Predicting Recessions*

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Abstract

This paper predicts recessions using the dispersion of deposit rates offered by banks on insured deposits. An increase in the dispersion of deposit rates can accurately predict recessions over long time horizons at the county, state, and national levels. We find that the growth of deposits, particularly uninsured deposits of riskier banks, slows down at the onset of a downturn, regardless of whether the downturn was preceded by a credit boom. In turn, riskier banks increase their deposit rates to attract more funding to support their balance sheet. The resulting increase in the dispersion of deposit rates predicts an impending economic downturn.

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1 Introduction

The foundations of macroeconomic stability lie in the predictability of economic recessions. Recessions are generally accompanied by high unemployment, low industrial production, asset price declines, and increased economic distress. The effects of recessions on the economy are far-reaching and long-lasting. Therefore, predicting recessions is critical for averting or mitigating their negative consequences through preemptive action. In the absence of accurate predictions, ill-timed and inadequate policies can have deleterious and destabilizing economic impacts. However, predicting recessions is challenging as the factors underlying business cycle fluctuations are difficult to underpin.[1]

This paper predicts recessions in the US using the dispersion of deposit rates offered by banks on insured deposits. 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 our 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.[2] 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 includes up to three year lags of the dispersion of deposit rates across banks within a county is 0.73.[3] This strong predictive value indicates that the dispersion of deposit rates offered by banks is a useful indicator for impending recessions.[4]

We build on this framework to test whether our model can predict recessions at a coarser geographical unit: state recessions. We calculate the average deposit rate and standard deviation of deposit rates for each state, through aggregation of the county characteristics. Our findings indicate that our model can accurately predict state recessions. We find that our base-

[1]For example, at the onset of the Great Financial Crisis of 2008, the median forecaster in the Survey of Professional Forecasters expected cumulative real GDP growth of 2.2 percent (Drautzburg et al. (2019)). Similarly, Zarnowitz and Braun (1993) show prediction errors are highest during recessions.

[2]We define recession as a contraction in GDP of 2% or above. Our findings are robust to alternate thresholds.

[3]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.

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

line model at the state level has an in-sample AUC of 0.86 and an out-of-sample AUC of 0.80. Collectively, our findings demonstrate that the dispersion of bank deposit rates is a valuable heuristic for predicting recessions. Finally, we 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 yields extremely accurate forecasts of national recessions.

The key question that arises is: why does the dispersion of deposit rates offered by banks predict recessions? To understand the mechanism at play, we examine the characteristics of banks that raise deposit rates on insured deposits. We find that banks that experience an outflow of uninsured deposits and a slower growth rate of insured deposits raise deposit rates in the following quarter. To sustain the asset side of their balance sheet, these banks raise deposit rates to attract insured deposits. Unsurprisingly, an increase in the deposit rate on insured deposits is accompanied by a higher growth rate of insured deposits. We also find that the banks that raise deposit rates report relatively higher risk-weighted assets as compared to other banks.

Overall, the findings are consistent with the following channel: before an economic contraction (recession), as economic activity slows and the growth rate of deposits slows, uninsured depositors move away from riskier banks. Thus, the onset of an economic contraction is accompanied by strain on the liability side of a bank's balance sheet. However, banks that lose deposits still need to continue to support the asset side of their balance sheet. As a result, these banks offer more competitive deposit rates in order to raise funding.[5] Hence, there is an increase in the dispersion of deposit rates offered for insured deposits across banks within a county. In effect, an increase in the dispersion of deposit rates is a precursor to an economic contraction.

In line with the mechanism detailed above, we find evidence that the predictive value of our model increases in counties where banks face more competition for deposits. The model's AUC increases monotonically with the number of banks in each county. Specifically, the model's AUC in counties with at least two banks is 0.73, compared to 0.80 in counties with more than four banks.[6] We also find that the predictive value of our model improves in metropolitan and urban counties, compared to rural counties. In areas where there is less com-

[5] Acharya and Mora (2015) show that in the Great Financial Crisis of 2008, banks faced a liquidity shortage since their lending commitments exceeded their deposits. As a response, banks increased their deposit rates to stem deposit outflows and to attract more deposits.

