# Local Recessions: Evidence from Bank Liquidity Squeezes*

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**Abstract**

This paper investigates the relation between bank liquidity and local business cycles. Our findings suggest that an increase in the dispersion of deposit rates offered by banks within a geographic area accurately predicts the onset of local recessions and the severity of the downturn over long time horizons. As a region heads to a recession, deposit growth slows down and banks differentially increase deposit rates to support their balance sheet. The increased dispersion of deposit rates reflects the liquidity squeeze faced by banks as a result of deteriorating economic conditions, in turn, signaling an oncoming recession. Our results hold important policy implications.

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# 1 Introduction

Business cycles are driven by a complex interaction of various factors including changes in money supply, credit growth, fluctuations in productivity and innovation, and shocks to the economy. However, an important element that cuts across most business cycles is the pivotal role that banks fulfill in supporting the economic activity (Zarnowitz (1999)). Banks provide deposits, an important medium of savings and transactions for households and firms. On the asset side of their balance sheet, banks provide credit to households to fund consumption and loans to firms for investments. Thus, irrespective of the underlying cause of the business cycle, banks are integral to the economic activity. As a result, fluctuations in business cycles are often reflected in banks' balance sheet.

This paper investigates whether bank liquidity conditions can predict local business cycles. The idea is simple: as an economy heads to a contractionary phase, deposit growth slows down.[1] This puts a strain on bank balance sheet because deposits are a significant component of bank liquidity. At the same time, on the asset side, banks may have a stretched balance sheet due to lending growth in the expansionary phase of the business cycle.[2] Thus, in order to support their balance sheet, banks may either raise deposit rates to attract more deposits and/or reduce lending growth.[3] As banks generally differ in their liquidity positions and lending commitments, some banks may respond differentially by offering more competitive deposit rates to meet their liquidity needs, resulting in an increase in the dispersion of deposit rates. This increase in dispersion may indicate an impending recession.

The basis for the predictive power of deposit rates draws on both the money view and the credit view of business cycles. The money view argues that a decrease in money growth is associated with contractions in the economy (Friedman and Schwartz (2008)).[4] On the other hand, credit view posits that large credit growth in the expansionary phase of a business cycle causes recessions (Mishkin (1978)).[5] Dispersion in deposit rates offered by banks aggregates information from both the slowdown in money growth (proxied by deposit growth) and the credit positions across banks in an economy.[6] Thus, without delving into which channel is more dominant cause of a recession, increase in dispersion in deposit rates captures the liquidity squeeze experienced by banks due to contraction in the underlying economic activity.

[1] See Appendix Table A.1.
[2] See Azariadis (2018) for discussion on pro-cyclicality of debt.
[3] Banks can also raise other sources of funding but these generally come at a higher cost than insured deposits.
[4] See also Romer et al. (1990), King and Plosser (1984), Baker et al. (2018).
[5] See also Bernanke (1983), Gertler (1988), Schularick and Taylor (2012).
[6] Note that even if there is no large credit growth, every business cycle generally has a credit cycle embedded in it to fund investments.

We begin by analyzing recessions at the county level in the United States to empirically investigate the association between bank liquidity and recessions. For each county, we obtain deposit rates on insured deposits offered by banks operating in that county. This allows us to calculate the dispersion of deposits rates across banks in each county, at each point in time. A county is defined as being in recession in a particular year if there is a contraction in GDP of 2 percent or more.[7] We develop a simple classifier which uses the dispersion of deposit rates to predict recessions several years in advance. We begin with the county as the smallest geographic unit of analysis and work our way up to demonstrate that our classifier can predict recessions at the county, state, and national levels.

We find that the dispersion of deposit rates offered by banks within a county is a strong predictor of future economic contractions in that county. Specifically, an increase in the dispersion of deposit rates offered by banks within a county predicts the likelihood of a recession, even four quarters ahead with high accuracy. To assess the predictive value of our model, we use an efficient, rank-based algorithm known as the *Area under the Receiver Operating Characteristic Curve* (AUC). We find that the AUC of our baseline model that forecasts recessions two years ahead, using the dispersion of deposit rates across banks within a county is 0.70.[8] This strong predictive value indicates that the dispersion of deposit rates is a useful indicator for impending recessions.[9]

Interestingly, we also find that an increase in the dispersion of deposit rates predicts the depth of a recession. Counties with a wider dispersion of deposit rates experience lower GDP growth in the future. Thus, an increase in the dispersion of deposit rates not only predicts the likelihood of a recession, but it also indicates the severity of the recession. It is worth noting that we do not claim that bank liquidity *causes* a recession or affects its severity. Our premise is simply that banks are an important channel through which economic activity is conducted. Thus, banks deposit rates can be useful aggregator of the underlying economic conditions. Footnote: Note that while average deposit rate also has predictive power, the average deposit rate is more affected by monetary policy changes. Thus, in contrast to dispersion where a higher level is always followed by worse economic activity, the same is not always the case for deposit rate.

[7] Our findings are robust to alternate thresholds.

[8] The AUC allows us to diagnose the accuracy of our model. An AUC of 1 indicates that a classifier can perfectly distinguish recessions from non-recessions and an AUC of 0 indicates that a classifier predicts all non-recessions as recessions and all recessions as non-recessions. To benchmark this estimate, Schularick and Taylor (2012) report that prostate cancer diagnostic tests find AUCs of about 0.75; Iyer et al. (2016) report that an AUC of 0.6 or greater indicates strong predictive value in information-scarce environments, and an AUC of 0.7 or greater indicates strong predictive value in more information-rich environments.

[9] We also find that the out-of-sample predictive power of the model is high.

We build on this framework to further examine whether our model can predict recessions at a coarser geographical unit: the state level. By aggregating county characteristics, we calculate the average deposit rate and deposit rate dispersion for each state. We find that our baseline model at the state level can accurately predict state recessions. The model reports an in-sample AUC of 0.82 and an out-of-sample AUC of 0.74. We find that, as with the county level, the dispersion of deposit rates predicts GDP growth at the state level. Collectively, our findings demonstrate that the dispersion of bank deposit rates is a valuable heuristic for predicting recessions and their severity. Finally, we use aggregate the predicted likelihoods of state recessions to forecast national recessions. We compare our forecasted outcomes to whether a recession actually occurred according to the NBER's Business Cycle Dating Committee. Our findings indicate that the model also yields accurate forecasts of national recessions.

To further explore the mechanism behind the results, we examine whether banks that increase deposit rates experience liquidity stress. Our findings indicate that banks that increase deposit rates experience a decline in deposit growth in the earlier quarters, suggesting liquidity stress. This slowdown in deposits is observed in both insured and uninsured deposits. However, the effect is differential across banks based on the magnitude of the rate hike; banks that raise rates more experience lower deposit growth in the preceding quarters. We complement these findings on bank deposit growth with findings on aggregate deposit growth at the county level. We find that counties that approach a recession experience lower deposit growth compared to other counties. Together, these findings indicate that while county deposit growth declines as a county heads into a recession, there are heterogeneous effects across banks operating within the county.

In addition, banks may alter their lending activity as a response to a liquidity squeeze. We find that, in general, banks that raise deposit rates have higher lending growth in the earlier quarters compared to other banks. However, as a recession approaches and deposit growth slows, these banks increase deposit rates more than other banks to support their expanded balance sheet. They subsequently reduce their lending growth in the quarters following the rate hike. Thus, as deposit growth slows, banks differentially adjust both their deposit rates and their lending volumes to support their balance sheet. Interestingly, we also find that as banks head into a recession, they increase their reliance on insured deposits relative to uninsured deposits as the ratio of insured to uninsured deposits increases. These results suggest that banks increase their deposit rate on insured deposits to access cheaper funding to support their balance sheet as economic activity and deposit growth declines. These effects vary across banks based on their existing liquidity and lending commitments.

We conduct several robustness checks to validate our results. We show that our baseline findings are robust to controlling for the Federal Funds Effective Rate and term spread. Moreover, we find that our model has high predictive value even in periods when changes in monetary policy are limited. Furthermore, while our baseline prediction model does not include time fixed effects, we find that dispersion of deposit rates can predict recessions at the county level even after accounting for time fixed effects.[10] The finding that dispersion of deposit rates has predictive power even after inclusion of time fixed effects suggests that the results are not purely an artifact of monetary policy changes. This also highlights that the model has predictive power to isolate the cross-section of counties that have a higher likelihood of a recession, at a given point in time. Thus, the model has predictive power both in the spatial and temporal dimension.

Do credit booms drive the results? One may be concerned that the increased dispersion of deposit rates is solely a result of banks' overextended balance sheets following excessive credit growth. However, our findings remain robust even when controlling for credit growth. Further, we find that the dispersion of deposit rates can predict recessions, even in the absence of significant credit expansion. Thus, our model can predict recessions that are not solely caused by a credit boom. It is worth noting that our model can also accurately predict recessions that follow periods of large credit expansions, as these are instances where bank liquidity is under stress. Thus, our model can predict recessions that are not solely caused by a credit boom. The model is relevant as long as banks play a central role in local economies and rely to a large extent on local deposit flows for lending.

While our study shows the usefulness of the dispersion of deposit rates in predicting local business cycles, it is also useful to understand the limitations of this model. The predictive power of the dispersion of deposit rates reflects the gradual build-up of liquidity shortages in banks as an economy heads towards a downturn. Hence, the dispersion of deposit rates should have little or no predictive power when contractions in an economy arise due to sudden shocks. To test this, we examine the impact of natural disasters on the dispersion of deposit rates. We do not find any increase in the dispersion of deposit rates prior to natural disasters in affected areas. However, after the disaster hits, we observe an immediate increase in the dispersion of deposit rates, which gradually declines. Relatedly, we also observe a slowdown in deposit growth rate for a few years after the shock. These results strengthen our central hy-

[10]Time fixed effects likely improve the model's predictive value, however we do not include them in our baseline specifications because they do not serve any purpose for forecasting. We report the results with time fixed effects in Section 4.4 to show that the results are robust to their inclusion.

pothesis that dispersion of deposit rates effectively capture the liquidity stress of banks during economic contractions.

Our results have important policy implications. One of the leading indicators of a recession is the inversion of the yield curve. Despite the debate regarding its accuracy, this indicator is only available at the national level.[11] In contrast, the granularity of our indicators allows for prediction of recessions at the regional levels over long horizons – county and state recessions. In addition, most of the indicators of recessions are only reliable for binary predictions (recession or no recession). We demonstrate that the dispersion of deposit rates can also predict the depth of a recession. Hence, our analysis provides a useful tool for regional authorities to obtain early warning signals of an economic contraction and implement stabilization policies. Furthermore, our analysis also complements the existing models used to predict recessions at the national level. The dispersion of deposit rates, apart from having high predictive power for recessions at the national level, is also an easy-to-measure, market-based metric that can be used as an additional warning signal for economic contractions. Finally, our analysis also highlights that banks increase their reliance on insured deposits to support their balance sheet as they approach an economic downturn. This has implications for design of deposit insurance schemes and the regulation of banks.

### 1.1 Related Literature

Our results contribute to several strands of the literature. There is a large body of work which documents that the slope of the Treasury yield curve (term premium) and corporate bond spreads can predict the likelihood of a recession in the very near term (e.g., Estrella and Hardouvelis (1991), Estrella and Mishkin (1998), Ang et al. (2006), Rudebusch and Williams (2009), and Engstrom and Sharpe (2019)).[12] We add to this literature by showing that a simple model that uses dispersion of bank deposit rates has power to predict recessions at longer horizons with a high degree of accuracy. In addition, we provide a simple measure to predict recessions at the county and state levels, which is not possible with the treasury term spread.

Our paper also speaks to the literature that studies the prediction of financial crises. Recent empirical research indicates that excessive credit expansion by financial intermediaries may result in financial crises, and thus in severe economic recessions (e.g., Mian and Sufi (2009), Schularick and Taylor (2012), Jordà et al. (2013), Jordà et al. (2016), Mian et al. (2017),

[11] Romer and Romer (1989) assess recession risk using the rise in unemployment rate induced by monetary policy contractions.

[12] Several papers use financial indicators such as stock returns, stock price volatility, and stock market liquidity to predict economic growth. See Fama (1990), Schwert (1990), Campbell et al. (2001), Levine and Zervos (1998).

López-Salido et al. (2017), Baron and Xiong (2017), Bordalo et al. (2018), Mian et al. (2019), Krishnamurthy and Muir (2017), Müller and Verner (2021), and Greenwood et al. (2022)). In contrast to the extant literature, which focuses on the expansionary part of the credit cycle, our paper finds that the dispersion of deposit rates offered by banks increases at the onset of a downturn – irrespective of whether a downturn is preceded by a credit boom. This, in turn, predicts an impending recession. In fact, we find that the increase in the dispersion of deposit rates has the power to predict recessions that are not accompanied by a credit boom.[13] Thus, our paper highlights that the changes in the liability side of a banks' balance sheet that occur at the onset of an economic contraction can be used to predict recessions.

Finally, our paper also contributes to the literature which finds that uninsured depositors respond to bank riskiness (e.g., Saunders and Wilson (1996), Calomiris et al. (1997), Acharya and Mora (2015), Iyer et al. (2016), Egan et al. (2017), Martin et al. (2018), Artavanis et al. (2022)). This literature mainly focuses on the response of uninsured depositors in times of crisis. We complement these findings by showing that uninsured depositors are also responsive at the onset of an economic contraction and withdraw deposits from riskier banks. In addition, our findings also highlight that riskier banks increase their reliance on insured deposits at the onset of a downturn. This relates to the literature that highlights the importance of the proper design of deposit insurance schemes and the need to regulate banks due to moral hazard concerns (e.g., Laeven (1983), Demirgüç-Kunt et al. (2008), Calomiris and Jaremski (2019)).

The remainder of this paper is structured as follows. Section 2 describes the datasets employed in this project. Section 3 proposes that the dispersion of bank deposit rates is a significant predictor of impending recessions. Section 4 rigorously tests this hypothesis through a basic forecasting framework and reports the findings. Section 5 explores the mechanism behind these findings. Section 6 documents how cross-sectional dimensions of heterogeneity, in terms of competition for deposits, affect our baseline predictions. Section 7 validates that our model has high predictive value out-of-sample. Section 8 demonstrates that bank deposit rates have predictive power in forecasting recessions, even when the recessions are not preceded by credit booms. Lastly, Section 9 concludes.

## 2 Data

This project employs several datasets. We describe the datasets below.

**Deposit Rates** We use data on deposit rates from S&P Ratewatch. S&P Ratewatch pro-

[13] Boissay et al. (2016) point out that it is difficult for the literature predicting financial crises to predict other types of recessions that are not accompanied by an expansion in credit. See also Muir (2017).

vides depository interest rate coverage on banks and credit unions in the US for more than 70 standard retail banking products, ranging from deposit products to consumer loan and mortgages at the weekly frequency. Deposit rates are available at a granular geographic level with zip code, county, and state identifiers. We focus on the deposit rates for 12-month certificates of deposit ($10K 12-month CDs) with a minimum account size of $10,000 because this is the most common deposit product. Our sample period is 2001 through 2020. Our dataset covers 8,361 distinct banks and 2,897 distinct counties (approximately 90% of all US counties).

**Gross Domestic Product** We obtain Gross Domestic Product (GDP) data from the Bureau of Economic Analysis (BEA) at the county, state, and national levels. GDP is the BEA's National Income and Product Accounts signature piece, measuring the value of the nation's output across various dimensions. The BEA estimates GDP at the national level for each quarter-year from 1947Q1. This data is reported at annual rates, for ease of comparison and is seasonally adjusted to remove the effects of yearly patterns such as holidays, inclement weather or factory production schedules. The BEA estimates the value of goods and services produced in each state (and DC), county, metropolitan areas and other statistical areas. State GDP data is available at the quarterly frequency from 2005Q1. County GDP data is available at the annual frequency from 2001. The BEA provides a breakdown of industries' contributions to each of the economies.

**Bank Balance Sheet and Income Statements** We extract bank balance sheet and income statement information from the Reports of Condition and Income (Call Reports) sourced from the Federal Reserve Bank of Chicago. This data is provided for most FDIC-insured institutions and is reported at the quarterly frequency. The data of all bank filings are regulated by the Federal Reserve System, Federal Deposit Insurance Corporation (FDIC), and the Comptroller of the Currency. We use this data from 2001 through 2020 and merge our S&P RateWatch dataset based on the FDIC Certificate ID.

**Bank Regulatory Data** We supplement data from the call reports using bank regulatory data from S&P Market Intelligence. Specifically, we use data on risk-weighted assets, tier 1 capital, tier 2 capital, and non-performing loans from S&P Market Intelligence. This data is reported at the quarterly frequency. We use this data from 2001 through 2020 and merge our S&P RateWatch dataset based on the FDIC Certificate ID.

**Insured and Uninsured Deposits** We use data on banks' insured and uninsured deposits from the FDIC Statistics on Depository Institutions (SDI). The FDIC SDI reports the total volume of insured and uninsured deposits and insured deposits for all FDIC insured banks. This data is reported at the quarterly frequency. We use this data from 2001 through 2020 and merge our S&P RateWatch dataset based on the FDIC Certificate ID.

**Small Business Lending** We use data on small business lending, collected under the Community Reinvestment Act (CRA). The CRA is intended to demonstrate whether depository institutions to meet the credit needs of communities in which they operate, including low- and moderate-income neighborhoods. A small business loan is defined as a commercial & industrial loan of $1 million or less. All FDIC- and Federal Reserve-supervised financial institutions are subject to CRA requirements if they have assets above a prespecified threshold in two of the previous calendar years. Banks report the number and dollar amounts of lending across loan, applicant, and geographic characteristics. We aggregate the CRA data to the bank $\times$ county $\times$ year level between 2001 and 2020.

**Mortgage Lending** We use data on mortgage lending, collected under the Home Mortgage Disclosure Act (HMDA). The HMDA is intended to demonstrate whether lenders are serving the housing needs of their communities. Financial institutions are required to collect, record, and report any HMDA data on closed-end mortgage loans or open-end lines of credit above prespecified thresholds in two of the previous calendar years. Banks report the number and dollar amounts of lending across loan, applicant, and geographic characteristics. We aggregate the HMDA data to the bank $\times$ county $\times$ year level between 2001 and 2020.

**Federal Funds Effective Rate** We collect the Federal Funds Effective Rate from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis. The Federal Funds Effective Rate is the weighted average interest rate at which borrowing institutions pay lending institutions for liquidity. The Federal Funds Effective rate is determined by the market, but influenced by the Federal Reserve through open market operations that aim to meet a target rate.

**Term Spread** We collect term spread data from the Federal Reserve Economic Data (FRED) maintained by the Federal Reserve Bank of St. Louis. The term spread is the 10-Year Treasury constant maturity minus the three-month Treasury constant maturity.

**Rural-Urban Continuum Codes** We use data on Rural-Urban continuum codes from the US Department of Agriculture Economic Research Service (USDA ERS). The Rural-Urban Continuum Codes are a classification scheme that distinguishes metropolitan counties by population size of their metropolitan area and non-metropolitan counties by the degree of urbanization and adjacency to a metropolitan county. There are three categories of metropolitan counties and six categories of non-metropolitan counties. The Rural-Urban Continuum Codes were developed in 1974 and have been updated each decennial (1983, 1993, 2003, 2013) with a slight revision in 1988. We use the 1993 Rural-Urban Codes.

**Natural Disaster Data** We use data on natural disasters from the Spatial Hazard Events and Losses Database for the United States (SHELDUS). The dataset spans from 2001 through 2018. SHELDUS provides detailed data on losses at the county level. SHELDUS sources information on natural disasters from the "Storm Data and Unusual Weather Phenomena" published by the National Climatic Data Center (NCDC). We restrict our sample to large natural disasters that last less than 31 days with total damages above $1 bn 2018 dollars.

**Business Cycle Expansions and Contractions** We use data on business cycles from the National Bureau of Economic Research (NBER) US Business Cycle Expansions and Contractions. The NBER's Business Cycle Dating Committee maintains a chronology of US business cycles, identifying the peak and trough months of economic activity. The NBER defines a recession as a decline in economic activity that is spread across the economy and lasts more than a few months. There are three criteria used to determine a recession – depth, diffusion, and duration, albeit, exceptional circumstances in one criteria can partially offset weaker indications from other criteria. We highlight recessions between 2001 and 2020 throughout our analysis.

# 3 Bank Deposit Rates and Recessions

This section proposes that the dispersion of bank deposit rates is a significant predictor of impending recessions. We develop a simple classifier which demonstrates how the dispersion of deposit rates within a region can forecast recessions several years in advance with a high degree of accuracy. The county is the smallest geographic unit in this analysis, while the nation is the largest. We begin by describing the deposit rates offered by banks as well as the dynamics of recessions across geographical units. We then present our main findings which establish that the dispersion of deposit rates provides a valuable heuristic for predicting recessions, in- and out-of-sample. We show that various cross-sectional dimensions affect the predictive value of these variables including whether the area is metropolitan, urban or rural, the number of banks operating in the area, and the size of the banks in the area. Lastly, we show that bank deposit rate characteristics can predict recessions, above and beyond credit booms, and, even in the absence of credit booms.

## 3.1 Deposit Rates and Recessions

This section examines bank deposit rates and recessions across geographies.

We primarily focus our analysis on banks which offer the 12-month certificate of deposit

(CD) with a minimum account size of $10,000 – the most common deposit product.[14] We begin by examining the number of such banks that operate in each county from 2001 through 2020. Figure 1 presents a heatmap of the average number of banks per county between 2001 and 2020. On average, three to four banks operate in each county while 83% of counties report more than one bank.

We begin by demonstrating that the dispersion of deposit rates can predict county recessions. We then work our way up to show that this heuristic can also predict state and national recessions. While national recessions may reflect widespread economic decline across regions and sectors in the country, not all counties and states enter economic downturn at the same time as the country. This is because the onset and duration of regional recessions depend on factors that differ in each business cycle such as the industrial composition of the region or idiosyncratic shocks (e.g., Hamilton and Owyang (2012); Brown et al. (2017)).[15] Moreover, from a statistical standpoint, there is neither any cross-sectional variation at the national level, nor is the frequency of recessions sufficiently large. For these reasons, we start by studying recessions at the county and state levels as that increases the power for statistical analysis and then move on to predicting national recessions.

