendar quarter *t*.

Appendix B: The effects of Negative bank sentiment 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 *Negative bank sentiment* measure and controls. The sample includes 2,965 banks from 1993:Q4 through 2016:Q4. All variables are described in Appendix A. Coefficients on constant terms are omitted for brevity. t-statistics are reported in parentheses and are based on standard errors clustered at a publicly-traded bank and year-quarter level. Statistical significance at the 10%, 5%, and 1% levels is denoted by *, **, and ***, respectively.

	(1) Cash/GTA	(2) Loans/GTA	(3) Loan cmt./GTA	(4) Deposits/GTA	(5) Liquid deposits/GTA
Negative bank sentiment	1.247***	-0.670	-1.227***	2.795***	3.607***
	(3.51)	(-1.34)	(-2.87)	(6.70)	(4.41)
Ln(GTA)	-0.003	0.020***	0.010	-0.044***	-0.051***
	(-1.23)	(2.76)	(0.94)	(-5.31)	(-5.17)
Sqr.Ln(GTA)	-0.000*	0.000	0.000	0.001**	0.001***
	(-1.86)	(1.03)	(0.45)	(2.10)	(3.36)
Capital ratio	-0.089	-0.093	0.046	-0.321***	0.262**
	(-1.48)	(-0.94)	(0.44)	(-4.23)	(2.38)
Earnings	-0.111***	0.110**	0.148*	0.007	0.247***
	(-3.92)	(2.52)	(1.76)	(0.14)	(3.53)
HHI	-0.003	0.003	0.018**	0.021**	0.028**
	(-0.68)	(0.26)	(2.07)	(2.49)	(2.50)
Population	-0.001	0.015	0.011	0.004	0.012
	(-0.24)	(1.61)	(0.78)	(0.42)	(1.10)
Tobin's Q	0.001***	-0.002*	-0.001	0.001	0.001
	(2.82)	(-1.90)	(-1.10)	(1.45)	(0.83)
Cash flows	0.018	-0.028	-0.048*	0.085***	0.057
	(1.43)	(-0.97)	(-1.68)	(2.77)	(1.24)
GDP growth	0.001*	-0.002**	-0.001**	0.001	0.002
	(1.80)	(-2.47)	(-2.17)	(1.19)	(1.33)
ICS	-0.000	-0.000	0.001***	-0.000	0.001*
	(-0.55)	(-0.28)	(4.07)	(-0.84)	(1.88)
Investor sentiment	-0.002**	0.005***	0.002	-0.005	-0.013**
	(-2.15)	(2.75)	(1.28)	(-1.38)	(-2.63)
Corporate sentiment	0.001	-0.000	-0.000	0.005**	0.007*
	(0.82)	(-0.18)	(-0.01)	(2.25)	(1.67)
TED spread	-0.008***	0.025***	0.004	-0.019***	-0.052***
	(-3.46)	(4.96)	(1.02)	(-3.03)	(-5.09)

EPU	0.019***	-0.043***	-0.033***	0.007	0.030**
	(5.03)	(-6.17)	(-5.23)	(0.99)	(2.19)
Bank FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	No	Yes	Yes	Yes
Adj. R-squared	0.551	0.788	0.912	0.794	0.788
Number of obs.	57841	57841	57841	57841	57841

Appendix C: Regressions of bank liquidity hoarding on negative sentiment with time fixed effects

This table presents coefficient estimates from regressions of the bank liquidity hoarding on the *Negative bank sentiment* and year-quarter time fixed effects. For the dependent variables, we consider total bank liquidity hoarding (*LH(total)*) normalized by the gross total asset (*GTA*). The sample includes 2,965 banks (57,841 bank-quarter observations) from 1993:Q4 through 2016:Q4. All variables are described in Appendix A. Coefficients on constant terms are omitted for brevity. *t*-statistics are reported in parentheses and are based on standard errors clustered at a publicly-traded 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(total)/GTA
Negative bank sentiment	1.078**	1.088**
	(2.08)	(2.10)
Ln(GTA)	-0.043***	-0.042***
	(-5.83)	(-5.47)
Sqr.Ln(GTA)	0.000	0.000
	(1.45)	(1.32)
Capital ratio	-0.789***	-0.788***
	(-8.55)	(-8.64)
Earnings	0.042	0.041
	(1.20)	(1.16)
HHI		0.002
		(0.15)
Population		-0.008
		(-0.88)
Tobin's Q		0.002**
		(2.14)
Cash flows		0.024
		(0.85)
Bank FE	Yes	Yes
Time FE	Yes	Yes
Adj. R-squared	0.848	0.849
Number of obs.	57841	57841

Appendix D: Regressions of bank liquidity hoarding on negative and positive words in 10-K