[6] The corresponding out-of-sample AUC is 0.62 for counties with at least two banks and 0.71 for counties with more than 4 banks.

petition for deposits, i.e., fewer banks, the need to raise deposit rates to attract funding is lower, thus, the dispersion of deposit rates has less power in predicting an economic downturn.[7]

We conduct several robustness checks to validate our results. First, we show that dispersion of deposit rates can predict impending recessions, even after accounting for changes in monetary policy. In all of our specifications, we control for lags of the average deposit rate offered by banks within in a county and show that the dispersion of deposit rates remains a meaningful predictor of impending recessions.[8] The key benefit of using the dispersion of deposit rates rather than the average deposit rate is that the average deposit rate is largely driven by monetary policy. In addition, we show that our baseline findings are robust to controlling for lagged values of the Federal Funds Effective Rate, and that our model has high predictive value even in periods when changes in monetary policy are limited. Second, we find that our results are robust to controlling for lagged values of credit growth. Moreover, the dispersion of deposit rates can predict recessions, even in periods that are not preceded by high credit growth. Therefore, our model can also predict recessions that are not a result of a credit boom. Together, our findings demonstrate that the liabilities side of banks' balance sheet is useful for macroeconomic predictions.

The central premise of our analysis is that banks are an important source of funding for the economy. Regardless of the causes of business cycles, the onset of a downturn can potentially lead to changes in the liability side of banks' balance sheet. Thus, our analysis is agnostic to the factors that contribute to business cycle fluctuations, and instead focuses on the effects on the liability side of banks' balance sheet that accompany a downturn for prediction purposes.

Our results have important policy implications. Most of the leading indicators of impending recessions, which use treasury yield curve data or survey-based indices can only predict national recessions.[9] In contrast, the granularity of our indicators allows for prediction of recessions at the regional levels -county and state recessions. 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-

[7] Drechsler et al. (2017) provide evidence that in areas where banks have more monopoly power, they are less likely to raise rates in response to a hike in the Federal Funds Effective Rate.

[8] We also show that the dispersion of deposit rates is an accurate predictor of recessions, independent of the average deposit rate.

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

measure, market-based metric that can be used as an additional warning signal for economic contractions. Finally, our analysis also highlights that riskier 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.

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)).[10] 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 at the national level.

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), 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.[11] 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 – especially riskier banks – 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., Iyer et al. (2016), Egan et al. (2017), Calomiris et al. (1997), Martin et al. (2018), Acharya and Mora (2015), Saunders and Wilson (1996), 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

[10] 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).

[11] 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).

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)).

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 provides 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.

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.

County Population We use data on population across counties from the US Census Bureau. The Census Bureau's Population Estimates Program (PEP) produces estimates of the population for the US, states, metropolitan, and micropolitan statistical areas, counties, cities, and towns. We use the 2005 county population distribution, as our quarterly, state GDP data begins in 2005.

County Employment We use data on employment across counties from the BEA. The BEA estimates the number of workers by industry in US states, counties, metropolitan, and micropolitan areas. We use the 2005 county employment distribution, as our quarterly, state GDP data begins in 2005.

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 in bank deposit rates is a significant predictor of impending recessions. We develop a simple classifier which demonstrates how the standard deviation of bank 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 standard deviation of bank 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 most common deposit product – 12-month certificates of deposit (CD) with a minimum account size of $10,000.[12] 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.

Figure 2 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, for each county in each month, we compute the standard deviation of the deposit rate across banks. 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.3 and Appendix Figure A.4 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 diverging pricing policies across counties, whereas after the GFC, banks' pricing policies

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

converged.[13] We find that the average standard deviation of deposit rates over the entire sample period is 0.27% – approximately equivalent to the median value of 0.26%.Figure 3 presents the dispersion in deposit rates over time. We find that banks exhibited very low dispersion in deposit rates in the period 2001 through 2004. The first sextile ranged from 0.00 to 0.14 and the sixth sextile 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 sextile in this period ranged from 0.00 to 0.19 and the sixth sextile ranged from 0.52 to 1.68. The average dispersion was 0.41%. Dispersion in deposit rates fell during and following the Great Financial Crisis of 2008 (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 in rates began increasing again. As compared to the period between 2011 to 2016, the average 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.[14]

Fluctuations in the dispersion of bank deposit rates over time motivate our inquiry into whether the second moment of bank deposit rates can predict recessions. Thus far, we have drawn inferences on the relation between the dispersion in 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 4. Figure 4 presents the average standard deviation 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 in 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 in deposit rates, while controlling for the average deposit rate in all of the analysis.