We conduct a case study, examining the relation between dispersion of banks' deposit rates and county recessions in two distinct counties: St. Louis, Missouri and Madison, Tennessee. We define a county to be in a recession if its GDP growth between two consecutive years is below -2%.[16] St. Louis, MO experienced recessions in 2011 and 2020. Madison, TN experienced recessions in 2009 and 2013. We present our results in Figure 2. Both Figure 2a and Figure 2b demonstrate that the dispersion of deposit rates among banks in the county increased in the immediate years preceding recessions. The dispersion narrowed in the years following recessions. Specifically, we find that the dispersion of deposit rates increased before the 2011 and 2020 recessions in St. Louis, MO and before the 2009 and 2013 recessions in Madison, TN. Interestingly, St. Louis, MO experienced a recession during the COVID-19 pandemic in 2020 which Madison, TN did not. Consistent with our conjecture, we find that there is a widening in the dispersion of deposit rates in St. Louis, MO from 2017. This stands in contrast to the flat trend in the dispersion of deposit rates in Madison, TN over the same period. This

[14] As discussed later, the results are robust to using other deposit contracts.

[15] Brown et al. (2017) note that downturns may be concentrated in particular sectors, hence, states with greater concentration in specific sectors may enter downturns earlier and remain in them longer. For example, states with a higher share of manufacturing experienced worse recessions in 2001. The $10^{th}$ Federal Reserve District – a district with a large share of energy production – entered in a recession in 2015 and 2016 after the 70% decline in oil prices from June 2014 through February 2016. In contrast, other non-energy producing states experienced steady growth during these periods.

[16] The results are robust to use of other thresholds.

case study demonstrates that trends in bank deposit rates in a county can indicate changes in local economic conditions.

We further investigate characteristics of county and state recessions. Figure 3 and Figure 4 present the timing and duration of recessions at the county and state levels, respectively. Figure 3a indicates the timing of when counties enter recessions. presents the percent of counties in recessions. We present heatmaps of GDP growth across counties by year in Appendix Figure **??**. We find that on average, 27% of counties are in a recession. The percent of counties in recession increased from 16% in 2005 to 50% in 2009. The percent of counties in recessions hovered from 20% to 30% between 2010 and 2019. During the COVID-19 pandemic, 53% of counties were in recession in 2020. Figure 3b presents a density probability plot of the percent of years in the sample period (2001-2020) that a county was in a recession. On average, counties were in recessions 25% of the sample period with a standard deviation of 12.45%. Similarly, we present heatmaps of GDP growth across states by year in Appendix Figure **??**. A state is defined to be in a recession if its GDP growth between two consecutive quarters is below -2%. Figure 4a indicates that 2% to 3% of states were in a recession in 2007. In 2008, 21% of states were in recession. This percentage fell in the aftermath of the GFC. The percent of states that were in recessions increased dramatically during the COVID-19 pandemic of 2020 to over 28%. Figure 4b shows that states were in recessions 5% of quarters in the sample period (2005-2020) with a standard deviation of 3.28%. Hence, the timing and duration of recessions exhibits wide heterogeneity across counties, states, and the country.

While these results suggest that there is a relation between the dispersion of local deposit rates and local recessions, it is unclear whether the dispersion of deposit rates can predict recessions at a coarser geographic unit. We study this next.

Figure A.4 presents a heatmap of the dispersion of deposit rates per county between 2001 and 2020. We construct the measure of the dispersion of deposit rates by exploiting the geographic variation in deposit rates across banks. First, we create a panel at the bank $\times$ county $\times$ month level, using the deposits rate data. Then, we compute the standard deviation of the deposit rate across banks for each county in each month. The annual dispersion of deposit rates is computed by averaging the monthly standard deviations. Interestingly, we find that there is variation in deposit rates even among large banks. Appendix Figure A.1 and Appendix Figure A.2 present the geographic dispersion of deposit rates for four of the largest banks in 2007 and 2014, respectively. We discover that prior to the recession caused by the GFC, banks had divergent pricing policies across counties, whereas after the GFC, banks' pricing policies converged.[17] We find that the average dispersion of deposit rates over the entire sample period is 0.27% – approximately equivalent to the median value of 0.26%. Figure 6 presents the dispersion of deposit rates over time. We find that banks exhibited very low dispersion of deposit rates in the period 2001 through 2004. The first quantile ranged from 0.00 to 0.14 and the sixth quantile ranged from 0.40 to 0.95. The average dispersion was 0.27%. In the run up to the financial crisis, between 2005 and 2007, dispersion substantially increased. The first quantile in this period ranged from 0.00 to 0.19 and the sixth quantile ranged from 0.52 to 1.68. The average dispersion was 0.41%. dispersion of deposit rates fell during and following the GFC. Average dispersion was 0.31% between 2008 and 2010 and 0.14% between 2011 and 2016. However, in the period between 2017 and 2019 dispersion of rates began increasing again. As compared to the period between 2011 to 2016, the average dispersion more than doubled to 0.33% between 2017 and 2019. This was followed by a recession in 2020. As before with the GFC, dispersion declined during the COVID-19 recession.[18]

Fluctuations in the dispersion of bank deposit rates over time motivate our inquiry into whether the second moment of bank deposit rates can predict national recessions. Thus far, we have drawn inferences on the relation between the dispersion of bank deposit rates and economic contractions by considering heterogeneity in the dispersion of bank deposit rates over various sample periods. We codify these relationships in Figure 7. Figure 7 presents the dispersion of deposit rates and average deposit rate across counties by month. The level and dispersion of deposit rates spike prior to national recessions, as defined by the NBER. This suggests that at the aggregate level, bank deposit rates are a harbinger of national recessions. Note that we also find that average deposit rate increases prior to recessions and drops during a recession. However, this could be an artifact of the monetary policy pursued by the Federal Reserve. Interestingly, the dispersion of deposit rates starts to trend upwards in the period 2015 to 2016, even when there are no noticeable changes in the average rate. Thus, for our analysis we focus mainly on dispersion of deposit rates, while controlling for the average deposit rate.

## 4 Predicting Recessions using Deposit Rates

In the previous section, we have documented a striking pattern which indicates that second moments of bank deposit rates may predict recessions. This section rigorously tests this hy-

[17] Uniform rate setting policies are more likely to occur during expansionary periods, supporting Granja and Paixao (2019) and Begenau and Stafford (2022) which find that large banks are likely to use uniform rate setting policies. Irrespective, our results are robust to excluding large banks from the analysis.

[18] As discussed later, we argue that the economy was in a downturn even before the COVID-19 shock occurred. COVID-19 shock served as a trigger.

pothesis through a basic forecasting framework which uses the recent history of the level and dispersion of bank deposit rates to predict recessions at the county, state, and national levels.

We begin by summarizing the data. Table 1 provides summary statistics for the main variables of interest from 2001 through 2020. Average annual county GDP growth is 1.39% with a standard deviation of 1.27%. Average quarterly state GDP growth is 0.3% with a standard deviation of 1.98%. We compute the average deposit rate and dispersion of deposit rates at the county and state levels, described in detail below. We find that across these measures, the average deposit rate is $\sim$ 1.30% with a standard deviation of 1.30% across the sample. The dispersion of deposit rates is $\sim$ 0.30% with a standard deviation of $\sim$ 0.20%.

### 4.1 Predicting County Recessions

We start our empirical framework with the most basic geographic unit. In the final reporting month of every year, we calculate the average deposit rate and dispersion of deposit rates for each county.[19] Using this data, we estimate a logit model of a county recession in county $c$ in year $t+k$ as a function of the deposit rates – the dispersion (standard deviation) of deposit rates and average deposit rate within a county – at year $t$. We consider up to three-year ($k = 1, 2, 3$) annual lead indicators of recessions.

$$logit(p_{c,t+k}) = \beta_0 + \beta_1 Rate_{c,t} + \beta_2 SD_{c,t} + \alpha_c + \epsilon_{c,t} \tag{1}$$

where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, $Rate$ denotes the average bank deposit rate, and $SD$ denotes the standard deviation of bank deposit rates. We assume that $\epsilon_{c,t}$ is well-behaved.

Our key empirical finding is that the dispersion of deposit rates is a salient indicator of economic recessions. Table 2 reports the average marginal effects. The independent variables are standardized for ease of interpretation. We account for the time-invariant heterogeneity associated with counties through county fixed effects. The county fixed effects also allow us to control for the banking structure (competition) and the type of banks that operate in each county which may affect the level of dispersion.[20] We also account for the effect of Fed Funds

[19] Our empirical findings are robust to alternate methods of constructing the average deposit rate and dispersion, such as averaging over different time horizons and using a variety of deposit rates. However, we focus on the deposit rates for 12-month certificates of deposit ($10K 12-month CDs) with a minimum account size of $10,000 because this is the most common deposit product that is uniformly observable across banks and years. For example, data on $250K 12-month CDs begins in 2004. Coverage of $250K 12-month CDs is sparse in 2004 but increases over time.

[20] Larger banks that operate in commercial paper and wholesale funding markets have more sources to access funding.

rate and macroeconomic conditions through inclusion of the average deposit rate. The dependent variable in columns 1 through 3 indicate whether a recession occurs one year ahead, two years ahead, and three years ahead, respectively. The dependent variable is a binary variable that takes a value of 1 if there is a recession, and 0, otherwise.[21] We conduct diagnostic tests of joint statistical significance and report the $\chi^2$ and associated p-values.

Our findings indicate that there is a greater probability of a recession following increases in the dispersion of deposit rates. Our point estimates remain economically meaningful and statistically significant at the 1% level across all forecasting horizons. We find that a pecking order across the estimates; the relation between the likelihood of a recession and the dispersion of deposit rates is largest for recessions one year ahead and smallest for recessions three years ahead. Column 1 indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 4.41 percentage points higher likelihood of a recession one year ahead. Column 2 indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 3.68 percentage points higher likelihood of a recession two years ahead. Column 3 indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 1.45 percentage points higher likelihood of a recession three years ahead. The diagnostic tests indicate that the covariates are jointly statistically significant at the 1% level. Thus, our findings indicate that within a county, there is a positive relationship between the dispersion of deposit rates and the probability of a future economic contraction. These relationships are economically meaningful, statistically significant, and stable.

The results from the estimation also indicate that the level of bank deposit rates are also significant predictors of recessions. However, these coefficients are quite unstable. The effect of the deposit rate on the probability of a recession is negative in column 1, yet it is positive in columns 2 and 3. Moreover, these rates are heavily influenced by the Federal Funds Effective Rate. That is, a higher point estimate associated with the average bank deposit rate may reflect the Federal Reserve's action of lowering interest rates when the economy is facing economic headwinds (like in 2008).[22]

We further examine the predictive value of the dispersion of deposit rates using the Receiver Operating Characteristic (ROC) curve. We use an efficient, rank-based algorithm known as the Area under the ROC Curve (AUC) which measures the model's predictions. The AUC

[21] Time fixed effects improve the model's predictive value, however we do not include them in our baseline specifications because they do not serve any purpose for forecasting. We report the results with time fixed effects in Section 4.4 to show that the results are robust to their inclusion.

[22] Deposit rates are generally lower as a result of the Fed's response of lowering interest rates to combat a recession. Consequently, the average deposit rate is higher in the preceding period before recessions. In effect, higher deposit rates appear to be a positive predictor of recession, but the effect may be mechanical.

measures the ability of a classifier to distinguish between positive and negative points. It is a diagnostic test of accuracy and discrimination that represents the probability that a randomly chosen recession case is ranked as more likely to be in a recession than a randomly chosen non-recession case. Essentially, the separation between the distributions of recessions and non-recessions give a prediction model its classification ability, as assessed by the AUC. An AUC of 1 indicates that a classifier can perfectly distinguish recessions from non-recessions points; an AUC of 0 indicates that a classifier predicts all non-recessions as recessions and all recessions as non-recessions. An AUC between 0.5 and 1 suggests that the classifier has greater predictive value than a coin toss. There is no "gold-standard" for the AUC benchmark because it is context-specific. As Iyer et al. (2016) note, an AUC of 0.6 or greater indicates strong predictive value in information-scarce environments, and an AUC of 0.7 or greater indicates strong predictive value in more information-rich environments.[23]

We examine the predictive value of our classifier through ROC curves. The AUC reported in Table 2 indicates that the AUC has substantial predictive value. We use the two-year forecast classifier in column 2 of Table 2 as our preferred specification and the benchmark for comparison. This specification yields an AUC of 0.7028 – above the random coin toss classifier. For completeness, the AUC associated with the one-year and three-year classifiers is 0.7014 and 0.6950, respectively. The ROC curve associated with our benchmark model is presented in Figure 8a. Overall, our findings suggest that the model has high predictive value.

### 4.2 Predicting State Recessions

This section builds upon the framework of Section 4 to establish that our model can predict recessions at a coarser geographical unit than the county. This section examines how the dispersion of bank deposit rates can predict recessions at the state level.

Since 2005, data on state recessions is available at the quarterly frequency, allowing us to analyze how the quarterly level and dispersion of deposit rates can predict state recessions. We calculate the average deposit rate and dispersion of deposit rates for each state, through aggregation of county characteristics. We construct the state deposit rate and dispersion by taking a weighted average of the county deposit rate and county dispersion of deposit rates for each state in the last reporting month of each quarter, weighted by the 2004 county GDP.[24]

[23]To benchmark this estimate, Schularick and Taylor (2012) report that prostate cancer diagnostic tests find AUCs of about 0.75.

[24]We verify that our findings are robust in Appendix Table **??**, in which we construct three measures of the level and dispersion of state deposit rates, using alternative weights: *Equal-Weight*, *Emp-Weight*, and *Pop-Weight*. The Equal-Weight measure calculates the state deposit rate and dispersion of deposit rates by taking an equal-weighted average of the county deposit rate and county dispersion of each state for the last reporting month of each quarter. The Emp-, and Pop-Weight measures are similarly constructed by taking an average of the county deposit rate

Analogous to the model of Equation 1 we estimate a logit model of a state recession in state $s$ in quarter-year $t$ as a function of the dispersion and level of deposit rates at quarter-year $t$. We consider up to 12 quarterly lead indicators of recessions. The baseline model is as follows:

$$logit(p_{s,t+k}) = \alpha + \beta_1 Rate_{s,t} + \beta_2 SD_{s,t} + \alpha_s + \epsilon_{s,t} \tag{2}$$

where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, $Rate$ denotes the average bank deposit rate, and $SD$ denotes the standard deviation of bank deposit rates. We assume that $\epsilon_{s,t}$ is well-behaved.

Table 4 reports the average marginal effects at the state level. As before, the independent variables are standardized for ease of interpretation. We account for the time-invariant heterogeneity associated with states through state fixed effects. The dependent variable in columns 1 through 3 indicate whether a recession occurs four quarters ahead, eight quarters ahead, and twelve quarters ahead, respectively. We account for the time-invariant heterogeneity across states through state fixed effects. Similar to the findings of Table 2, the dispersion of the deposit rate is a salient predictor of economic recessions. Column 1 indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 4.90 percentage points higher likelihood of a recession four quarters ahead. Column 2 indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 4.24 percentage points higher likelihood of a recession eight quarters ahead. Thus, an increase in the dispersion of deposit rates offered by banks within a state is associated with a higher probability of a future economic contraction.

Next, we examine the predictive value of our state level classifier through ROC curves, using the two-year forecast classifier. The AUC reported in Table 4 indicates that the AUC is 0.7895 – considerably higher than the county level predictive value of 0.7028. Moreover, we find that the pseudo $R^2$ is mostly driven by variation in deposit rates rather than county-and state-specific factors.[25] The ROC curve associated with the model of column 2 is presented in Figure 8b.

and county dispersion, weighted by the 2004 county GDP, employment, and population, respectively, in each state for the last reporting month of each quarter.

[25]This is established by comparing the (unreported) pseudo $R^2$ from a model without county/state fixed effects to a model with county/state fixed effects.

### 4.3 Forecasting National Recessions

Thus far, we have demonstrated that a simple logit model can be used to predict recessions at the county and state levels using the dispersion of bank deposit rates. In this section, we apply our model to forecast national recessions.

We begin by predicting the likelihood of a state recession by estimating the model parameters of a eight-quarter moving average model of Equation 2 for the sample period of 2005 through 2020.[26] We then use this classifier to forecast recessions. The "expected likelihood" of a national recession is calculated by taking a weighted sum of the predicted state probabilities, weighted by the 2004 state GDPs.[27] The country is determined to be in a recession if this expected likelihood is below the $25^{th}$ percentile of values. We report our model forecast and compare it to whether a recession occurred according to the NBER's Business Cycle Dating Committee.

Table **??** reports our forecast indicator for recessions along with an indicator for NBER recessions by quarter. We find that our model predicts 100% of recessions that occurred, according to the NBER. Our model also forecasts seven "recessions" that the NBER did not call. However, one must wary of gleaning too much from the false positives. Our model forecasts recessions in the three quarters preceding the Great Recession, and two quarters preceding and following the COVID-19 recession. Even though COVID-19 was an unexpected shock, our analysis suggests that the national economy was exhibiting weakness from the last quarter of 2019 – even before the shutdowns caused by COVID-19.[28] These false positives are very much indicative of periods of slowing economic growth, even if they do not meet the NBER's definition of a recession.[29] The confusion matrix below Table **??** summarizes the number of true positives, false negatives, false positives, and true negatives. Our findings are robust to alternative forecasting models including the twelve-quarter moving average model (Appendix Table **??**), 12- and 8-quarter moving average model (Appendix Table **??**), and 12-, 8-, and 4-quarter moving average model (Appendix Table **??**).

[26] We report our baseline findings using the moving average model for the county level in Appendix Table **??** and state level in Appendix Table **??**.

[27] Running the model with deposit rates at the national level lacks statistical power as there are very few recessions at the national level in the sample period.

[28] The yield curve (10Y-3M) had inverted on March 22, 2019, suggesting an impending economic recession.

[29] The NBER defines a recession as a "significant decline in economic activity that is spread across the economy and that lasts more than a few months." The Business Cycle Dating Committee uses three criteria – depth, diffusion and duration in calling a recession.

### 4.4 Robustness

This section investigates the robustness of our main finding that the dispersion of deposit rates is a salient indicator of economic recessions. First, we show that the dispersion of deposit rates can independently, accurately predict impending recessions even without deposit rate controls. Second, we show that our main findings are robust to the inclusion of the Federal Funds Effective Rate, dispelling the hypothesis that our results may be driven by changes in monetary policy. Third, we show that our main findings are robust to the inclusion of the term spread, demonstrating that the dispersion has predictive value above and beyond the leading indicator of recessions. This finding also demonstrates that time effects can enhance the predictive value of our model.

We begin by showing that the dispersion of deposit rates is independently, an accurate predictor of impending recessions. A common conception may be that the dispersion of deposit rates and average deposit rate are highly correlated – when rates increase, the dispersion also increases – therefore, the dispersion does not have additional predictive value. However, Figure 7 and Figure 2a indicate that while the average deposit rate remained relatively stable in the run-up to the COVID-19 recession, the dispersion widened. We test the hypothesis that the dispersion of deposit rates has predictive value in Appendix Table **??**. Column 1 indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 3.99 percentage points higher likelihood of a recession one year ahead. Column 2 indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 4.54 percentage points higher likelihood of a recession two years ahead. Column 3 indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 2.36 percentage points higher likelihood of a recession three years ahead. These estimates are statistically significant at the 1% level and are quantitatively similar to the point estimates of Table 2. Moreover, the pseudo $R^2$ exhibits minute differences between the two tables, indicating that most of the variation in recessions is explained by the dispersion of deposit rates, rather than the level. Lastly, the AUC is 0.70, suggesting that the classifier has high predictive value. Overall, our findings indicate that the average deposit rates is not necessary to generate a high model predictive value.

Thus far, our findings show that the inclusion of county fixed effects improves the predictive value of our model. However average deposit rates are influenced by the Federal Funds Effective Rate, hence, we include the Federal Funds Effective Rate to our baseline empirical specifications to control for the macroeconomic environment (Drechsler et al. (2017); Drechsler et al. (2022)).[30] These results are reported at the county level in Appendix Table **??** and Appendix Table **??** at the state level. The addition of the Federal Funds Effective Rate does not quantitatively or qualitatively affect the precision of our baseline point estimates reported in Table 2; the point estimates remain economically meaningful and statistically significant, though attenuated. Moreover, the point estimates associated with the Federal Funds Effective Rate are smaller than the point estimates associated with the dispersion of deposit rates. Moreover, the inclusion of the Federal Funds Effective Rate does not add considerable explanatory power or predictive value as reflected in the changes to the AUCs and the pseudo $R^2$. We further demonstrate that the predictive value of our model is not driven by movements in the Federal Funds Effective Rate by examining the predictive value of our model between 2011 and 2016 (see Section 8)– a period with little variation in the Federal Funds Effective Rate. These results add reassurance that the dispersion of deposit rates has predictive value, even after accounting for a key instrument of monetary policy and the macroeconomic milieu.

We consider how the inclusion of the term spread – the leading indicator of impending recessions – affects the predictive value of our model. The term spread is the 10-Year Treasury constant maturity minus the three-month Treasury constant maturity. These results are reported at the county level in Appendix Table A.6 and Appendix Table **??** at the state level. Consistent with the seminal work of Estrella and Hardouvelis (1991), we find that there is an inverse relation between the term spread and the likelihood of an impending recession. However, the dispersion of the deposit rate remains economically meaningful and statistically significant, after accounting for the term spread. Thus, the dispersion of deposit rates is a useful complement to the usage of treasury yield curve data for predicting recessions.

Lastly, recessions often reflect widespread economic decline across regions. The widespread economic decline may be driven by aggregate or common time-varying factors. In unreported regressions, we include year and quarter-year fixed effects to our baseline empirical specifications for predicting county and state recessions. The results reported in Table 2 and Table 4 are robust to the inclusion of time fixed effects. Addition of year fixed effects improves the AUC from $\sim$0.70 to $\sim$0.78 at the county level and from $\sim$0.80 to $\sim$0.91 at the state level. Hence, accounting for common or aggregate time-varying factors of recessions can improve the model's ability to predict recessions. However, from a forecasting perspective, any predictive model that incorporates time fixed effects is useless for forecasting as the effects are unknown ex ante.

[30]We omit the average deposit rate from these specifications, due to issues of multicollinearity.

## 5 Explaining the Dispersion of Deposit Rates

In the previous sections, we have shown that the dispersion of deposit rates can predict recessions at the county, state, and national levels. This section explores the mechanism behind these findings.

At an intuitive level, there must be some funding pressure on banks in order for them to increase the rates offered on insured deposits. Based on this premise, we begin by examining the relation between changes in deposit rates and the growth of insured and uninsured deposits. We sort banks at each time period into quartiles based on the changes in their deposit rates. The deposit rate changes are computed on a quarterly basis as call report data is available on a quarterly basis. We first compute banks' average deposit rate in each quarter across all counties. We then calculate the quarterly changes in banks' deposit rate. The dispersion of deposit rates is reflected by the quartile indicators for banks' quarterly changes in the deposit rate.