This table presents coefficient estimates from regressions of the bank liquidity hoarding on the ratio of negative and positive words and controls. For the dependent variables, we consider total bank liquidity hoarding (*LH(total)*) normalized by the gross total asset (*GTA*). The sample includes 2,965 banks (57,841 bank-quarter observations) from 1993:Q4 through 2016:Q4. All variables are described in Appendix A. Coefficients on constant terms are omitted for brevity. *t*-statistics are reported in parentheses and are based on standard errors clustered at a publicly-traded 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(total)/GTA	(3) LH(total)/GTA
Negative only words	5.244***	5.299***	3.756***
	(3.61)	(3.74)	(3.99)
Positive only words	-5.089**	-5.070**	-2.505
	(-2.54)	(-2.58)	(-1.56)
Ln(GTA)	-0.045***	-0.043***	-0.040***
	(-4.76)	(-4.45)	(-4.66)
Sqr.Ln(GTA)	0.000	0.000	0.000
	(0.58)	(0.42)	(0.90)
Capital ratio	-0.560***	-0.557***	-0.506***
	(-4.56)	(-4.57)	(-4.93)
Earnings	0.124*	0.121*	0.058
	(1.90)	(1.96)	(1.23)
HHI		-0.003	-0.001
		(-0.15)	(-0.09)
Population		-0.018**	-0.013
		(-1.99)	(-1.29)
Tobin's Q		0.003	0.004***
		(1.12)	(2.95)
Cash flows		0.154***	0.089*
		(2.70)	(1.88)
GDP growth			0.003**
			(2.33)
ICS			0.000
			(1.18)
Investor sentiment			-0.013***
			(-2.92)
Corporate sentiment			0.007*
			(1.94)
TED spread			-0.049***
			(-4.76)
EPU			0.076***
			(5.06)
Bank FE	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes
Adj. R-squared	0.799	0.800	0.827
Number of obs.	57841	57841	57841

Appendix E: Description of variables for the samples used in bank supply/demand choices versus customer choices analyses

This table presents a description of the variables used in bank supply/demand choices versus customer choice analyses. The observations are at the credit facility–bank level from 1993:Q4 through 2016:Q4.

Variable	Description
Bank loan variables	
Credit spread	The all-in spread drawn defined as the borrowing spread and annual fee (if any) the borrower pays in percentage 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 credit facility's issue date.
Secured	A binary variable equal to one if a credit facility is secured by collateral and zero otherwise.
Covnt. Index	Covenant intensity index based on Bradley and Roberts (2015), which is defined as the sum of all covenants embedded in the loan (i.e., two or more restricted accounting ratios, secured loans, dividend restriction, asset sweep, debt sweep, equity sweep).
Term loans	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.
Revolvers	Credit types in the LPC DealScan data: Revolver/Line < 1 Yr or Revolver/Line ≥ 1 Yr.
Borrowing firms 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 total assets.
Z_score	$(3.3 \times$pre-tax income $+$ sales $+ 1.4 \times$retained earnings $+ 1.2 \times$(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.
Bank deposit variables	
Checking accounts deposit spreads	Checking account deposit spread defined as checking account rate minus 3-month T-bill rate. Checking account rate is defined as the average rate of same checking account products across all balances requirements in percentage.

Savings accounts deposit spreads	Savings account deposit spread defined as savings account rate minus 3-month T-bill rate. Savings account rate is defined as the average rate of same savings account products across all balances requirements in percentage.
Money market accounts deposit spreads	Money market account deposit spread defined as money market account rate minus 3-month T-bill rate. Money market account rate is defined as the average rate of same money market account products across all balances requirements in percentage.

Appendix F: Instrumental variable analysis for BHCs with banks operating in multiple states

Panel A: Second stage regressions of liquidity hoarding measures on *Negative bank sentiment* instrumented by LASSO-chosen instrument variables

	Second Stage			
	(1) *LH(total)/GTA*	(2) *LH(asset)/GTA*	(3) *LH(liab)/GTA*	(4) *LH(off)/GTA*
Negative bank sentiment (IV)	28.425*** (6.91)	7.365*** (2.76)	19.826*** (10.25)	1.234 (1.16)
Controls	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes
Number of obs.	34330	34330	34330	34330

Panel B: Second stage regressions of the price of bank loans and deposits on *Negative bank sentiment* instrumented by LASSO-chosen instrument variables

	Second Stage				
	(1) *Term loans Credit spreads*	(2) *Revolvers Credit spreads*	(3) *Checking accounts Deposit spreads*	(4) *Savings account Deposit spreads*	(5) *Money market accounts Deposit spreads*
Negative bank sentiment (IV)	121.207*** (3.23)	7.592 (0.39)	248.316*** (4.25)	442.714*** (7.72)	371.550*** (8.73)
Controls	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
Seasonal FE	Yes	Yes	Yes	Yes	Yes
Number of obs.	8923	24643	8094	34343	83962