Our empirical framework regresses bank $b$'s outcome variable on quartile indicators for banks' quarterly changes in the deposit rate at time $t$ (quarter-year), an indicator for whether there is a recession in the next eight quarters, and the interaction of these variables. $k$ denotes the lead/lag of the dependent variable and ranges from -3 to +3.

$$\begin{aligned}\Delta ln(Y)_{b,t+k} = \beta_0 &+ \beta_1 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} \times \text{Rec.}_t \\ &+ \beta_2 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} \times \text{Rec.}_t + \beta_3 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} \times \text{Rec.}_t \\ &+ \beta_4 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} + \beta_5 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} \\ &+ \beta_6 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} + \alpha_t + \epsilon_{b,t}\end{aligned} \tag{3}$$

where $\Delta ln(Y)$ denotes growth in the outcome variable, $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$, $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$, $\mathbb{1}_{\text{Dep Rate Change}>P75}$ denote the second, third, or fourth quartile of a bank's deposit rate change between two consecutive quarters, respectively, and Rec. denotes whether there is a recession within the next eight quarters. Our regression specification includes quarter-year fixed effects to control for aggregate shocks.[31]

Table A.8 presents the dynamics of the relation between the deposit growth rates for insured and uninsured deposits and the quarterly change in banks' deposit rates. In Panel A, the dependent variable is the growth in banks' insured deposits. In Panel B, the dependent variable is the growth in banks' uninsured deposits. The vast majority of depositor households have deposits below the insured limit. Uninsured depositors are typically large depositors

[31] Quarter-Year fixed effects absorb the *Recession* variable, hence, we omit this from our regression specification.

such as nonfinancial or financial corporations, wealthy or sophisticated individuals. We find that the insured deposit growth declines in the quarters preceding rate changes; all banks face slower growth, regardless of the change in their deposit rates. We also find a comparable slowing in uninsured deposits. Interestingly, we observe that for banks which eventually raise rates to a greater extent, the growth of uninsured deposits declines by a greater amount. In other words, banks that experience greater uninsured deposit withdrawals raise deposit rates in the following quarter by a larger margin. Moreover, as an economy approaches a recession, banks experience additional uninsured deposit withdrawals in the quarter in which rates are raised, as indicated by the point estimate associated with $\mathbb{1}_{\text{Dep Rate Change}>P75,b,t} \times \text{Rec.}_t$. Unsurprisingly, we also find higher growth in both insured and uninsured deposits in the quarter after rates are raised.[32]

In Table 7 we directly examine the growth in the ratio of insured to uninsured deposits to better understand the dynamics in the composition of funding around deposit rate changes. Our analysis shows that, for the most part, the growth in the ratio of insured to uninsured deposits does not exhibit any meaningful variation in the quarters before and after deposit rate changes as well as across banks of various risk profiles. However, consistent with our findings in Table A.8, we do find that banks in the fourth quartile (in terms of rate changes) experience a significant increase in the growth of insured to uninsured deposits in the quarter before rates are raised.[33] In addition, as an economy approaches a recession, these banks experience an additional increase in the growth of insured to uninsured deposits in the quarter that rates are raised. These findings corroborate our findings of Table A.8 and reinforce our conjecture that banks that raise deposit rates by a larger margin experience larger withdrawals of uninsured deposits.

What is the association between a change in the riskiness of banks and a change in deposit rates? Table **??** investigates these dynamics. Panel A examines the dynamics of the relation between the growth in RWA and deposit rate changes. Panel B examines the dynamics of the relation between the growth in tier 1 capital and deposit rate changes. We find that during periods of normal economic growth, higher RWA growth precedes higher rate changes. In these periods, banks continue growing their RWA in quarters following rate changes. Specifically, there is a monotonic relation between the RWA growth rate and deposit rate changes. Banks in the fourth quartile experience greater RWA growth compared to banks in the first, second, and third quartiles in these periods. We find similar patterns with tier 1 capital growth.[34]

[32] Unreported, these banks also increase the rate on uninsured deposits.

[33] This is because of a decline in uninsured deposits.

[34] We also find similar results with tier 2 capital growth in Appendix Table **??**.

During periods of normal economic growth, tier 1 capital growth is higher for banks in the fourth quartile relative to banks which operate in the first, second, and third quartiles of rate changes. However, these findings are different during recessionary periods. As an economy approaches a recession, we find that all banks reduce expansion of RWA and tier 1 capital. Banks in the fourth quartile of deposit rate changes reduce RWA and tier 1 capital growth by a greater margin than banks in the first, second, and third quartiles.[35] These findings suggest that during periods of normal economic growth, banks increase rates to expand their balance sheet and banks with higher rate changes increase the riskiness of their assets. In contrast, at the onset of a recession, banks increase rates to reduce the riskiness of their assets and also experience a reduction in tier 1 capital.

Finally, we examine the relation between the growth in lending and growth in non-performing loans with changes in deposit rates to understand the assets side adjustments of banks' balance sheet. Panel A of Table 8 indicates that higher lending growth precedes higher rate changes. Specifically, we find that during periods of normal economic growth, banks in the fourth quartile report higher lending growth in the quarters preceding rate changes. However, as an economy approaches a recession, these banks experience lower lending growth relative to banks which operate in the first, second, and third quartiles of rate changes. While the relative magnitudes of differential lending growth across quartiles of banks are small (0.8 percentage points for the fourth quartile relative to the first quartile), the results paint an interesting picture. The results show that in periods of normal economic growth, banks that increase rates by more, do so to support their asset side growth. However, as an economy approaches a recession, the differential lending growth across banks in different quartiles starts converging.[36] This suggests that at the onset of a recession, the banks that raise their rates by a larger margin, do so to support their balance sheet, rather than to expand it. In Panel B, we examine growth rates of non-performing loans. We find that banks in the fourth quartile report higher non-performing loan (NPL) growth, following the quarter of rate changes. This suggests that banks that increase deposit rates by a larger margin experience an increase in their overall riskiness due to higher losses.

Overall, our findings suggest the following channel at work. As an economy approaches an economic downturn, insured deposit growth decreases across all banks. In addition, uninsured depositors withdraw deposit funding from riskier banks. As a result, to make up the difference in funding and support their balance sheet, these risky banks raise deposit rates to

[35] For example, in the quarter that the rate changes occur, the net effect of RWA growth is 0.0030 for the fourth quartile. This is the sum of unconditional effect of 0.0065 and the interaction of -0.0035.

[36] In the quarter before the rate changes occur, the net effect of lending growth is 0.0036 for the fourth quartile. This is the sum of unconditional effect of 0.0084 and the interaction of -0.0048.

attract funds from insured depositors. Thus, dispersion of deposit rates results across banks at the onset of a recession.

For further illustration of our proposed mechanism, consider the following example. Assume that there are two banks in an economy: Bank A and Bank B. Bank A and Bank B fund \$100 of their assets with \$10 of uninsured deposits and \$90 of insured deposits. However, Bank A and Bank B invest in different projects. As the economy heads towards a recession, there is an increase in riskiness of bank A. Uninsured depositors perceive Bank A as being risky, ergo, they withdraw their funds from Bank A. In response, Bank A increases the rates on insured deposits to attract more deposits to make up the shortfall in liabilities to support its balance sheet.[37] Bank B does not experience a withdrawal, hence they do not change their rates on insured deposits as it faces no funding shortfall. The divergence in rates between Bank A and Bank B is reflected in the higher dispersion of deposit rates. Therefore, an increase in the dispersion of deposit rates acts as a precursor to a recession and has predictive power.

The simple example above highlights two important things. Neither a preceding period of high credit growth nor the materialization of NPLs are necessary for our hypothesis. Our proposed mechanism is agnostic to the causes of economic contractions. While credit booms may aggravate the "rate-dispersion" channel by widening the funding gap between loans and deposits, they are not necessary for uninsured depositors to withdraw funding. The response of uninsured depositors is driven by their perception of increase in riskiness of banks' balance sheet. Indeed, we find that we are able to predict recessions in counties and states without credit booms, as discussed later in Section 8. Further, it is also not necessary for risk to materialize in the form of NPLs for uninsured depositors to withdraw deposit funding from risky banks.[38]

Overall, the findings suggest that at the onset of an economic contraction, the increase in the dispersion of deposit rates is an outcome of riskier banks raising deposit rates to attract insured deposits to fill the funding shortfall created by uninsured deposits moving away.

# 6 Heterogeneous Effects

The mechanism described above suggests that some banks face funding squeeze at the onset of a recession and this translates into them offering higher deposit rates to attract deposits. A natural extension of this argument is that the predictive value of our model increases in

[37] The rate on insured deposits is generally lower than uninsured deposits.

[38] Our evidence is consistent with Artavanis et al. (2022) that finds higher deposit rates are offered by banks to depositors in order to keep them in the bank during times of high uncertainty.

areas where banks face more competition for deposits. This section deconstructs our baseline results in order to better understand how cross-sectional dimensions of heterogeneity, in terms of competition for deposits, affect recession predictions. First, we study whether the effects are pronounced based on the number of banks that operate within a geographic area. Then, we examine whether the effects differ for metropolitan, urban, and rural geographic areas.

Our hypothesis is that areas with a greater number of banks face stiffer competition for deposit funding. In areas where there is less competition for deposits, i.e., fewer banks, the need to raise deposit rates to attract funding is lower and thus, the dispersion of deposit rates has less power in predicting an economic downturn. Thus, we hypothesize that when competition is higher, local economic conditions exhibit greater sensitivity to the dispersion of deposit rates. We test this hypothesis at the county- and state levels. Appendix Table A.4 presents the results at the county level. Panel A estimates Equation 1 for counties with more than two banks. Panel B estimates Equation 1 for counties with more than three banks. Panel C estimates Equation 1 for counties with more than four banks. Focusing on the two-year forecast classifier, we find that as we move from Panel A to Panel C, the magnitude of the point estimate associated with the dispersion of deposit rates increases. Specifically, we find that in counties with more than four banks, a one standard deviation increase in the dispersion of deposit rates is associated with a 6.67 percentage points increase in the likelihood of a recession two years ahead in that county. These figures are 6.16 percentage points and 4.37 percentage points in counties with more than three banks and counties with more than two banks, respectively – higher than our baseline figure of 3.68 percentage points. Moreover, we find that the AUC is higher in markets with a larger number of banks as shown in Figure A.7. The two-year forecast classifier produces an AUC of 0.7028 in counties with at least two banks, 0.7123 in counties with more than two banks, 0.7294 in counties with more than three banks, and 0.7442 in counties with more than four banks. Appendix Table **??** presents the results at the state level.

Next, we examine the heterogeneity in predictive values across different geographies. The USDA ERS's Rural-Urban Continuum Codes from 1993 are used to distinguish metropolitan counties from urban and rural counties. Appendix Figure **??** presents a heatmap of metropolitan, urban, and rural counties. We estimate Equation 1 separately for metropolitan, urban, and rural areas in Appendix Table **??** and plot the ROC curves in Figure A.6. We find that the point estimates associated with the dispersion of deposit rates are highest for metropolitan counties. Moreover, while we find that our model has predictive value across geographies, there is a positive association between the degree to which a county is metropolitan and the AUC. Specifically, we find that the AUC associated with the two-year forecast classifier is 0.7463 in metropolitan counties, compared to 0.6700 in urban counties, and 0.6615 in rural counties. These results are again consistent with the idea that the dispersion of deposit rates has higher predictive value in settings where there is likely more competition for funds.[39]

## 7 Out-of-Sample Predictions

An important aspect of any predictive modeling is out-of-sample model validation – how accurately does the model perform in practice? We evaluate the predictive value of our model through k-fold cross validation. Specifically, our dataset is partitioned into $k$ subsamples of equal size. $k-1$ subsamples are used as the training set while one subsample is retained as the validation or testing set in which we evaluate the predictive performance (AUC). We estimate the AUC iteratively $k$ times, so that each of the $k$ subsamples is used as the testing set once. We plot the $k$-fold ROC curves and estimate the average AUC across the $k$-folds and bootstrapping the cross-validated AUC for statistical inference. Our default number for $k$ is 10. k-fold cross-validation is a powerful tool that tests a model's ability to generalize to new cases that were not used in the estimation process. This allows us to flag issues such as overfitting and selection bias and produce realistic estimates of predictive value.

Figure 10 and Figure 11 report the k-fold ROC curves and summarizes the cross-validated AUC at the county and state levels. We find that our predictive model generalizes well to independent datasets and reports a high model prediction performance. Specifically, we find that at the county level, the cross-validated AUC is 0.580 with a standard deviation of 0.013 in counties with at least two banks. The predictive accuracy increases monotonically with the number of banks in each county. We find that the cross-validated AUC is 0.584 (s.d. = 0.012) in counties that report greater than two banks, 0.605 (s.d. = 0.016) in counties that report greater than three banks, and 0.626 (s.d. = 0.022) in counties that report greater than four banks. At the state level, we find that the k-fold cross-validated AUC is 0.743 (s.d. = 0.054). Like in Figure 10, we find that the predictive accuracy increases monotonically with the average number of banks per county in each state. The cross-validated AUC is 0.753 (s.d. = 0.075) in counties that report greater than two banks, 0.771 (s.d. = 0.087) in counties that report greater than three banks, and 0.837 (s.d. = 0.122) in counties that report greater than four banks. Hence, our out-of-sample results validate the model. The dispersion of bank deposit rates can accurately

[39] Metropolitan areas are likely to have more banks as compared to other areas. The AUCs obtained are very similar for metropolitan areas and for counties with more than four banks. We further posit that metropolitan areas are more likely to feature larger banks relative to non-metropolitan areas. For direct comparison, we compare the AUC from a model that uses the dispersion of deposit rates and average deposit rate for stress-tested banks to those for all other banks. The results, reported in Appendix Figure **??**, indicate that the AUC is 0.7336 using deposit rates from stress-tested banks and 0.7034 for all other banks.

predict recessions, particularly in more competitive deposit markets where the goodness of fit is higher.

## 8 Deposit Rates and Credit Booms

Thus far, we have established in previous sections that the dispersion of bank deposit rates can be used to forecast recessions. An important question that arises is whether the predictive power of bank deposit rates is limited to recessions that are preceded by a credit boom.[40] In other words, can dispersion of deposit rates predict recessions that are not preceded by periods of high credit growth? In this section, first, we show that the dispersion of deposit rates can predict recessions, even after accounting for credit growth. Second, we show that the dispersion of deposit rates can predict recessions, even in the absence of credit booms.

We examine credit growth at the county level using data on small business lending and mortgage lending. Table 10 runs a horse-race between our measure of the dispersion of deposit rates against measures of credit growth including mortgage lending growth and total lending growth (sum of mortgage and small business lending). Panel A includes mortgage lending growth in our baseline estimation. Panel B includes total lending growth. The point estimate associated with the dispersion of deposit rates remains economically meaningful and statistically significant at the 1% level with the addition of credit growth variables. That is, Panel A indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 4.83 percentage points higher likelihood of a recession one year ahead, 3.45 percentage points higher likelihood of a recession two years ahead and 1.36 percentage points higher likelihood of a recession three years ahead. Panel B indicates that a one standard deviation increase in the dispersion of deposit rates is associated with a 4.78 percentage points higher likelihood of a recession one year ahead, 3.47 percentage points higher likelihood of a recession two years ahead and 1.36 percentage points higher likelihood of a recession three years ahead. Importantly, neither the addition of mortgage growth nor total lending growth add explanatory power, as evinced by the change in the pseudo $R^2$, nor improve the predictive value, as evinced by the change in the AUC. The addition of the credit growth measures do not quantitatively or qualitatively affect the precision of our baseline point estimates reported in Table 2.

Not all recessions result from credit booms. However, credit is an important component of every business cycle (Zarnowitz (1999)).[41] Thus, a deterioration in the economic fundamen-

[40] Mian and Sufi (2016) contends there is a strong link between household debt and business cycles.
[41] Firms in an economy rely at least in part on banks to fund their operations.

tals of a region at the onset of a recession may be sufficient to affect the riskiness of banks and raise deposit rates in that region. Thus, the "rate-dispersion" channel may have power to predict recessions, agnostic to the underlying causes for the business cycle dynamics. To test this, we study county and state recessions between 2011 and 2016 – a period in which credit growth was stagnant. Appendix Figure A.5 report these findings for county and state recessions, respectively. We find that our model can predict county and state recessions with considerable accuracy. The AUC at the county level is 0.6998 and at the state level is 0.7296. The high performance of the model in a period of stagnant credit growth demonstrates that dispersion of deposit rates can predict recessions, even in the absence of credit booms. These findings highlight that, in general, changes in the liabilities side of banks' balance sheet is useful for macroeconomic predictions.

## 9 Conclusion

The underlying causes and consequences of business cycles vary across economies and over time. Regardless of these characteristics, a common thread that cuts across most of them is that banks play an important part as a funding source (Zarnowitz (1999)). Thus, in this paper, we emphasize that changes in the liability side of banks' balance sheet can signal an impending economic contraction.

We predict recessions using the dispersion of deposit rates on insured deposits across banks. Our framework can predict county, state, and national recessions over long time horizons of up to three years. We also find that the predictability is higher in areas with a larger number of banks. The AUC of the two-year forecast classifier within a county (state) is 0.70 (0.79).

We examine the mechanism behind the predictive power of the dispersion of deposit rates and find that banks which experience an outflow of uninsured deposits and a slower growth rate of insured deposits increase deposit rates in the following quarter. The banks that increase deposit rates by a larger margin are riskier banks. Riskier banks offer higher deposit rates to attract deposits in order to support their balance sheet when funding is scarce. Overall, our results suggest that at the onset of an economic contraction, there is an increase in the dispersion of deposit rates as banks increase rates to attract deposits in response to deposit withdrawals – especially, uninsured deposits. Therefore, an increase in the dispersion of deposit rates, regardless of whether there has been a preceding credit boom, can predict an impending recession.

The leading indicator of an impending recession is an inversion of the yield curve. However, a shortcoming of this predictor is that it can only be used to predict national recessions. The granularity of our indicator – the dispersion of deposit rates – allows for prediction of localized downturns at regional levels. Our market-based measure is easy to construct and use and thus provides a useful early warning signal of an impending downturn that can complement existing metrics. Our finding that riskier banks increase their reliance on insured deposits as they approach a downturn raises concerns about moral hazard arising from deposit insurance schemes.

Our analysis raises several questions. How well does the dispersion of deposit rates offered by banks predict recessions in other countries and time periods? How would banks respond to a funding squeeze at the start of a downturn if there was no deposit insurance? Addressing these questions is an important avenue for future research.

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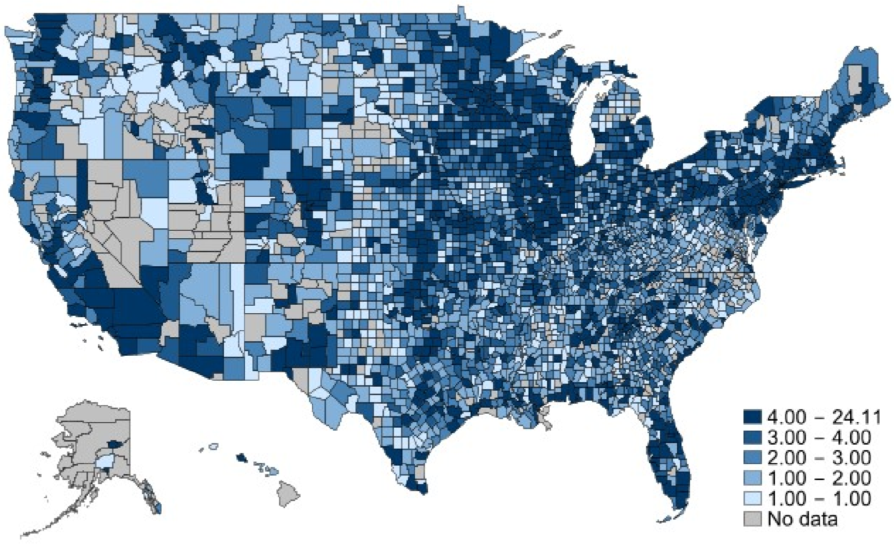
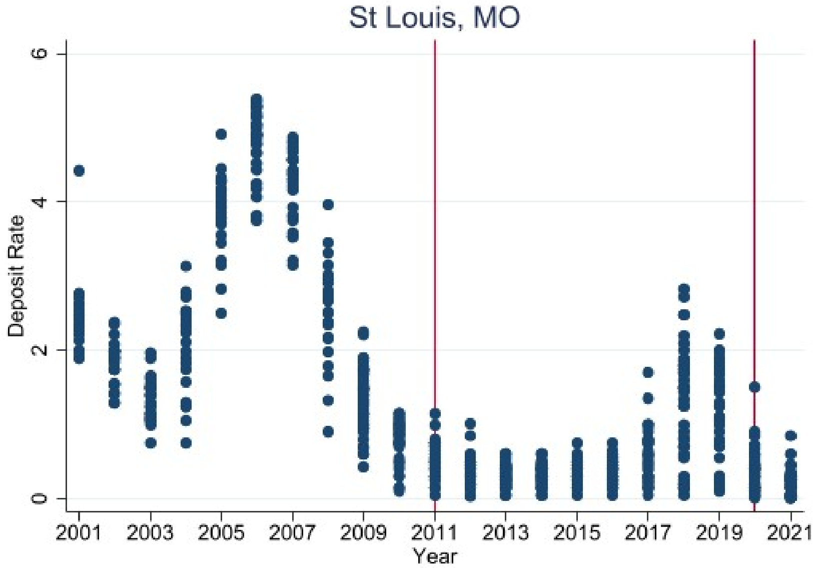
## 10 Figures and Tables

Figure 1: Number of Banks per County (2001-2020)

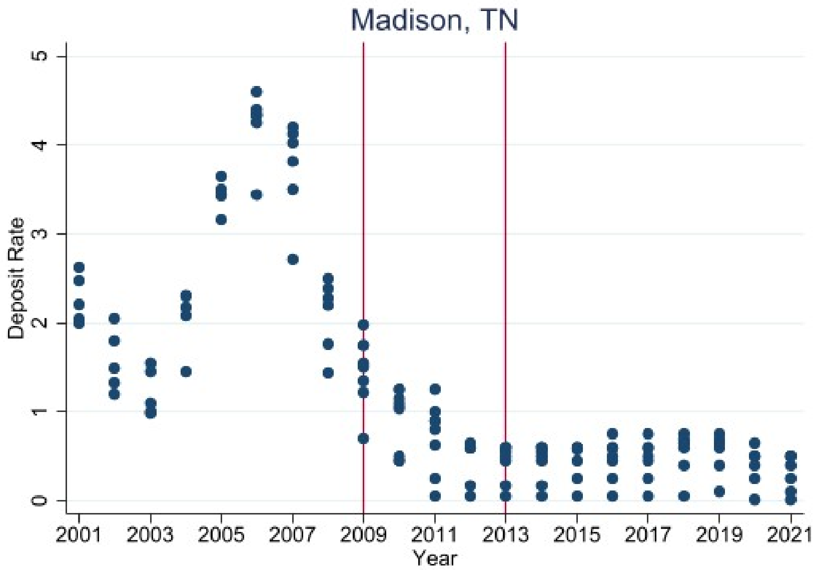



*Notes:* This figure uses RateWatch data to present a heatmap of the average number of banks that offer 12-month certificates of deposit of at least $10,000 in each county from 2001 to 2020. The intensity of the blue shading represents the number of banks operating in a particular county.

Figure 2: Dispersion of Deposit Rates and County Recessions



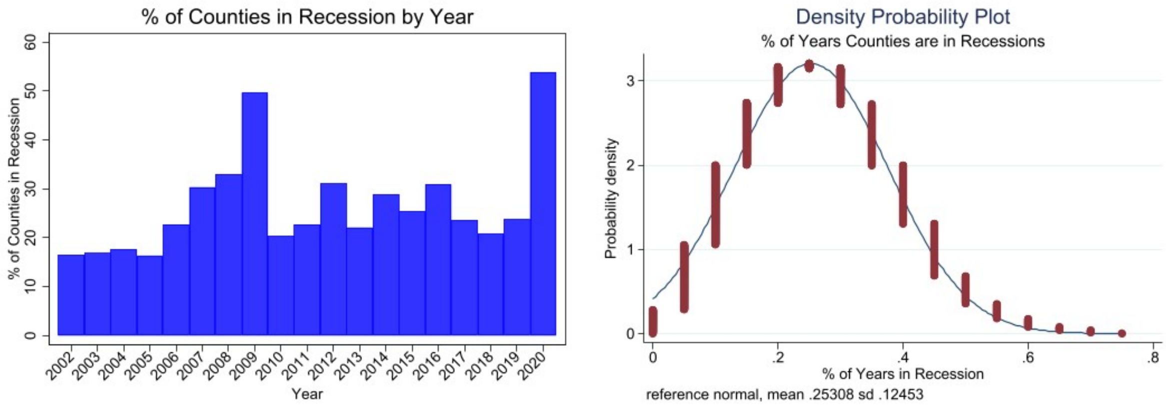

(a) St. Louis, MO




(b) Madison, TN

*Notes:* This figure uses RateWatch data to present a scatter plot of banks' deposit rates (12-month, $10K CDs) from January 2001 through December 2020 in St. Louis, MO and Madison, TN. The red lines demarcate county recessions. A county is in a recession if its GDP growth between two consecutive years is below -2%.

Figure 3: Recessions Across Counties and Time

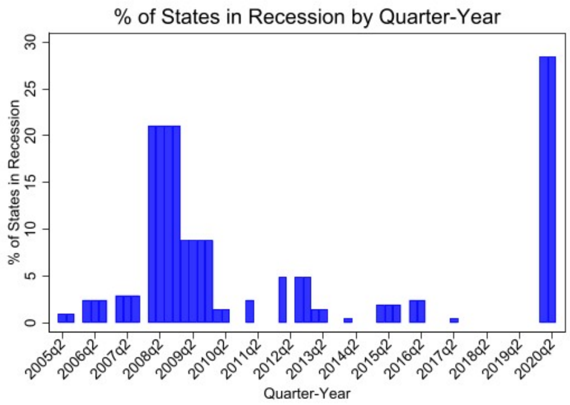



(a) % of Counties in Recession

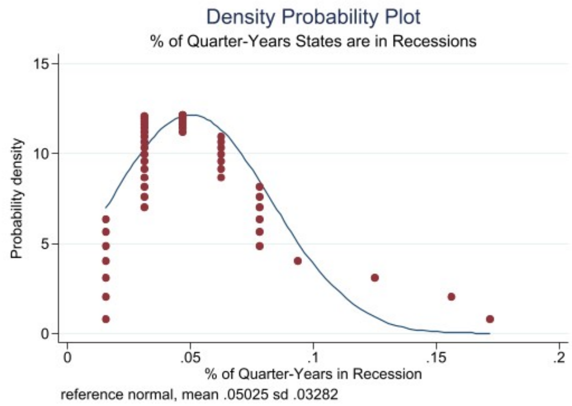
(b) % of Recessions within Counties

*Notes:* This figure presents the percentage of counties in recessions by year in Figure 3a, and a density probability plot of the percent of year counties are in recessions in Figure 3b based on County GDP data from the Bureau of Economic Analysis. County GDP data is available at the annual frequency from 2001. A county is in a recession if its GDP growth between two consecutive years is below -2%.

Figure 4: Recessions Across States and Time



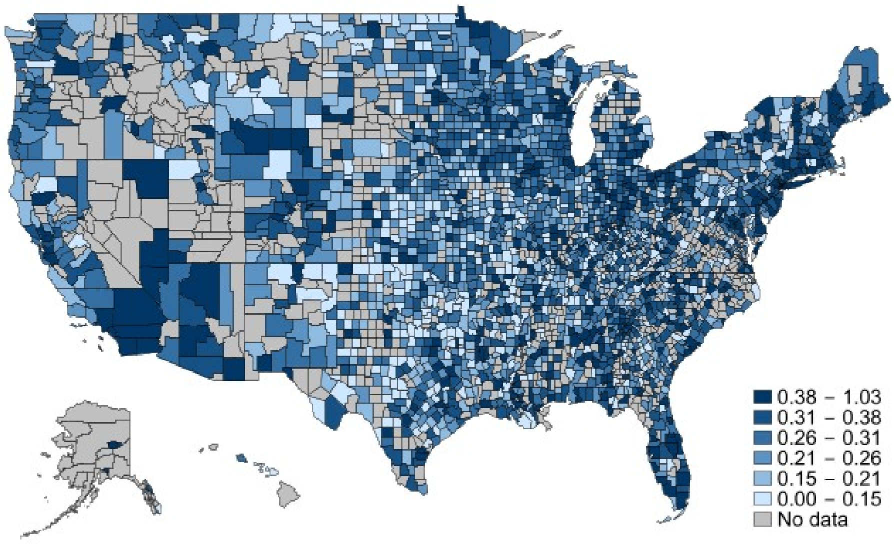

(a) % of States in Recession




(b) % of Recessions within States

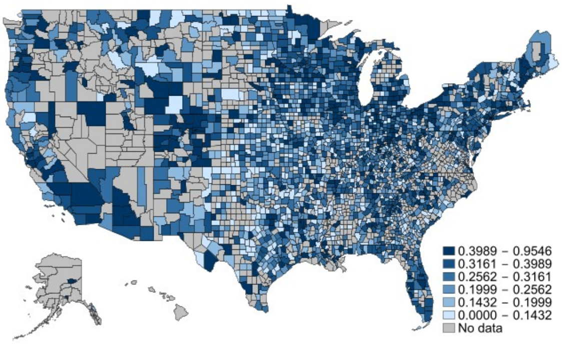
*Notes:* This figure presents the percentage of states in recessions by quarter-year in Figure 3a, and a density probability plot of the percent of quarter-years states are in recessions in Figure 3b based on State GDP data from the Bureau of Economic Analysis. State GDP data is available at the quarterly frequency from 2005. A state is in a recession if its GDP growth between two consecutive quarters is below -2%.

Figure 5: Dispersion of Deposit Rates by County (2001-2020)

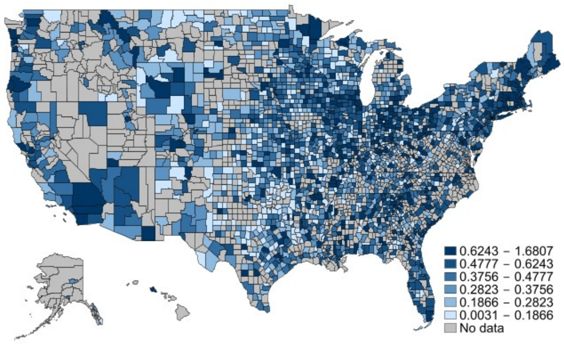



*Notes:* This figure uses RateWatch data to present a heatmap of the average standard deviation of deposit rates (12-month, \$10K CDs) from 2001 to 2020. The deposit rate is the rate on the 12-month certificate of deposit of at least \$10,000. The intensity of the blue shading represents the sextile range of deposit rate standard deviation.

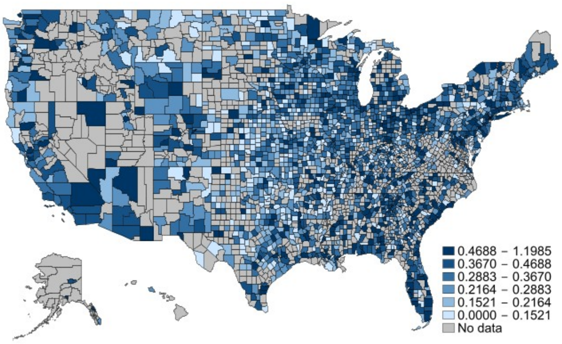
Figure 6: Dispersion of Deposit Rates Over Time



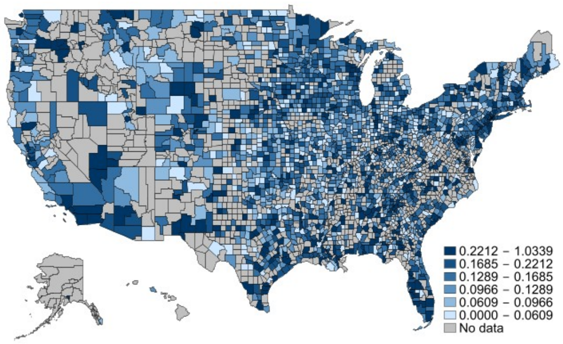

(a) 2001-2004



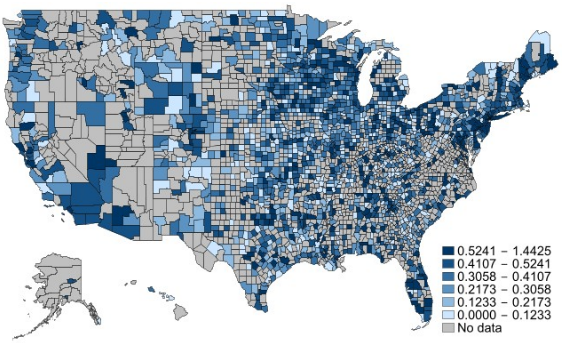

(b) 2005-2007



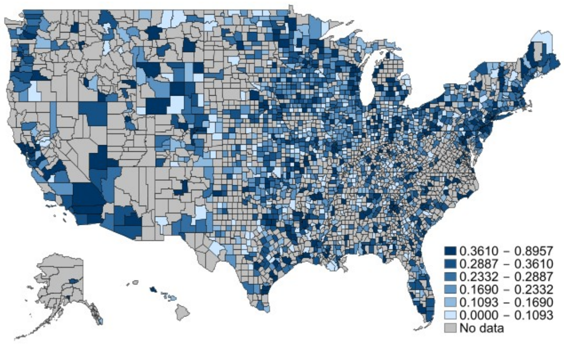

(c) 2008-2010




(d) 2011-2016



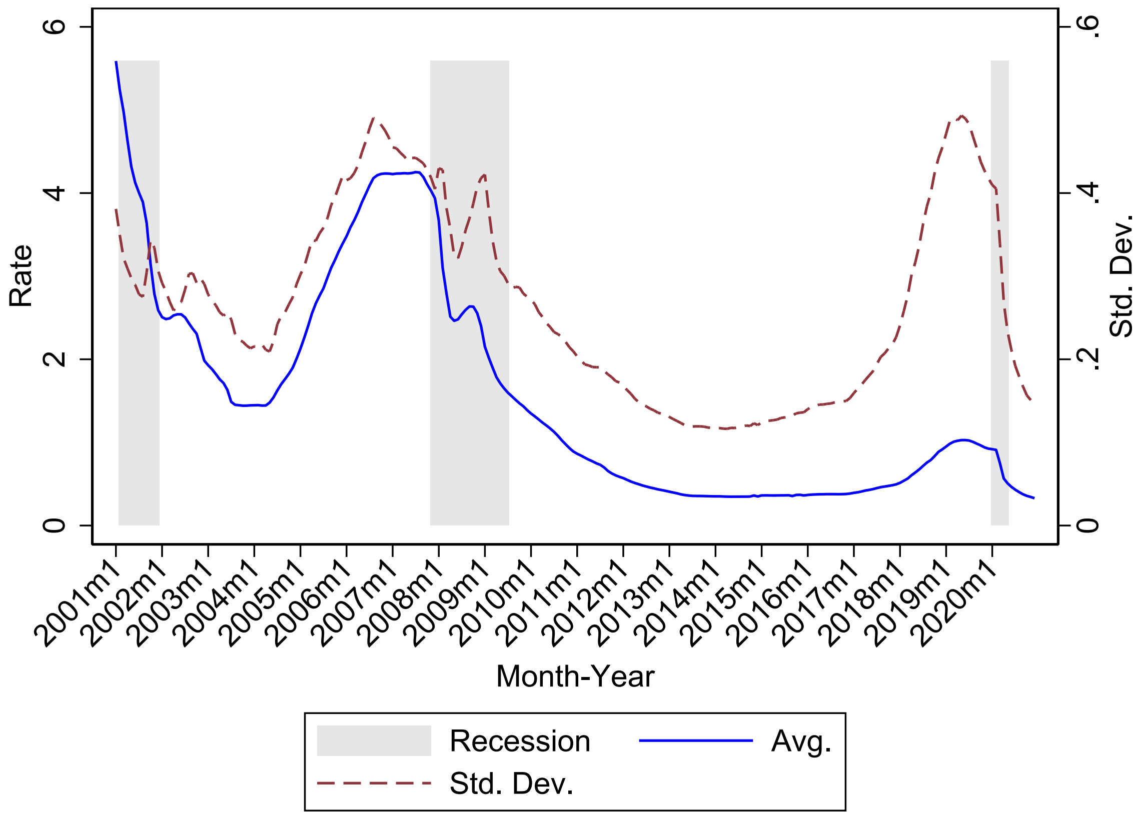

(e) 2017-2019




(f) 2020

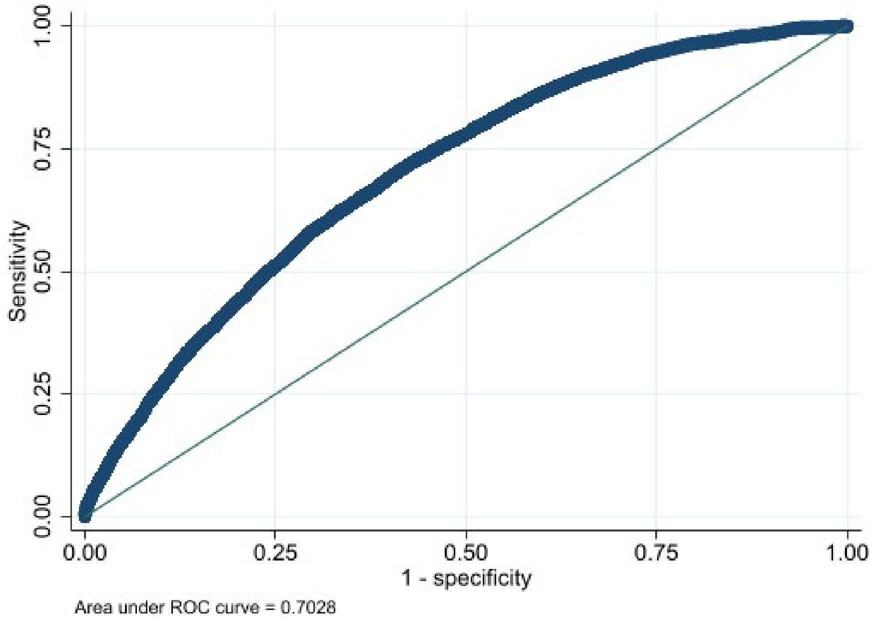
*Notes:* This figure uses RateWatch data to present a heatmap of the average standard deviation of deposit rates (12-month, $10K CDs). Figure 6a presents the time-series average of the standard deviation of deposit rates from 2001-2004; Figure 6b presents the time-series average of the standard deviation of deposit rates from 2005-2007; Figure 6c presents the time-series average of the standard deviation of deposit rates from 2008 to 2010; Figure 6d presents the time-series average of the standard deviation of deposit rates from 2011 to 2016; Figure 6e presents the time-series average of the standard deviation of deposit rates from 2017 to 2019; and Figure 6f presents the time-series average of the standard deviation of deposit rates for 2020. The deposit rate is the rate on the 12-month certificate of deposit of at least $10,000. The intensity of the blue shading represents the sextile range of deposit rate standard deviation.

Figure 7: Average Deposit Rate and Dispersion of Deposit Rate (2001-2020)

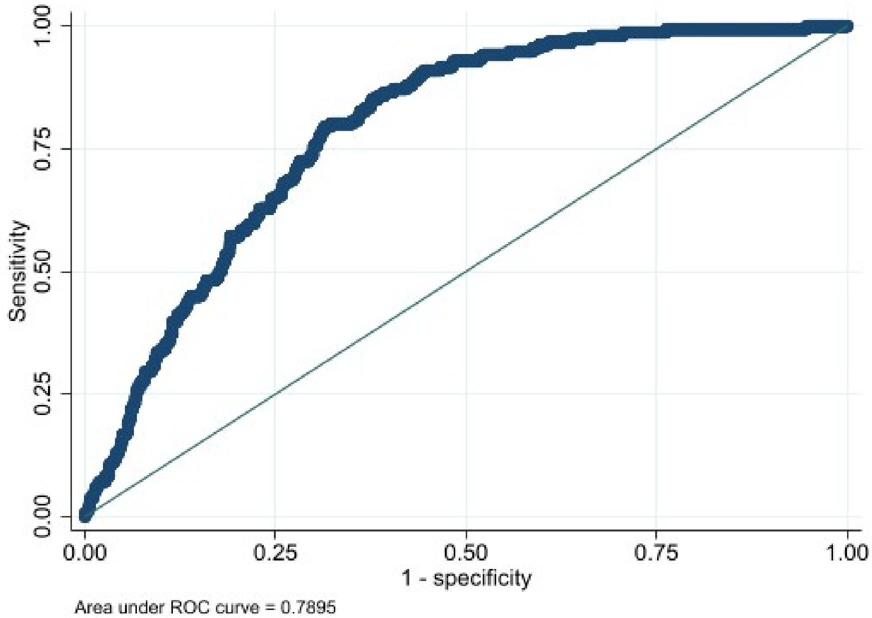



*Notes:* This figure uses RateWatch data to present a time-series plot of the average deposit rate and average standard deviation of deposit rates (12-month, $10K CDs) from January 2001 through December 2020. The data is at the monthly frequency.

Figure 8: Two-Year Dispersion of Deposit Rates Predicts Recessions



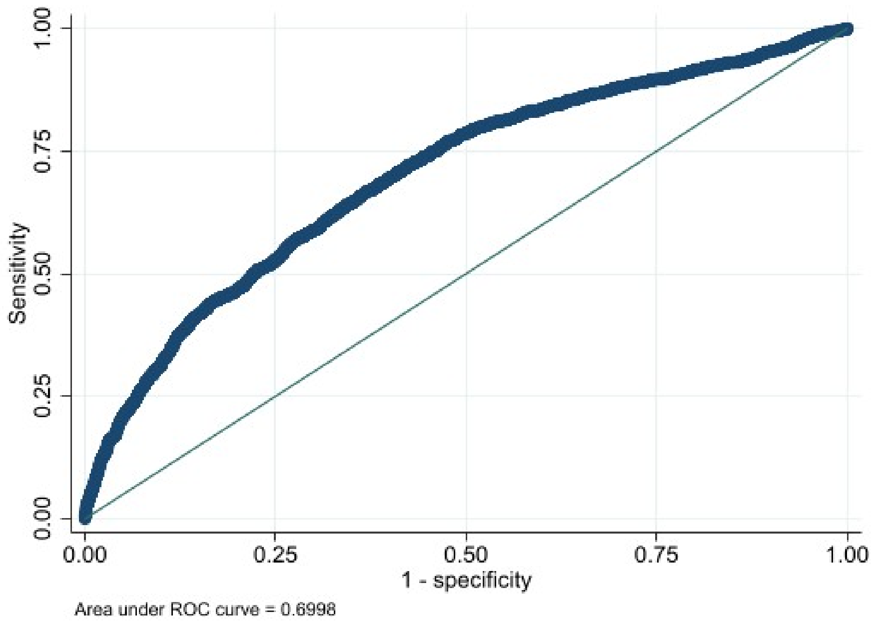

(a) County



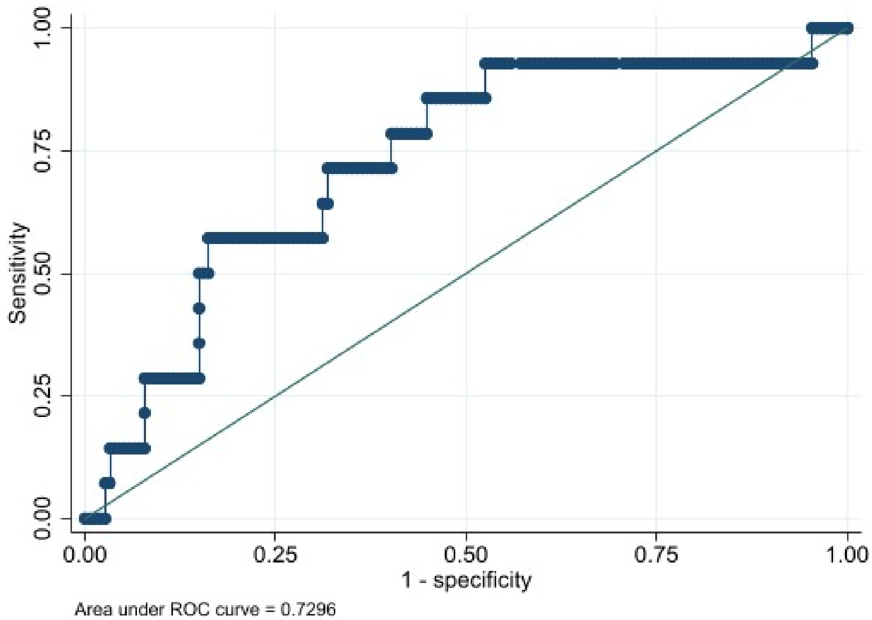

(b) State

*Notes:* This figure plots the Receiver Operating Characteristic (ROC) curves. Figure 8a presents the ROC curve associated with the model of column 2 in Table 2. Figure 8b presents the ROC curve associated with the model of column 2 in Table 4.

Figure 9: Dispersion of Deposit Rates Predicts Recessions: 2011-2016



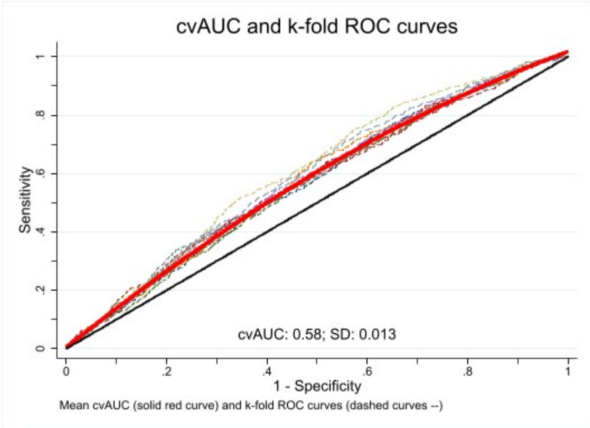

(a) County



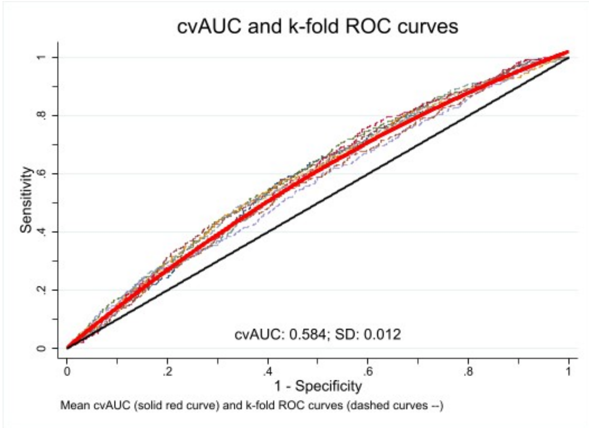

(b) State

*Notes:* This figure plots the Receiver Operating Characteristic (ROC) curves. Figure A.5a presents the ROC curve associated with the model of column 2 in Table 2 for the period 2011-2016. Figure A.5b presents the ROC curve associated with the model of column 2 in Table 4 for the period 2011-2016.

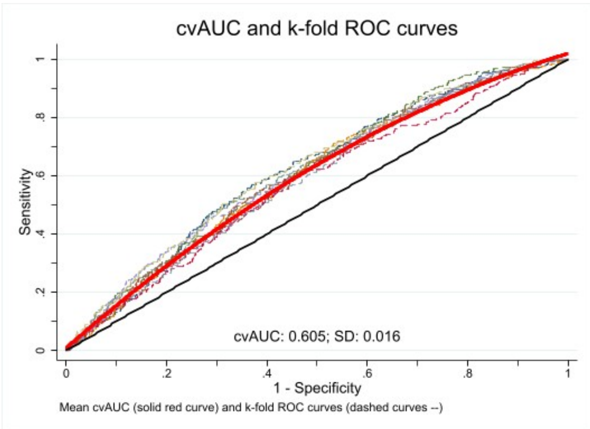
Figure 10: Out-of-Sample Estimation: Dispersion of Deposit Rates Predicts Recessions Better in Counties with More Banks



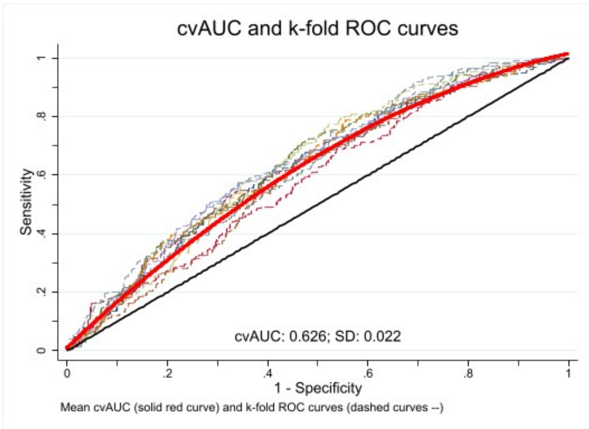

(a) All




(b) >2 Banks



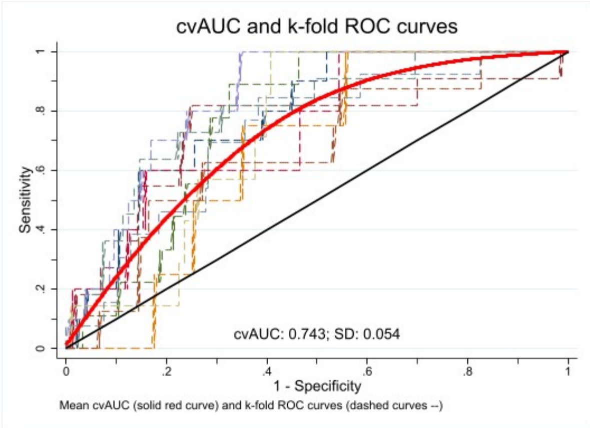

(c) >3 Banks



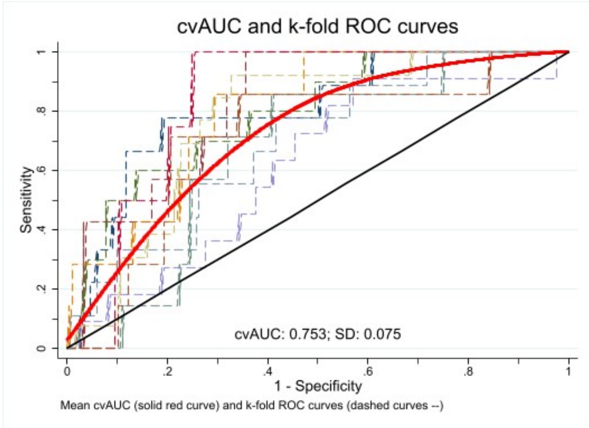

(d) >4 Banks

*Notes:* This figure presents the k-fold cross-validated ROC curves and AUC. The dataset is partitioned into $k$ subsamples of equal size. $k-1$ subsamples are used as the training set while one subsample is retained as the validation or testing set in the AUC is evaluated. The AUC iteratively $k$ times, so that each of the $k$ subsamples is used as the testing set once. Each fold is analyzed using the logistic regression specification of column 2 in Table 2 on all training sets and the value of the AUC is calculated from predictions on the test set. The cross-validated AUCs are averaged from each fold. 10 folds are used to produce these figures. Figure 10a presents the cross-validated results for all counties. Figure 10b presents the cross-validated results for counties with more than two banks; Figure 10c presents the cross-validated results for counties with more than three banks; Figure 10d presents the cross-validated results for counties with more than four banks.

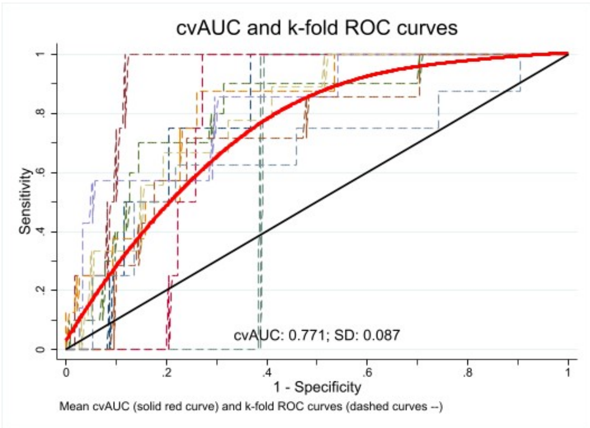
Figure 11: Out-of-Sample Estimation: Dispersion of Deposit Rates Predicts Recessions Better in States with More Banks



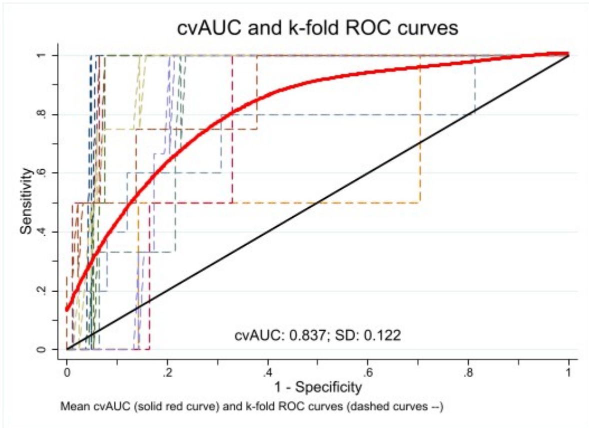

(a) All




(b) >2 Banks



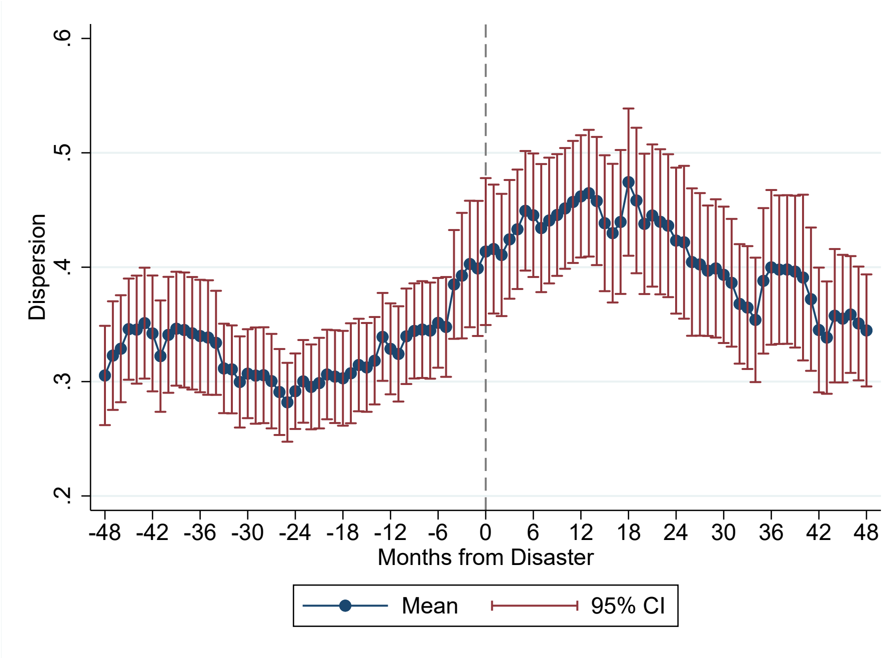

(c) >3 Banks



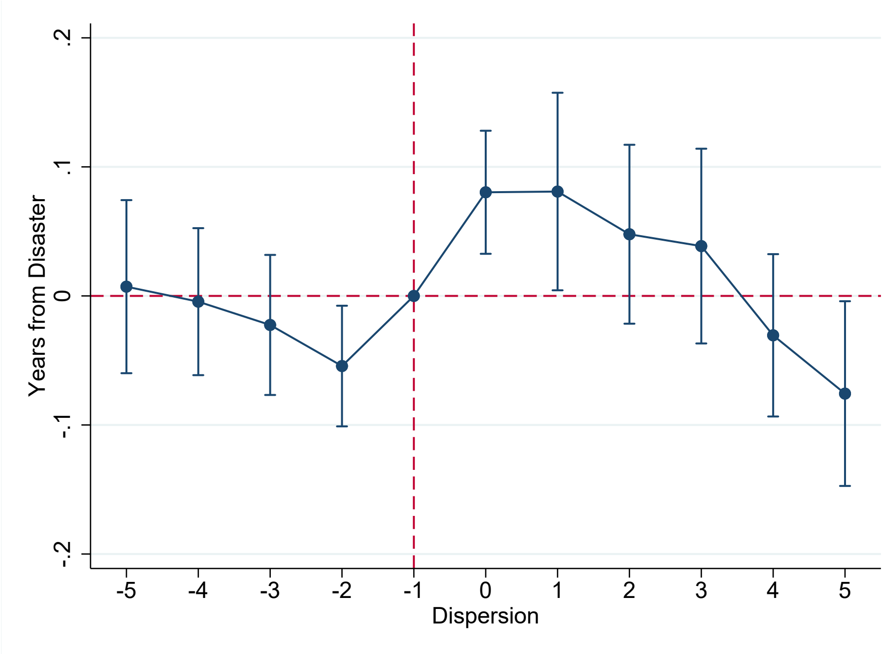

(d) >4 Banks

*Notes:* This figure presents the k-fold cross-validated ROC curves and AUC. The dataset is partitioned into $k$ subsamples of equal size. $k-1$ subsamples are used as the training set while one subsample is retained as the validation or testing set in the AUC is evaluated. The AUC iteratively $k$ times, so that each of the $k$ subsamples is used as the testing set once. Each fold is analyzed using the logistic regression specification of column 2 in Table 4 on all training sets and the value of the AUC is calculated from predictions on the test set. The cross-validated AUCs are averaged from each fold. 10 folds are used to produce these figures. Figure 11a presents the cross-validated results for all states. Figure 11b presents the cross-validated results for states with more than two banks per county on average; Figure 11c presents the cross-validated results for states with more than three banks per county on average; Figure 11d states with more than four banks per county on average.

Figure 12: Dispersion of Deposit Rates around Natural Disasters




(a) Average SD for Disaster Counties by Month from Event




(b) Regressions Margins: SD for Disaster Counties by Year from Event

*Notes:* The figure presents the dispersion in deposit rates around the timing of a natural disasters. The sample is restricted to natural disasters that last less than 31 days with total damages above $1 bn 2018 dollars. Figure 12a plots the mean standard deviation of bank deposit rates by month from event, along with the 95% confidence intervals. Figure 12b plots the $\delta_{t+d}$ coefficients in the following regression specification of $SD_{c,t} = \beta_0 + \sum_{k=-5}^{5} \delta_{t+d} + \alpha_c + \epsilon_{c,t}$ where $d$ refers to the year of the natural disaster. The base year is -1 years from the disaster. Standard errors are clustered by county FIPS.

Table 1: Summary Statistics (2001-2020)

| | N | P25 | Median | P75 | Mean | SD |
|---|---|---|---|---|---|---|
| Monthly Bank Deposit Rate | 585,096 | 0.4500 | 1.1521 | 2.4500 | 1.5984 | 1.3574 |
| Monthly Bank Dep. Rate SD | 422,045 | 0.1061 | 0.2121 | 0.3754 | 0.2686 | 0.2181 |
| Annual County Deposit Rate | 54,327 | 0.3667 | 0.8632 | 2.1500 | 1.3873 | 1.2590 |
| Annual County Dep. Rate SD | 37,904 | 0.0995 | 0.1945 | 0.3585 | 0.2573 | 0.2177 |
| Annual County GDP Growth | 59,127 | -0.0230 | 0.0122 | 0.0455 | 0.0125 | 0.0780 |
| Quarterly State Deposit Rate | 3,247 | 0.3859 | 0.6785 | 1.9781 | 1.3265 | 1.3075 |
| Quarterly State Dep. Rate SD | 3,247 | 0.1959 | 0.3067 | 0.4862 | 0.3517 | 0.1813 |
| Quarterly State GDP Growth | 3,197 | -0.0026 | 0.0042 | 0.0105 | 0.0030 | 0.0198 |

*Notes:* The table summarizes the key measures of the level and dispersion of bank deposit rates, as well as GDP growth. The columns, left to right, denote the variable of interest, number of observations, $25^{th}$ percentile value, median, $75^{th}$ percentile value, mean, and standard deviation in Columns 2-7.

Table 2: Dispersion of Deposit Rates Predicts County Recessions

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | 0.0441*** | 0.0368*** | 0.0145*** |
| | (0.0029) | (0.0032) | (0.0035) |
| Rate | -0.0089*** | 0.0164*** | 0.0145*** |
| | (0.0027) | (0.0029) | (0.0031) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 31,805 | 30,132 | 28,614 |
| pseudo $R^2$ | 0.0874 | 0.0895 | 0.0826 |
| AUC | 0.7014 | 0.7028 | 0.6950 |
| Overall test statistic, $\chi^2$ | 2799.7020 | 2847.9940 | 2359.6318 |
| p-value | 0.0000 | 0.0000 | 0.0000 |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county $c$ at time (year) $t+k$: $logit(p_{c,t+k}) = \beta_0 + \beta_1 SD_{c,t} + \beta_2 Rate_{c,t} + \alpha_c + \epsilon_{c,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, *Rate* denotes the average bank deposit rate, *SD* denotes the standard deviation of bank deposit rates, $t$ denotes the current year, and $k$ denotes the number of leading years ($k = 1, 2, 3$). The independent variables are standardized.

Table 3: Dispersion of Deposit Rates Predicts Depth of County Recession

| $\Delta$ln (GDP) | (1) | (2) | (3) |
|---|---|---|---|
| | 1 Year Ahead | 2 Years Ahead | 3 Years Ahead |
| SD | -0.0058*** | -0.0032*** | -0.0007 |
| | (0.0005) | (0.0006) | (0.0006) |
| Rate | 0.0029*** | 0.0001 | 0.0007 |
| | (0.0005) | (0.0005) | (0.0006) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 33,018 | 31,417 | 29,779 |
| $R^2$ | 0.0680 | 0.0696 | 0.0797 |

Standard errors are clustered by county in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following regression of GDP growth in county $c$ at time (year) $t + k$: $\Delta ln(GDP)_{t+k} = \beta_0 + \beta_1 SD_{c,t} + \beta_2 Rate_{c,t} + \alpha_c + \alpha_t + \epsilon_{c,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, *Rate* denotes the average bank deposit rate, *SD* denotes the standard deviation of bank deposit rates, $t$ denotes the current year, and $k$ denotes the number of leading years ($k = 1, 2, 3$). The independent variables are standardized.

Table 4: Dispersion of Deposit Rates Predicts State Recessions

| $\mathbb{1}_{Recession}$ | (1) | (2) | (3) |
|---|---|---|---|
| | 4 Qtrs Ahead | 8 Qtrs Ahead | 12 Qtrs Ahead |
| SD | 0.0490*** | 0.0424*** | 0.0088 |
| | (0.0060) | (0.0071) | (0.0073) |
| Rate | 0.0005 | 0.0008 | 0.0092 |
| | (0.0044) | (0.0061) | (0.0068) |
| State FE | ✓ | ✓ | ✓ |
| $N$ | 3,041 | 2,837 | 2,634 |
| pseudo $R^2$ | 0.1623 | 0.1227 | 0.0579 |
| AUC | 0.8163 | 0.7895 | 0.6958 |
| Overall test statistic, $\chi^2$ | 267.9579 | 229.5261 | 68.6178 |
| p-value | 0.0000 | 0.0000 | 0.0610 |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following logit model of a state recession in state $s$ at time (quarter-year): $logit(p_{s,t+k}) = \beta_0 + \beta_1 Rate_{s,t} + \beta_2 SD_{s,t} + \alpha_s + \epsilon_{s,t}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, *Rate* denotes the average bank deposit rate, *SD* denotes the standard deviation of bank deposit rates, and $k$ denotes the number of leading quarters ($k = 4, 8, 12$). The independent variables are standardized.

Table 5: Dispersion of Deposit Rates Forecasts National Recessions

| Year | Quarter | Forecast | Actual |
|---|---|---|---|
| 2003 | 1 | 0 | 0 |
| 2003 | 2 | 0 | 0 |
| 2003 | 3 | 0 | 0 |
| 2003 | 4 | 0 | 0 |
| 2004 | 1 | 0 | 0 |
| 2004 | 2 | 0 | 0 |
| 2004 | 3 | 0 | 0 |
| 2004 | 4 | 0 | 0 |
| 2005 | 1 | 0 | 0 |
| 2005 | 2 | 0 | 0 |
| 2005 | 3 | 0 | 0 |
| 2005 | 4 | 0 | 0 |
| 2006 | 1 | 0 | 0 |
| 2006 | 2 | 0 | 0 |
| 2006 | 3 | 0 | 0 |
| 2006 | 4 | 0 | 0 |
| 2007 | 1 | 0 | 0 |
| 2007 | 2 | 1 | 0 |
| 2007 | 3 | 1 | 0 |
| 2007 | 4 | 1 | 0 |
| 2008 | 1 | 1 | 1 |
| 2008 | 2 | 1 | 1 |
| 2008 | 3 | 1 | 1 |
| 2008 | 4 | 1 | 1 |
| 2009 | 1 | 1 | 1 |
| 2009 | 2 | 1 | 1 |
| 2009 | 3 | 0 | 0 |
| 2009 | 4 | 0 | 0 |
| 2010 | 1 | 0 | 0 |
| 2010 | 2 | 0 | 0 |
| 2010 | 3 | 0 | 0 |
| 2010 | 4 | 0 | 0 |
| 2011 | 1 | 0 | 0 |
| 2011 | 2 | 0 | 0 |
| 2011 | 3 | 0 | 0 |
| 2011 | 4 | 0 | 0 |
| 2012 | 1 | 0 | 0 |
| 2012 | 2 | 0 | 0 |
| 2012 | 3 | 0 | 0 |
| 2012 | 4 | 0 | 0 |
| 2013 | 1 | 0 | 0 |
| 2013 | 2 | 0 | 0 |
| 2013 | 3 | 0 | 0 |
| 2013 | 4 | 0 | 0 |
| 2014 | 1 | 0 | 0 |
| 2014 | 2 | 0 | 0 |
| 2014 | 3 | 0 | 0 |
| 2014 | 4 | 0 | 0 |
| 2015 | 1 | 0 | 0 |
| 2015 | 2 | 0 | 0 |
| 2015 | 3 | 0 | 0 |
| 2015 | 4 | 0 | 0 |
| 2016 | 1 | 0 | 0 |
| 2016 | 2 | 0 | 0 |
| 2016 | 3 | 0 | 0 |
| 2016 | 4 | 0 | 0 |
| 2017 | 1 | 0 | 0 |
| 2017 | 2 | 0 | 0 |
| 2017 | 3 | 0 | 0 |
| 2017 | 4 | 0 | 0 |
| 2018 | 1 | 0 | 0 |
| 2018 | 2 | 0 | 0 |
| 2018 | 3 | 0 | 0 |
| 2018 | 4 | 0 | 0 |
| 2019 | 1 | 0 | 0 |
| 2019 | 2 | 0 | 0 |
| 2019 | 3 | 1 | 0 |
| 2019 | 4 | 1 | 0 |
| 2020 | 1 | 1 | 1 |
| 2020 | 2 | 1 | 1 |
| 2020 | 3 | 1 | 0 |
| 2020 | 4 | 1 | 0 |
| 2021 | 1 | 0 | 0 |
| 2021 | 2 | 0 | 0 |
| 2021 | 3 | 0 | 0 |
| 2021 | 4 | 0 | 0 |
| 2022 | 1 | 0 | 0 |
| 2022 | 2 | 0 | 0 |
| 2022 | 3 | 0 | |
| 2022 | 4 | 0 | |

**Prediction Outcome**

| | | **p** | **n** | **Total** |
|---|---|---|---|---|
| **Actual Value** | **p′** | True Positive = 8 | False Negative =0 | 8′ |
| | **n′** | False Positive = 7 | True Negative =63 | 70′ |
| | **Total** | 15 | 63 | |

*Notes:* This table indicates our model-generated forecast of a recession and an indicator for whether a recession actually occurred according to the NBER's Business Cycle Dating Committee. First, the likelihood of a state recession is predicted using the eight-quarter moving average standard deviation and rate in Equation 2. Then, the "expected likelihood" of a national recession is calculated by taking a weighted sum of the predicted state probabilities, weighted by the 2004 state GDPs. The forecast is 1 (0) if the expected likelihood is below (above) the $25^{th}$ percentile of values. The in-sample estimated model parameters and model threshold are used to forecast recessions in 2022Q3, 2022Q4, and 2023Q1. We summarize the number of true positives, false negatives, false positives, and true negatives in a confusion matrix.

Table 6: Uninsured and Insured Deposit Growth and Deposit Rate Changes

**Panel A:** Insured Deposit Growth

| $\Delta$ln(Insured Deposits) | (1) t-3 | (2) t-2 | (3) t-1 | (4) t | (5) t+1 | (6) t+2 | (7) t+3 |
|---|---|---|---|---|---|---|---|
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50} \times$ Rec. | -0.0018 | -0.0034** | -0.0003 | -0.0030** | -0.0036** | 0.0004 | -0.0005 |
| | (0.0016) | (0.0014) | (0.0019) | (0.0014) | (0.0014) | (0.0012) | (0.0013) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75} \times$ Rec. | -0.0015 | 0.0018 | 0.0040** | 0.0004 | -0.0017 | -0.0002 | 0.0020 |
| | (0.0013) | (0.0016) | (0.0018) | (0.0014) | (0.0013) | (0.0011) | (0.0018) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75} \times$ Rec. | -0.0018 | -0.0027 | -0.0009 | -0.0017 | -0.0020 | -0.0027** | -0.0017 |
| | (0.0013) | (0.0017) | (0.0016) | (0.0016) | (0.0019) | (0.0012) | (0.0014) |
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ | 0.0003 | 0.0010 | -0.0022*** | 0.0029*** | 0.0046*** | 0.0022*** | 0.0021*** |
| | (0.0007) | (0.0007) | (0.0007) | (0.0008) | (0.0008) | (0.0006) | (0.0007) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ | 0.0009 | -0.0023*** | -0.0052*** | 0.0016** | 0.0069*** | 0.0035*** | 0.0002 |
| | (0.0007) | (0.0008) | (0.0011) | (0.0008) | (0.0009) | (0.0005) | (0.0010) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75}$ | 0.0019** | 0.0012 | -0.0020* | 0.0061*** | 0.0090*** | 0.0067*** | 0.0034*** |
| | (0.0008) | (0.0008) | (0.0011) | (0.0008) | (0.0009) | (0.0008) | (0.0008) |
| Quarter-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N$ | 317,672 | 323,595 | 329,908 | 330,109 | 323,901 | 317,997 | 312,268 |
| $R^2$ | 0.0417 | 0.0462 | 0.0453 | 0.0437 | 0.0453 | 0.0475 | 0.0492 |

**Panel B:** Uninsured Deposit Growth

| $\Delta$ln(Uninsured Deposits) | (1) t-3 | (2) t-2 | (3) t-1 | (4) t | (5) t+1 | (6) t+2 | (7) t+3 |
|---|---|---|---|---|---|---|---|
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50} \times$ Rec. | 0.0004 | 0.0096* | 0.0015 | -0.0110** | -0.0013 | 0.0023 | 0.0010 |
| | (0.0042) | (0.0051) | (0.0041) | (0.0049) | (0.0044) | (0.0051) | (0.0052) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75} \times$ Rec. | 0.0053 | 0.0087** | 0.0045 | -0.0042 | -0.0103** | -0.0074 | -0.0025 |
| | (0.0048) | (0.0043) | (0.0053) | (0.0051) | (0.0049) | (0.0068) | (0.0101) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75} \times$ Rec. | -0.0035 | 0.0029 | 0.0030 | -0.0138*** | 0.0008 | 0.0008 | -0.0038 |
| | (0.0039) | (0.0044) | (0.0045) | (0.0045) | (0.0042) | (0.0065) | (0.0052) |
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ | -0.0005 | -0.0018 | -0.0034 | 0.0066* | 0.0063* | -0.0011 | -0.0004 |
| | (0.0029) | (0.0033) | (0.0031) | (0.0037) | (0.0032) | (0.0033) | (0.0034) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ | 0.0018 | -0.0035 | -0.0077** | -0.0010 | 0.0127*** | 0.0037 | -0.0028 |
| | (0.0034) | (0.0029) | (0.0038) | (0.0047) | (0.0032) | (0.0034) | (0.0047) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75}$ | 0.0050* | 0.0023 | -0.0108*** | 0.0067 | 0.0070** | 0.0029 | 0.0033 |
| | (0.0027) | (0.0029) | (0.0034) | (0.0040) | (0.0033) | (0.0033) | (0.0034) |
| Quarter-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N$ | 316,120 | 322,015 | 328,294 | 328,500 | 322,328 | 316,458 | 310,757 |
| $R^2$ | 0.0671 | 0.0685 | 0.0681 | 0.0685 | 0.0683 | 0.0690 | 0.0692 |

Standard errors are two-way clustered by bank and quarter-year in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*Notes:* The table presents the coefficients estimated from the following regression for bank $b$ at time $t$ (quarter-year): $\Delta ln(Deposits)_{b,t+k} = \beta_0 + \beta_1 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} \times \text{Rec.}_t + \beta_2 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} \times \text{Rec.}_t + \beta_3 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} \times \text{Rec.}_t + \beta_4 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} + \beta_5 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} + \beta_6 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} + \alpha_t + \epsilon_{b,t}$ where $\Delta ln(Deposits)_{b,t+k}$ denotes growth in insured deposits (Panel A) and uninsured deposits (Panel B), $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t}$, $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t}$, $\mathbb{1}_{\text{Dep Rate Change}>P75,b,t}$ denote the second, third, or fourth quartile of a bank's deposit rate change between two consecutive quarters, respectively, and Rec. denotes whether there is a recession within the next eight quarters. $k$ denotes the number of lead/lag quarters. A bank's average deposit rate is computed for each quarter across all counties, using RateWatch Data. The change is computed based on the averages. Data on insured and uninsured deposits comes from the FDIC's SDI.

Table 7: Growth in Insured/Uninsured Ratio and Deposit Rate Changes

| $\Delta ln(\frac{\text{Insured}}{\text{Uninsured}})$ | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
|---|---|---|---|---|---|---|---|
| | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 |
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50} \times$ Rec. | -0.0028 | -0.0122$^{**}$ | -0.0011 | 0.0077 | -0.0021 | -0.0020 | -0.0013 |
| | (0.0040) | (0.0054) | (0.0042) | (0.0050) | (0.0043) | (0.0053) | (0.0054) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75} \times$ Rec. | -0.0056 | -0.0059 | -0.0003 | 0.0042 | 0.0089$^{*}$ | 0.0069 | 0.0047 |
| | (0.0052) | (0.0048) | (0.0051) | (0.0051) | (0.0050) | (0.0069) | (0.0093) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75} \times$ Rec. | 0.0008 | -0.0033 | -0.0027 | 0.0123$^{***}$ | -0.0030 | -0.0038 | 0.0027 |
| | (0.0038) | (0.0045) | (0.0043) | (0.0046) | (0.0045) | (0.0068) | (0.0052) |
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ | 0.0011 | 0.0031 | 0.0008 | -0.0034 | -0.0019 | 0.0031 | 0.0024 |
| | (0.0031) | (0.0035) | (0.0032) | (0.0038) | (0.0034) | (0.0036) | (0.0035) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ | -0.0009 | 0.0017 | 0.0019 | 0.0026 | -0.0058$^{*}$ | -0.0003 | 0.0031 |
| | (0.0035) | (0.0030) | (0.0038) | (0.0045) | (0.0034) | (0.0033) | (0.0050) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75}$ | -0.0033 | -0.0012 | 0.0084$^{**}$ | -0.0008 | 0.0019 | 0.0037 | 0.0001 |
| | (0.0026) | (0.0030) | (0.0033) | (0.0040) | (0.0033) | (0.0035) | (0.0037) |
| Quarter-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N$ | 310,330 | 316,137 | 322,218 | 328,496 | 322,324 | 316,244 | 310,441 |
| $R^2$ | 0.0812 | 0.0813 | 0.0807 | 0.0805 | 0.0799 | 0.0804 | 0.0809 |

Standard errors are two-way clustered by bank and quarter-year in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* The table presents the coefficients estimated from the following regression for bank $b$ at time $t$ (quarter-year): $\Delta ln(\frac{Insured}{Uninsured})_{b,t+k} = \beta_0 + \beta_1 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} \times \text{Rec.}_t + \beta_2 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} \times \text{Rec.}_t + \beta_3 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} \times \text{Rec.}_t + \beta_4 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} + \beta_5 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} + \beta_6 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} + \alpha_t + \epsilon_{b,t}$ where $\Delta ln(\frac{Uninsured}{Insured})_{b,t+k}$ denotes growth in the ratio of insured to uninsured deposits, $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t}$, $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t}$, $\mathbb{1}_{\text{Dep Rate Change}>P75,b,t}$ denote the second, third, or fourth quartile of a bank's deposit rate change between two consecutive quarters, respectively, and Rec. denotes whether there is a recession within the next eight quarters. $k$ denotes the number of lead/lag quarters. A bank's average deposit rate is computed for each quarter across all counties, using RateWatch Data. The change is computed based on the averages. Data on insured and uninsured deposits comes from the FDIC's SDI.

Table 8: Lending Growth and Deposit Rate Changes

| **Panel A:** Loan Growth | | | | | | | |
|---|---|---|---|---|---|---|---|
| $\Delta$ln(Loans) | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 |
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50} \times$ Rec. | -0.0029** | -0.0025* | -0.0026** | -0.0037** | -0.0034*** | -0.0024 | -0.0020* |
| | (0.0013) | (0.0013) | (0.0013) | (0.0016) | (0.0012) | (0.0015) | (0.0011) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75} \times$ Rec. | -0.0004 | -0.0004 | -0.0021 | -0.0021 | 0.0001 | -0.0004 | -0.0008 |
| | (0.0015) | (0.0015) | (0.0013) | (0.0013) | (0.0013) | (0.0010) | (0.0012) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75} \times$ Rec. | -0.0011 | -0.0041** | -0.0048*** | -0.0054*** | -0.0030*** | -0.0036*** | -0.0037*** |
| | (0.0019) | (0.0017) | (0.0016) | (0.0015) | (0.0011) | (0.0012) | (0.0009) |
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ | 0.0007 | 0.0020*** | 0.0025*** | 0.0037*** | 0.0015** | 0.0016*** | 0.0016*** |
| | (0.0006) | (0.0006) | (0.0006) | (0.0008) | (0.0006) | (0.0006) | (0.0005) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ | -0.0009 | 0.0010 | 0.0038*** | 0.0024*** | 0.0005 | 0.0014* | 0.0018** |
| | (0.0009) | (0.0009) | (0.0006) | (0.0007) | (0.0007) | (0.0007) | (0.0009) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75}$ | 0.0026*** | 0.0053*** | 0.0084*** | 0.0077*** | 0.0035*** | 0.0044*** | 0.0043*** |
| | (0.0009) | (0.0008) | (0.0009) | (0.0009) | (0.0008) | (0.0008) | (0.0006) |
| Quarter-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N$ | 289,459 | 295,245 | 301,389 | 301,992 | 296,350 | 290,572 | 284,938 |
| $R^2$ | 0.0210 | 0.0206 | 0.0206 | 0.0211 | 0.0227 | 0.0259 | 0.0267 |

| **Panel NPL:** NPL Growth | | | | | | | |
|---|---|---|---|---|---|---|---|
| $\Delta$ln(NPL) | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 |
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50} \times$ Rec. | 0.0057 | 0.0068 | 0.0044 | -0.0132 | -0.0043 | -0.0077 | -0.0139 |
| | (0.0092) | (0.0094) | (0.0120) | (0.0115) | (0.0109) | (0.0077) | (0.0095) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75} \times$ Rec. | 0.0178 | 0.0115 | 0.0091 | 0.0115 | -0.0132 | 0.0060 | -0.0129 |
| | (0.0127) | (0.0127) | (0.0122) | (0.0105) | (0.0099) | (0.0102) | (0.0089) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75} \times$ Rec. | -0.0011 | 0.0036 | -0.0149 | 0.0020 | -0.0075 | -0.0069 | -0.0075 |
| | (0.0107) | (0.0095) | (0.0126) | (0.0104) | (0.0097) | (0.0090) | (0.0086) |
| $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ | -0.0024 | -0.0015 | 0.0020 | 0.0036 | -0.0044 | 0.0092* | 0.0008 |
| | (0.0047) | (0.0066) | (0.0062) | (0.0055) | (0.0049) | (0.0046) | (0.0055) |
| $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ | -0.0052 | -0.0069 | -0.0024 | -0.0025 | 0.0089 | 0.0065 | 0.0067 |
| | (0.0050) | (0.0076) | (0.0058) | (0.0056) | (0.0055) | (0.0058) | (0.0068) |
| $\mathbb{1}_{\text{Dep Rate Change}>P75}$ | 0.0019 | 0.0005 | 0.0016 | 0.0041 | 0.0109** | -0.0002 | 0.0050 |
| | (0.0053) | (0.0050) | (0.0069) | (0.0062) | (0.0046) | (0.0045) | (0.0056) |
| Quarter-Year FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N$ | 228,730 | 232,654 | 236,770 | 237,306 | 233,706 | 230,297 | 226,953 |
| $R^2$ | 0.0071 | 0.0070 | 0.0070 | 0.0069 | 0.0070 | 0.0071 | 0.0072 |

Standard errors are two-way clustered by bank and quarter-year in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* The table presents the coefficients estimated from the following regression for bank $b$ at time $t$ (quarter-year): $\Delta ln(y)_{b,t+k} = \beta_0 + \beta_1 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} \times \text{Rec.}_t + \beta_2 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} \times \text{Rec.}_t + \beta_3 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} \times \text{Rec.}_t + \beta_4 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} + \beta_5 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} + \beta_6 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} + \alpha_t + \epsilon_{b,t}$ where $y$ denotes lending (Panel A) and non-performing loans (Panel B), $\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t}$, $\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t}$, $\mathbb{1}_{\text{Dep Rate Change}>P75,b,t}$ denote the second, third, or fourth quartile of a bank's deposit rate change between two consecutive quarters, respectively, and Rec. denotes whether there is a recession within the next eight quarters. $k$ denotes the number of lead/lag quarters. A bank's average deposit rate is computed for each quarter across all counties, using RateWatch Data. The change is computed based on the averages. Data on bank lending and non-performing loans comes from Call Reports and S&P Market Intelligence, respectively.

Table 9: Dispersion of Deposit Rates Predicts County Recessions controlling for Macro-Trends

**Panel A:** Term Spread (10Y-3M)

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | 0.0245*** | 0.0196*** | 0.0044 |
| | (0.0027) | (0.0027) | (0.0030) |
| Term Spread | -0.0378*** | -0.0679*** | -0.0526*** |
| | (0.0023) | (0.0025) | (0.0026) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 31,805 | 30,132 | 28,614 |
| pseudo $R^2$ | 0.0948 | 0.1105 | 0.0943 |
| AUC | 0.7101 | 0.7290 | 0.7094 |
| Overall test statistic, $\chi^2$ | 3094.3043 | 3617.7140 | 2889.0765 |
| p-value | 0.0000 | 0.0000 | 0.0000 |

**Panel B:** Time Fixed Effects

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | 0.0186*** | 0.0142*** | 0.0086** |
| | (0.0030) | (0.0032) | (0.0035) |
| Rate | 0.0255** | 0.0180 | 0.0896*** |
| | (0.0124) | (0.0129) | (0.0141) |
| County FIPS FE | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |
| $N$ | 31,805 | 30,132 | 28,614 |
| pseudo $R^2$ | 0.1592 | 0.1559 | 0.1543 |
| AUC | 0.7787 | 0.7756 | 0.7735 |
| Overall test statistic, $\chi^2$ | 4996.1506 | 4705.5481 | 4478.6054 |
| p-value | 0.0000 | 0.0000 | 0.0000 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county $c$ at $t+k$: $logit(p_{c,t+k}) = \beta_0 + \beta_1 SD_{c,t} + \beta_2 Rate_{c,t} + \alpha_c + \epsilon_{c,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, *Rate* denotes the average bank deposit rate, *SD* denotes the standard deviation of bank deposit rates, $t$ denotes the current year, and $k$ denotes the number of leading years ($k = 1, 2, 3$). Panel A includes the term spread (10Y-3M). Panel B includes year fixed effects. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Dispersion of Deposit Rates Predicts County Recessions controlling for Credit Growth

**Panel A:** Mortgage Credit Growth

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | 0.0483*** | 0.0345*** | 0.0136*** |
| | (0.0030) | (0.0032) | (0.0036) |
| Rate | -0.0053* | 0.0240*** | 0.0223*** |
| | (0.0028) | (0.0030) | (0.0031) |
| Δln(Mtg) | -0.0642*** | 0.0611*** | -0.0719*** |
| | (0.0077) | (0.0085) | (0.0089) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 29,788 | 28,263 | 26,686 |
| pseudo $R^2$ | 0.0896 | 0.0934 | 0.0857 |
| AUC | 0.7039 | 0.7069 | 0.6984 |
| Overall test statistic, $\chi^2$ | 2731.6212 | 2865.3616 | 2362.2291 |
| p-value | 0.0000 | 0.0000 | 0.0000 |

**Panel B:** Total Credit Growth

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | 0.0478*** | 0.0347*** | 0.0136*** |
| | (0.0030) | (0.0032) | (0.0036) |
| Rate | -0.0054* | 0.0243*** | 0.0217*** |
| | (0.0028) | (0.0030) | (0.0031) |
| Δln(Total) | -0.0735*** | 0.0805*** | -0.0667*** |
| | (0.0096) | (0.0105) | (0.0109) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 29788 | 28263 | 26686 |
| pseudo $R^2$ | 0.0893 | 0.0936 | 0.0849 |
| AUC | 0.7034 | 0.7072 | 0.6974 |
| Overall test statistic, $\chi^2$ | 2722.6376 | 2877.8228 | 2327.3488 |
| p-value | 0.0000 | 0.0000 | 0.0000 |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county $c$ at time (year) $t+k$: $logit(p_{c,t+k}) = \beta_0 + \beta_1 SD_{c,t} + \beta_2 Rate_{c,t} + \beta_3 CG_{c,t} + \alpha_c + \epsilon_{c,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, $Rate$ denotes the average bank deposit rate, $SD$ denotes the standard deviation of bank deposit rates, $CG$ denotes credit growth (mortgage lending in Panel A and sum of mortgage lending and small business lending in Panel B), $t$ denotes the current year, and $k$ denotes the number of leading years ($k = 1, 2, 3$). The independent variables are standardized. Mortgage lending data comes from HMDA and small business lending data comes from the CRA.

Table 11: Dispersion of Deposit Rates Predicts County Recessions Better in Non-Disaster Counties

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| $\mathbb{1}_{\text{Disaster}} \times$ SD $\times$ Shock | -0.0689 | 0.0180 | -0.1678 |
| | (0.1242) | (0.0973) | (0.1125) |
| $\mathbb{1}_{\text{Disaster}} \times$ Rate $\times$ Shock | -0.0590 | 0.0188 | 0.1304 |
| | (0.1065) | (0.0837) | (0.0988) |
| $\mathbb{1}_{\text{Disaster}} \times$ SD | 0.0652** | 0.0220 | -0.0445 |
| | (0.0262) | (0.0296) | (0.0302) |
| $\mathbb{1}_{\text{Disaster}} \times$ Rate | 0.0658*** | 0.0666*** | 0.0662*** |
| | (0.0191) | (0.0219) | (0.0223) |
| SD | 0.0362*** | 0.0144*** | 0.0136*** |
| | (0.0032) | (0.0035) | (0.0037) |
| Rate | 0.0145*** | 0.0125*** | -0.0097*** |
| | (0.0030) | (0.0031) | (0.0031) |
| Shock | -0.0627 | 0.0932 | 0.4092*** |
| | (0.0798) | (0.0646) | (0.0684) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 30,129 | 28,602 | 27,024 |
| pseudo $R^2$ | 0.0909 | 0.0835 | 0.0812 |
| AUC | 0.7042 | 0.6963 | 0.6923 |
| Overall test statistic, $\chi^2$ | 2875.5387 | 2375.7655 | 2145.1290 |
| p-value | 0.0000 | 0.0000 | 0.0112 |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county $c$ at time (year) $t+k$: $logit(p_{c,t+k}) = \beta_0 + +$ $\beta_1 \mathbb{1}_{Disaster,c} \times SD_{c,t} \times Shock_{c,t} + \beta_2 \mathbb{1}_{Disaster,c} \times Rate_{c,t} \times Shock_{c,t} + \beta_3 \mathbb{1}_{Disaster,c} \times SD_{c,t} + \beta_4 \mathbb{1}_{Disaster,c} \times Rate_{c,t} + \beta_5 SD_{c,t} + \beta_6 Rate_{c,t} + \beta_7 Shock_{c,t} + \alpha_c + \epsilon_{c,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, $\mathbb{1}_{Disaster}$ denotes if county $c$ experiences any natural disasters in the sample period, *Shock* denotes whether county $c$ experiences a natural disaster at time $t$, *Rate* denotes the average bank deposit rate in county $c$ at time $t$, *SD* denotes the standard deviation of bank deposit rates in county $c$ at time $t$, $t$ denotes the current year, and $k$ denotes the number of leading years ($k = 1, 2, 3$). The sample is restricted to natural disasters that last less than 31 days with total damages above $1 bn 2018 dollars. The independent variables are standardized.

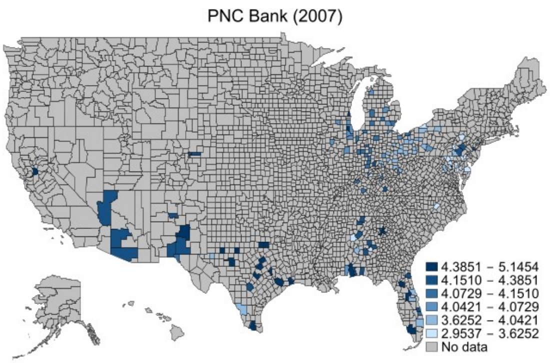
## Online Appendix for:

*Local Recessions: Evidence from Bank Liquidity Squeezes*

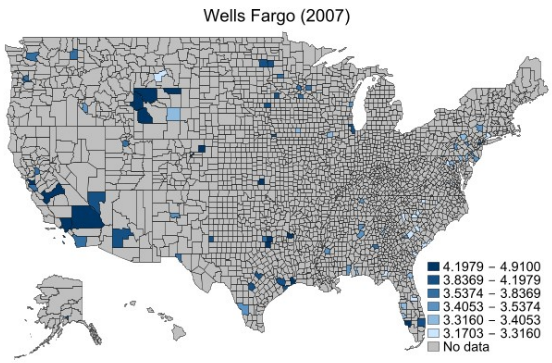
# Appendix A Figures and Tables

## A.1 Figures

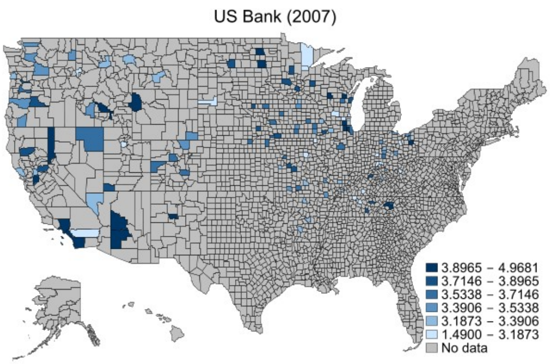
Figure A.1: Bank Deposit Rates: 2007



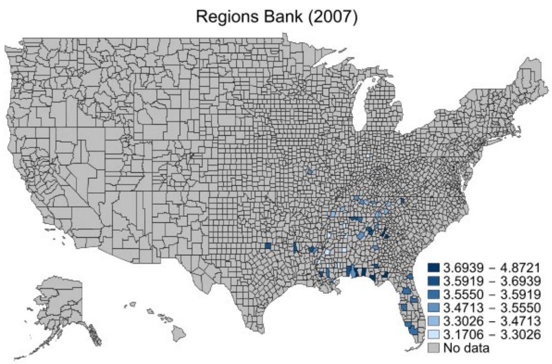

(a) PNC Bank



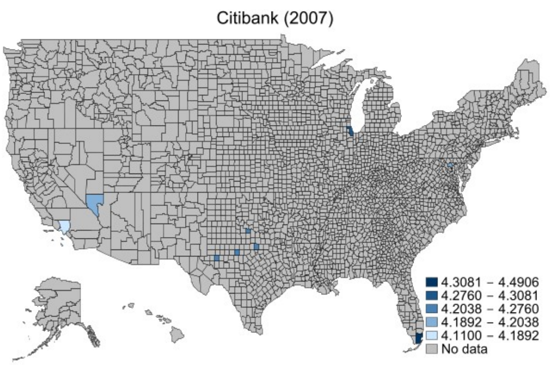

(b) Wells Fargo



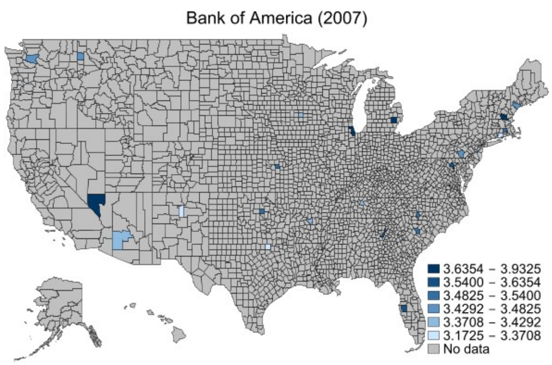

(c) US Bank



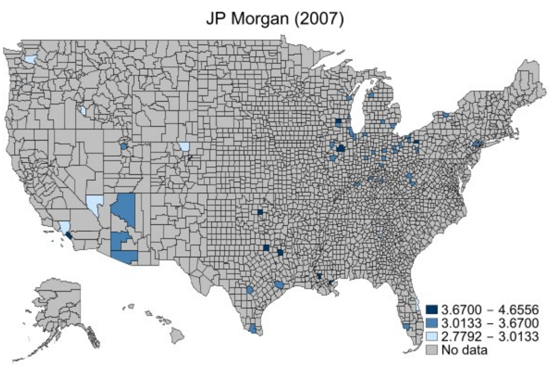

(d) Regions Bank




(e) Citi



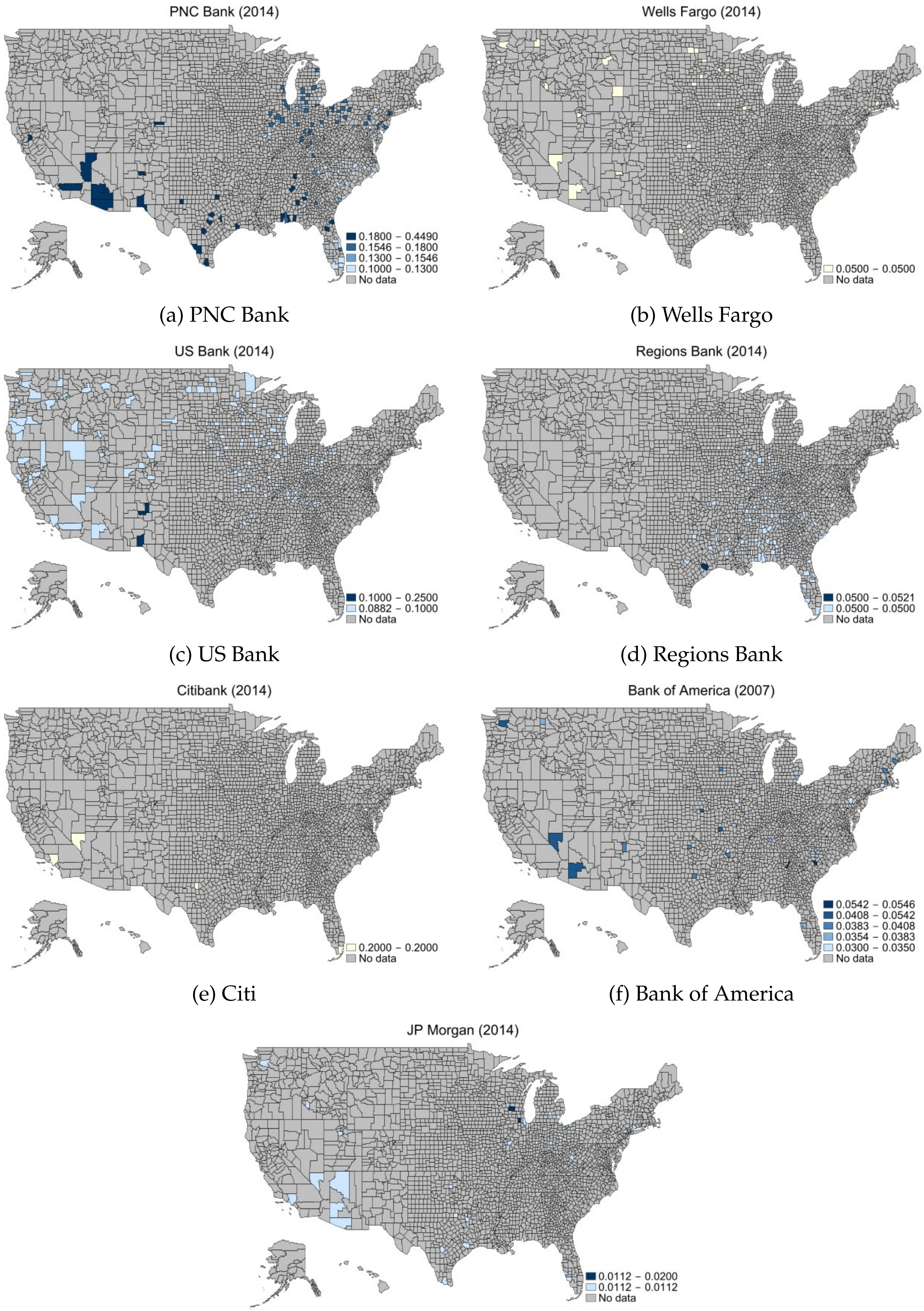

(f) Bank of America




(g) JPMorgan

*Notes:* This figure uses RateWatch data to present a heatmap of the deposit rates of PNC Bank (Appendix Figure A.1a), Wells Fargo Bank (Appendix Figure A.1b), US Bank (Appendix Figure A.1c), Regions Bank (Appendix Figure A.1d), Citibank (Appendix Figure A.1e), Bank of America (Appendix Figure A.1f), and JPMorgan (Appendix Figure A.1g) in 2007. The deposit rate is the rate on the 12-month certificate of deposit of at least $10,000. The intensity of the blue shading represents the sextile range of the deposit rate.

Figure A.2: Bank Deposit Rates: 2014




(a) PNC Bank

(b) Wells Fargo

(c) US Bank

(d) Regions Bank

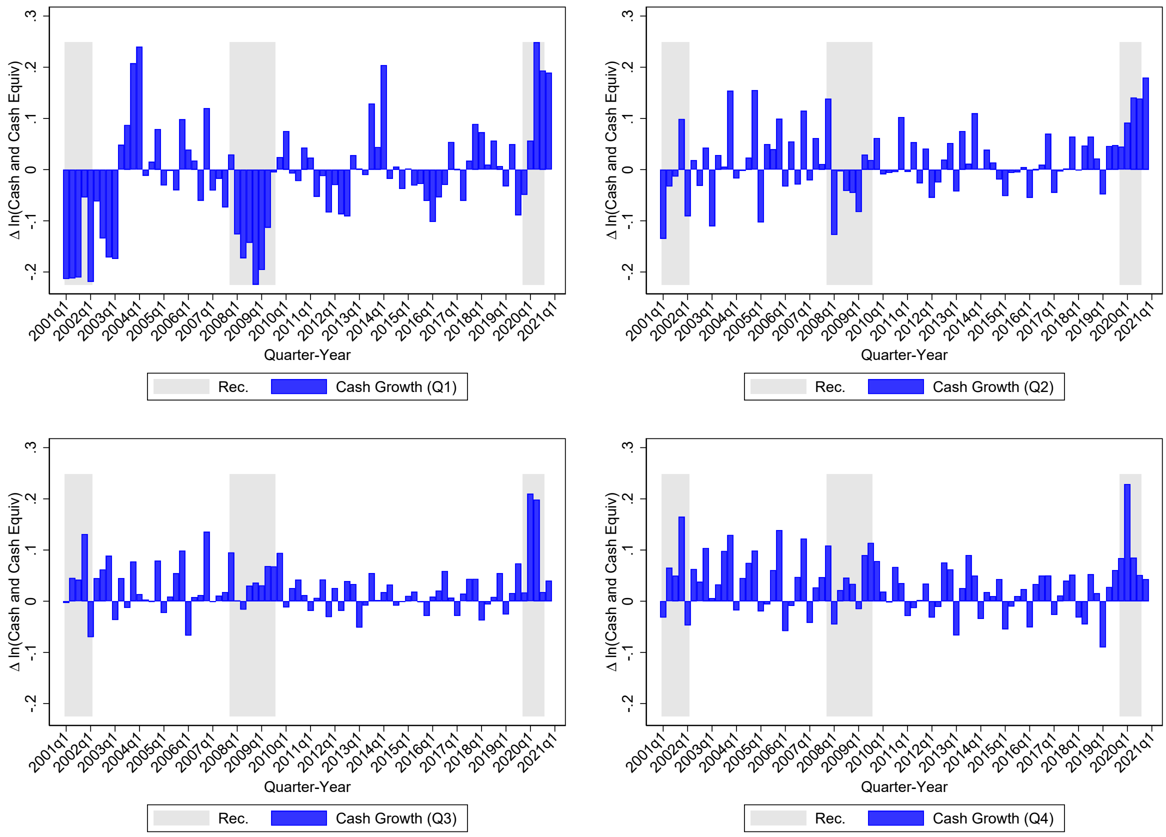
(e) Citi

(f) Bank of America

(g) JPMorgan

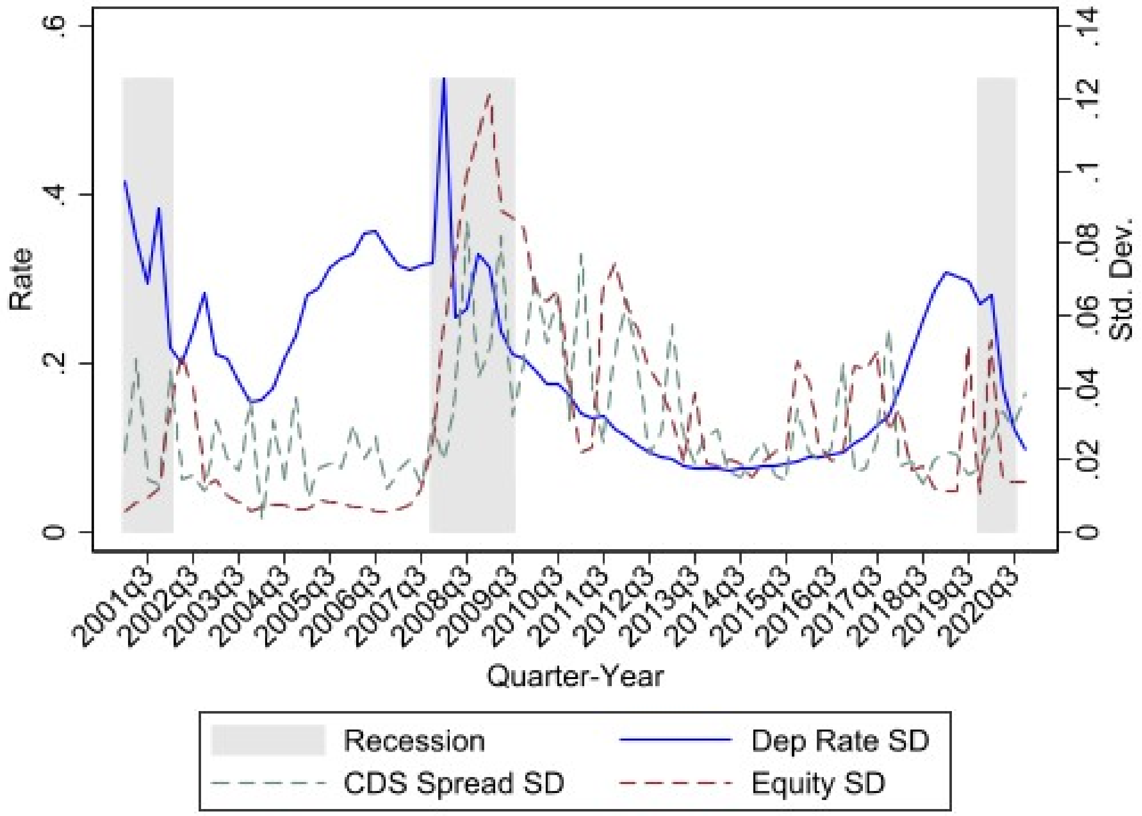
*Notes:* This figure uses RateWatch data to present a heatmap of the deposit rates of PNC Bank (Figure A.2a), Wells Fargo Bank (Figure A.2b), US Bank (Figure A.2c), Regions Bank (Figure A.2d), Citibank (Figure A.2e), Bank of America (Figure A.2f), and JP Morgan (Figure A.2g) in 2014. The deposit rate is the rate on the 12-month certificate of deposit of at least $10,000. The intensity of the blue shading represents the sextile range of the deposit rate.

Figure A.3: Growth in Cash and Cash Equiv. by Profit Quartile (2001-2020)



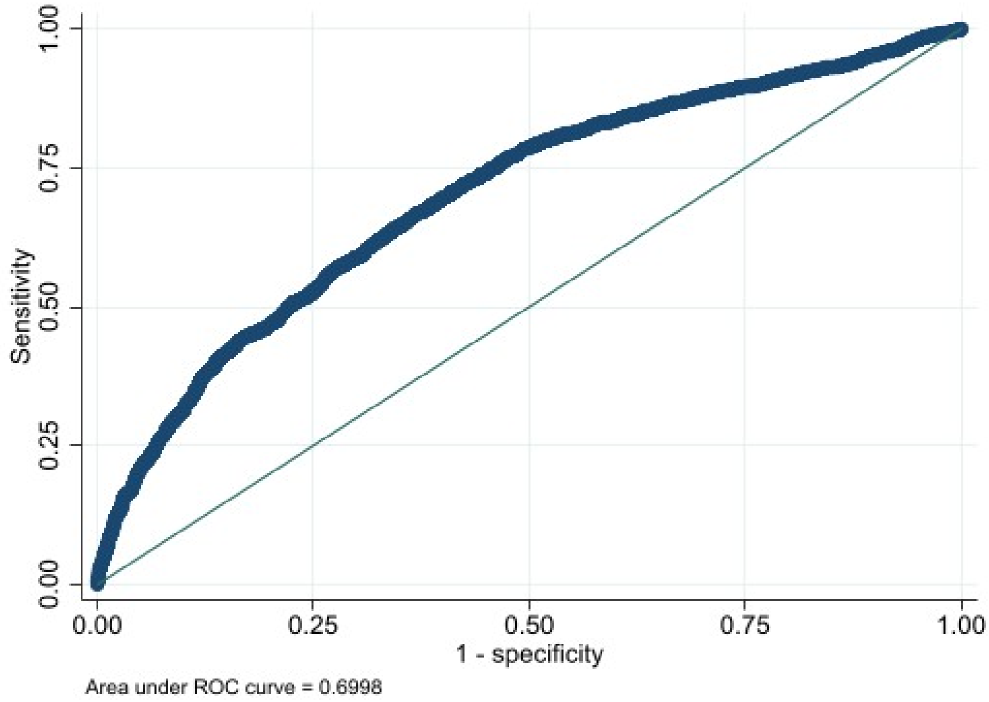

*Notes:* This figure presents histograms of the mean growth in cash and cash equivalents by firms' profit quartile. The quartile is assigned based on the time-series average of each firm's profit (ratio of net income to assets). The data is at the quarterly frequency and spans from 2001Q1 through 2020Q4.

Figure A.4: Dispersion of Deposit Rates, CDS Spreads, and Equity Returns (2001-2020)

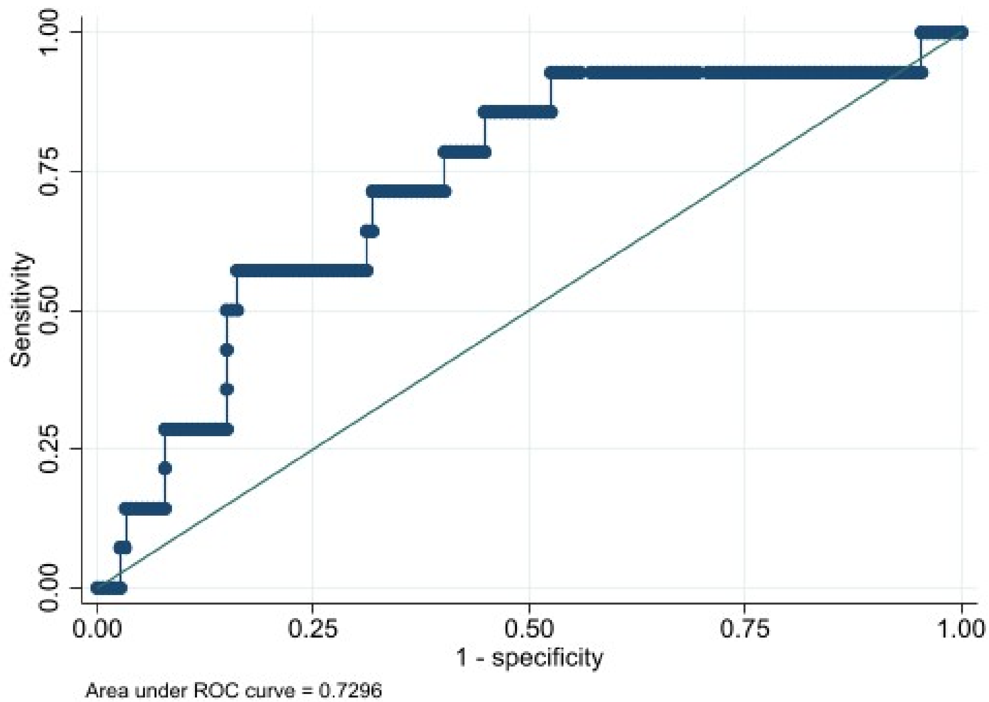



*Notes:* This figure presents a time-series plot of the mean standard deviation of: deposit rates (12-month, $10K CDs), CDS spread for financial firms, and equity returns for banks. The data is at the quarterly frequency and spans from 2001Q1 through 2020Q4.

Figure A.5: Dispersion of Deposit Rates Predicts Recessions in Areas without Credit Booms



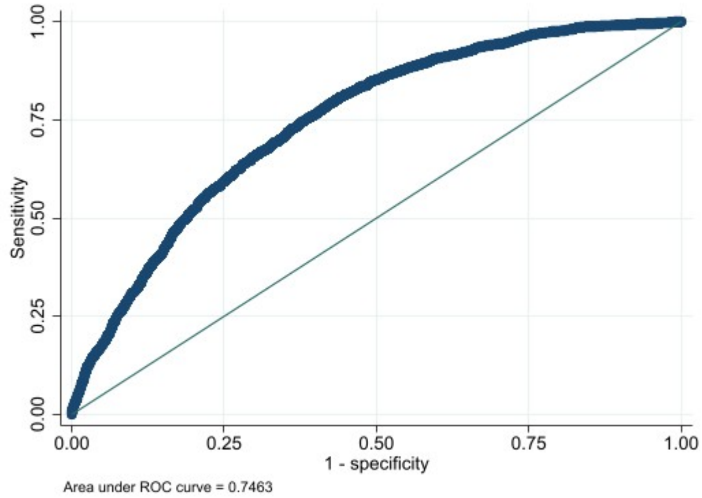

(a) County



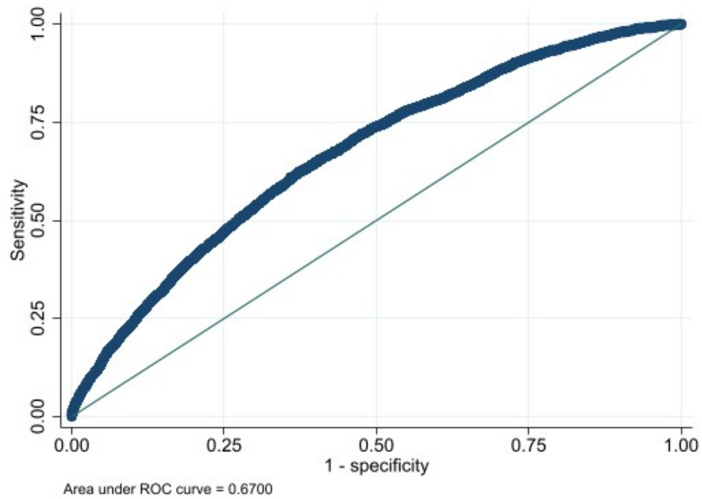

(b) State

*Notes:* This figure plots the Receiver Operating Characteristic (ROC) curves. Figure A.5a presents the ROC curve associated with the model of column 3 in Table 2 for the period of 2011-2016. Figure A.5b presents the ROC curve associated with the model of column 3 in Table 4 for the period of 2011-2016.

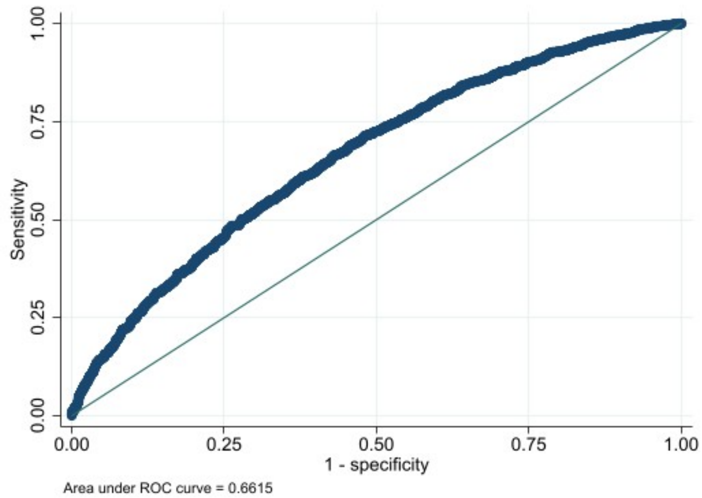
Figure A.6: Two-Year Dispersion of Deposit Rates Predicts Recessions in Metro, Urban, and Rural Counties




(a) Metro



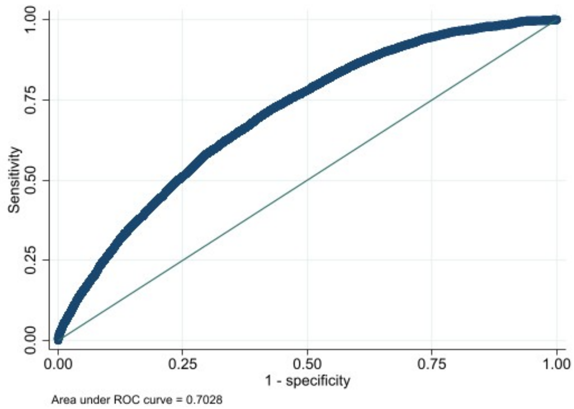

(b) Urban



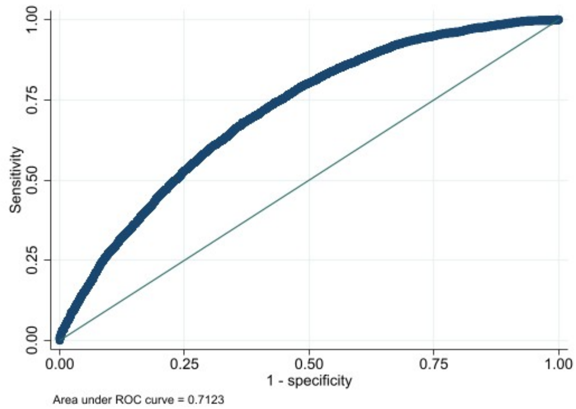

(c) Rural

*Notes:* This figure plots the Receiver Operating Characteristic (ROC) curves. The figures plot the ROC curves associated with the model of column 2 in Table 2. Figure A.6a estimates the model separately for metropolitan counties. Figure A.6b estimates the model separately for urban counties. Figure A.6c estimates the model separately for urban counties. The USDA ERS's Rural-Urban Continuum Codes from 1993 are used to define metropolitan counties as counties with codes between one and three, urban counties as counties with between four and seven, and rural counties as counties with codes of eight or nine. See Appendix Figure **??** note for more details.

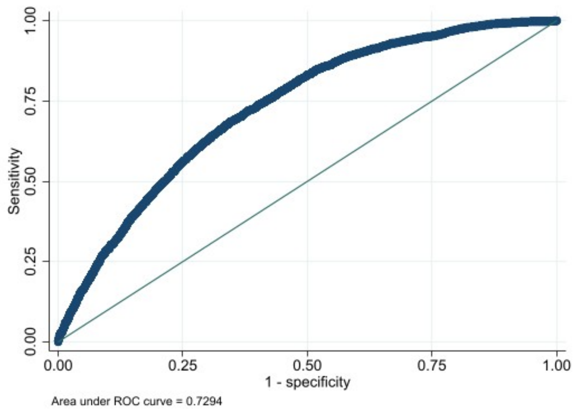
Figure A.7: Two-Year Dispersion of Deposit Rates Predicts Recessions Better in Counties with More Banks



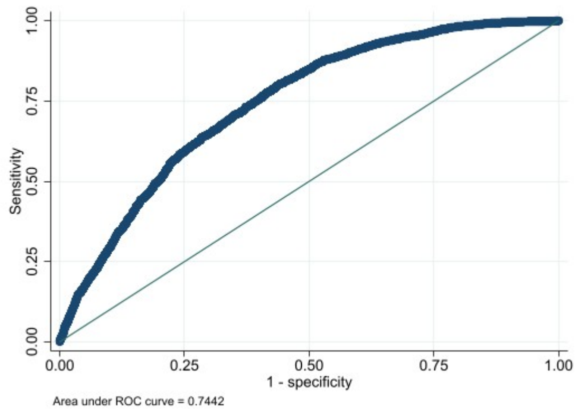

(a) All




(b) >2 Banks




(c) >3 Banks




(d) >4 Banks

*Notes:* This figure plots the Receiver Operating Characteristic (ROC) curves. The figures plot the ROC curves associated with the model of column 2 in Table 2. Figure A.7a estimates the model for all counties. Figure A.7b estimates the model separately for counties with more than two counties. Figure A.7c estimates the model separately for counties with more than three counties. Figure A.7d estimates the model separately for counties with more than four counties.

## A.2 Tables

Table A.1: Dispersion of Other Deposit Rates Predicts County Recessions

| | | | |
|---|---|---|---|
| **Panel A:** 1-month CD of Minimum $10K | | | |
| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
| SD | 0.0299*** | 0.0450*** | 0.0115 |
| | (0.0090) | (0.0095) | (0.0108) |
| Rate | -0.0009 | 0.0135 | 0.0295*** |
| | (0.0095) | (0.0099) | (0.0109) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 5,510 | 5,015 | 4,540 |
| pseudo $R^2$ | 0.1163 | 0.1227 | 0.1176 |
| AUC | 0.7337 | 0.7397 | 0.7294 |
| Overall test statistic, $\chi^2$ | 618.3251 | 599.6467 | 508.6830 |
| p-value | 0.2936 | 0.3937 | 0.9824 |
| **Panel B:** 12-month CD (Uninsured) | | | |
| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
| SD | 0.0532*** | 0.1154*** | 0.0808*** |
| | (0.0047) | (0.0060) | (0.0091) |
| Rate | 0.0033 | -0.0007 | -0.0225** |
| | (0.0054) | (0.0071) | (0.0092) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 14,015 | 12,060 | 10,745 |
| pseudo $R^2$ | 0.1163 | 0.1407 | 0.1185 |
| AUC | 0.7295 | 0.7542 | 0.7318 |
| Overall test statistic, $\chi^2$ | 1784.6095 | 1960.9860 | 1383.3549 |
| p-value | 0.0000 | 0.0000 | 0.7919 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county $c$ at time (year) $t+k$: $logit(p_{c,t+k}) = \beta_0 + \beta_1 SD_{c,t} + \beta_2 Rate_{c,t} + \alpha_c + \epsilon_{c,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, *Rate* denotes the average bank deposit rate, *SD* denotes the standard deviation of bank deposit rates, $t$ denotes the current year, and $k$ denotes the number of leading years ($k = 1, 2, 3$). Panel A computes the average bank deposit rate and standard deviation using the rates on 1-month CDs with a minimum account size of $10,000 (Panel A) and uninsured deposits. Panel B computes the average bank deposit rate and standard deviation using the rates on 12-month CDs with a minimum account size of $100K before October 2008 and minimum account size of $250 after October 2008. The independent variables are standardized.

Table A.2: Dispersion of Deposit Rates Predicts County GDP Growth with Macro Controls

| $\Delta ln(GDP)$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | -0.0026*** | -0.0011* | -0.0006 |
| | (0.0006) | (0.0006) | (0.0007) |
| Rate | -0.0012 | -0.0023 | -0.0174*** |
| | (0.0023) | (0.0023) | (0.0027) |
| County FIPS FE | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |
| $N$ | 33,018 | 31,417 | 29,779 |
| $R^2$ | 0.1020 | 0.1043 | 0.1147 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following regression of a county recession in county $c$ at time (year) $t+k$: $\Delta ln(GDP)_{c,t+k} = \beta_0 + \beta_1 SD_{c,t} + \beta_2 Rate_{c,t} + \alpha_c + \alpha_t + \epsilon_{c,t}$ where $\Delta ln(GDP)$ denotes the GDP growth, *Rate* denotes the average bank deposit rate, *SD* denotes the standard deviation of bank deposit rates, $t$ denotes the current quarter-year, and $k$ denotes the number of leading years ($k = 1, 2, 3$). The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Deposit Growth and County Recessions

| $\Delta$ ln(Dep Amt) | (1) | (2) | (3) |
|---|---|---|---|
| $\mathbb{1}_{\text{Recession in 1 Year}}$ | -0.0041*** | | |
| | (0.0010) | | |
| $\mathbb{1}_{\text{Recession in 2 Years}}$ | | 0.0009 | |
| | | (0.0011) | |
| $\mathbb{1}_{\text{Recession in 3 Years}}$ | | | 0.0039*** |
| | | | (0.0012) |
| County FE | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |
| $N$ | 51,974 | 48,906 | 45,835 |
| $R^2$ | 0.0859 | 0.0883 | 0.0916 |

Standard errors are clustered by county in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* This table presents the relation between deposit growth in county $c$ at time (year) $t$ and recessions in county $c$ at time $t+1$ (column 1), $t+2$ (column 2), and $t+3$ (column 3), respectively. The regression specification is the following: $\Delta ln(\text{Dep Amt})_{c,t} = \beta_0 + \delta_0 \mathbb{1}_{Recession,c,t+k} + \alpha_c + \alpha_t + \epsilon_{c,t}$ where $\mathbb{1}_{Recession,c,t+k}$ indicates whether county $c$ is in recession at time $t+k$ and $k$ denotes the number of years after $t$ ($k = 1, 2, 3$).

Table A.4: Dispersion of Deposit Rates Predicts Recessions Better in Counties with More Banks

**Panel A:** > 2 Banks

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | 0.0539*** | 0.0437*** | 0.0248*** |
| | (0.0036) | (0.0041) | (0.0044) |
| Rate | -0.0135*** | 0.0168*** | 0.0148*** |
| | (0.0034) | (0.0037) | (0.0038) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 21,572 | 20,587 | 19,697 |
| pseudo $R^2$ | 0.0931 | 0.0944 | 0.0861 |
| AUC | 0.7114 | 0.7123 | 0.7025 |
| Overall test statistic, $\chi^2$ | 2006.9224 | 2041.4684 | 1667.2815 |
| p-value | 0.0000 | 0.0000 | 0.0000 |

**Panel B:** > 3 Banks

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | 0.0682*** | 0.0616*** | 0.0321*** |
| | (0.0043) | (0.0050) | (0.0055) |
| Rate | -0.0156*** | 0.0173*** | 0.0187*** |
| | (0.0041) | (0.0045) | (0.0048) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 14,492 | 13,754 | 13,149 |
| pseudo $R^2$ | 0.0991 | 0.1057 | 0.0910 |
| AUC | 0.7211 | 0.7294 | 0.7101 |
| Overall test statistic, $\chi^2$ | 1442.1974 | 1520.1871 | 1158.9102 |
| p-value | 0.0000 | 0.0000 | 0.0002 |

**Panel C:** > 4 Banks

| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
|---|---|---|---|
| SD | 0.0750*** | 0.0667*** | 0.0230*** |
| | (0.0051) | (0.0060) | (0.0066) |
| Rate | -0.0139*** | 0.0225*** | 0.0310*** |
| | (0.0048) | (0.0054) | (0.0057) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 10,268 | 9,747 | 9,371 |
| pseudo $R^2$ | 0.1056 | 0.1172 | 0.0907 |
| AUC | 0.7316 | 0.7442 | 0.7147 |
| Overall test statistic, $\chi^2$ | 1104.5077 | 1178.2014 | 799.6673 |
| p-value | 0.0000 | 0.0000 | 0.0065 |

Standard errors in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county $c$ at time (year) $t + k$: $logit(p_{c,t+k}) = \beta_0 + \beta_1 SD_{c,t} + \beta_2 Rate_{c,t} + \alpha_c + \epsilon_{c,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, $Rate$ denotes the average bank deposit rate, $SD$ denotes the standard deviation of bank deposit rates, $t$ denotes the current quarter-year, and $k$ denotes the number of leading years ($k = 1, 2, 3$). Panel A restricts the sample to counties with greater than 2 banks; Panel B restricts the sample to counties with greater than 3 banks; Panel C restricts the sample to counties with greater than 4 banks. The independent variables are standardized.

Table A.5: Dispersion of Deposit Rates Predicts County Recessions with Small and Large # of Branches

| **Panel A:** Small # of Branches | | | |
|---|---|---|---|
| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
| SD | 0.0281*** | 0.0302*** | 0.0119*** |
| | (0.0035) | (0.0039) | (0.0043) |
| Rate | 0.0018 | 0.0199*** | 0.0114*** |
| | (0.0034) | (0.0037) | (0.0039) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 19,565 | 18,443 | 17,386 |
| pseudo $R^2$ | 0.0848 | 0.0902 | 0.0827 |
| AUC | 0.7000 | 0.7050 | 0.6955 |
| Overall test statistic, $\chi^2$ | 1620.6464 | 1735.7972 | 1422.0740 |
| p-value | 0.0000 | 0.0000 | 0.0002 |

| **Panel B:** Large # of Branches | | | |
|---|---|---|---|
| $\mathbb{1}_{Recession}$ | (1) 1 Year Ahead | (2) 2 Years Ahead | (3) 3 Years Ahead |
| SD | 0.0543*** | 0.0375*** | 0.0222*** |
| | (0.0036) | (0.0040) | (0.0043) |
| Rate | -0.0050 | 0.0350*** | 0.0309*** |
| | (0.0036) | (0.0038) | (0.0040) |
| County FIPS FE | ✓ | ✓ | ✓ |
| $N$ | 16,740 | 16,115 | 15,408 |
| pseudo $R^2$ | 0.0966 | 0.1026 | 0.0926 |
| AUC | 0.7158 | 0.7220 | 0.7117 |
| Overall test statistic, $\chi^2$ | 1591.5501 | 1692.0144 | 1374.4130 |
| p-value | 0.0000 | 0.0000 | 0.0016 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county $c$ at time (year) $t$: $logit(p_{c,t}) = \alpha + \beta_1 Rate_{c,t-1} + \beta_2 SD_{c,t-1} + \beta_3 Rate_{c,t-2} + \beta_4 SD_{c,t-2} + \beta_5 Rate_{c,t-3} + \beta_6 SD_{c,t-3} + \epsilon_{c,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, $Rate$ denotes the average bank deposit rate, and $SD$ denotes the standard deviation of bank deposit rates. Panel A restricts the sample to banks with small (below-median) number of branches. Panel B restricts the sample to banks with large (above-median) number of branches. The independent variables are standardized.

Table A.6: Dispersion of Deposit Rates Predicts State Recessions with Macro Controls

**Panel A:** Term Spread (10Y-3M)

| $\mathbb{1}_{Recession}$ | (1)<br>1 Year Ahead | (2)<br>2 Years Ahead | (3)<br>3 Years Ahead |
|---|---|---|---|
| SD | 0.0432*** | 0.0215*** | -0.0016 |
| | (0.0056) | (0.0052) | (0.0058) |
| Term Spread | -0.0081** | -0.0317*** | -0.0310*** |
| | (0.0036) | (0.0053) | (0.0058) |
| State FE | ✓ | ✓ | ✓ |
| $N$ | 3,041 | 2,837 | 2,634 |
| pseudo $R^2$ | 0.1653 | 0.1629 | 0.0910 |
| AUC | 0.8206 | 0.8161 | 0.7474 |
| Overall test statistic, $\chi^2$ | 262.3724 | 249.3268 | 151.2274 |
| p-value | 0.0000 | 0.0000 | 0.0000 |

**Panel B:** Time Fixed Effects

| $\mathbb{1}_{Recession}$ | (1)<br>1 Year Ahead | (2)<br>2 Years Ahead | (3)<br>3 Years Ahead |
|---|---|---|---|
| SD | 0.0182 | 0.0269* | 0.0165 |
| | (0.0161) | (0.0155) | (0.0160) |
| Rate | 0.0546 | 0.2100*** | 0.2608*** |
| | (0.0639) | (0.0739) | (0.0758) |
| State FE | ✓ | ✓ | ✓ |
| Quarter-Year FE | ✓ | ✓ | ✓ |
| $N$ | 1,304 | 1,174 | 1,044 |
| pseudo $R^2$ | 0.3240 | 0.3468 | 0.3647 |
| AUC | 0.9002 | 0.9134 | 0.9153 |
| Overall test statistic, $\chi^2$ | 147.5822 | 138.0154 | 129.8375 |
| p-value | 0.0000 | 0.0000 | 0.0000 |

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in state $s$ at quarter-year $(t+k)$: $logit(p_{s,t+k}) = \beta_0 + \beta_1 SD_{s,t} + \beta_2 Rate_{s,t} + \alpha_s + \epsilon_{s,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, *Rate* denotes the average bank deposit rate, *SD* denotes the standard deviation of bank deposit rates, $t$ denotes the current quarter-year, and $k$ denotes the number of leading quarters ($k = 4, 8, 12$). Panel A includes the term spread (10Y-3M). Panel B includes year fixed effects. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.7: Dispersion of Deposit Rates Predicts Depth of State Recession

| $\Delta$ln (GDP) | (1) | (2) | (3) |
|---|---|---|---|
| | 4 Quarters Ahead | 8 Quarters Ahead | 12 Quarters Ahead |
| SD | -0.0027*** | 0.0005 | 0.0006 |
| | (0.0010) | (0.0012) | (0.0007) |
| Rate | 0.0004 | -0.0017* | -0.0011 |
| | (0.0007) | (0.0010) | (0.0007) |
| State FE | ✓ | ✓ | ✓ |
| $N$ | 3,041 | 2,837 | 2,634 |
| $R^2$ | 0.0260 | 0.0175 | 0.0124 |

Standard errors are clustered by state in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* The table presents the average marginal effects of the covariates estimated from the following regression of GDP growth in state $s$ at time (quarter-year) $t + k$: $\Delta ln(GDP)_{s,t+k} = \beta_0 + \beta_1 SD_{s,t} + \beta_2 Rate_{s,t} + \alpha_s + \alpha_t + \epsilon_{s,t+k}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, *Rate* denotes the average bank deposit rate, *SD* denotes the standard deviation of bank deposit rates, $t$ denotes the current year, and $k$ denotes the number of leading years ($k = 4, 8, 12$). The independent variables are standardized.

Table A.8: Bank Rate and Deposit Changes around County Natural Disasters

| $\Delta$ ln(Dep Amt) | t-3 | t-2 | t-1 | t | t+1 | t+2 | t+3 |
|---|---|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| $\mathbb{1}_{Disaster}$ | -0.0138 | -0.0260 | -0.0077 | 0.0189 | -0.0474*** | -0.0209* | -0.0084 |
| | (0.0181) | (0.0192) | (0.0198) | (0.0221) | (0.0155) | (0.0122) | (0.0129) |
| County FIPS FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| Bank $\times$ County FE | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ |
| $N$ | 364,956 | 413,283 | 468,935 | 534,915 | 534,915 | 469,184 | 413,665 |
| $R^2$ | 0.2265 | 0.2251 | 0.2185 | 0.2103 | 0.2103 | 0.1681 | 0.1545 |

Standard errors are two-way clustered by county and bank in parentheses

$^{*}$ $p < 0.1$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$

*Notes:* This table presents the relation between bank $b$'s change in the deposit rate/total amount of deposits in county $c$ at time (year) $t + k$ and an indicator for a county recession. The regression specification is the following: $\Delta ln(\text{Dep Amt})_{b,c,t+k} = \beta_0 + \delta_0 \mathbb{1}_{Disaster,c,t} + \alpha_c + \alpha_{b,c} + \epsilon_{b,c,t+k}$ where $\Delta ln(DepAmt)_{b,c,t+k}$ is the change in the total amount of deposits, and $k$ denotes the number of years around the county natural disaster ($k = -3, -2, \ldots, 2, 3$). The sample is restricted to natural disasters that last less than 31 days with total damages above $1 bn 2018 dollars.