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

[13] 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.

[14] 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.

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.

While our results, so far, indicate that the level and dispersion of aggregate deposit rates are a harbinger of national recessions, it is unclear whether dispersion in local deposit rates can predict recessions at a more granular level. To investigate this, we conduct a case study, examining the relation between dispersion in 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 5. Both Figure 5a and Figure 5b demonstrate that the dispersion in deposit rates among banks in the county increased in the immediate years preceding recessions. The dispersion narrows in the years following recessions. Specifically, we find that the dispersion in deposit rates increases 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 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 6 and Figure 7 present the timing and duration of recessions at the county and state levels, respectively. Figure 6a 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 A.1. 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 recession, 53% of

[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.

counties were in recessions in 2020. Figure 6b 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.2. A state is defined to be in a recession if its GDP growth between two consecutive quarters is below -2%. Figure 7a indicates that only 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. Figure 7b 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.

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 hypothesis 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 standard deviation 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 in 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 standard deviation of deposit rates for each county.[17] Using this data, we estimate a logit model of a county recession in

[17]Our empirical findings are robust to alternate methods of constructing the average deposit rate and standard deviation, 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.

county c in year t as a function of the lagged deposit rates at year t. We consider up to three-year annual lags of the standard deviation of deposit rates ("standard deviation") and average deposit rate within a county. The baseline model is as follows:

$$\begin{aligned} logit(p_{c,t}) = \alpha &+ \beta_1 Rate_{c,t-1} + \beta_2 SD_{c,t-1} + \beta_3 Rate_{c,t-2} + \beta_4 SD_{c,t-2} \\ &+ \beta_5 Rate_{c,t-3} + \beta_6 SD_{c,t-3} + \epsilon_{c,t} \end{aligned} \tag{1}$$

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 in deposit rates is a salient indicator of economic recessions. Table 2 reports the average marginal effects. Independent variables are standardized for ease of interpretation. We account for the time-invariant heterogeneity across counties through county fixed effects. The county fixed effects also allows us to control for the banking structure (competition) and the type of banks that operate in each county which could affect the level of dispersion.[18] We also account for the effect of fed funds rate and macroeconomic conditions through lagged values of the average deposit rate. In column 1, we consider the three-year lagged standard deviation, and control for the three-year lagged average deposit rate. In columns 2 and 3, we successively add the two-year lagged and one-year lagged standard deviation and average deposit rate values. The pseudo R^2 sizably increases as we add these variables.[19] We conduct diagnostic tests of joint statistical significance and report the χ^2 and associated p-values.

Our findings indicate that there is a greater probability of a recession following increases in the dispersion in deposit rates. Our point estimates remain economically meaningful and statistically significant at the 1% level across all specifications. In column 1, we find that a one standard deviation increase in the one-year lagged standard deviation of deposit rates is associated with a 1.50 percentage points increase in the likelihood of a recession in three years in that county. In column 2, we find that a one standard deviation increase in the two-year lagged standard deviation of deposit rates is associated with a 3.74 percentage points increase in the likelihood of a recession in two years in that county. In column 3, we find that a one standard deviation increase in the one-year lagged standard deviation of deposit

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

[19] 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.

rates is associated with a 3.49 percentage points increase in the likelihood of a recession in the next year in that county. Moreover, column 3 indicates that the two-year lagged standard deviation remains statistically significant and economically meaningful even with the addition of the one-year lagged values. The diagnostic tests also show that the covariates are jointly statistically significant at the 1% level. Thus, our findings indicate that there is a positive relationship between the dispersion in deposit rates and the probability of a future economic contraction within a county. These relationships are economically meaningful, statistically significant, and stable.

The results from the estimation also show that lagged bank deposit rates are also significant predictors of recession. However, these coefficients are quite unstable. The effect of the three-year lagged deposit rate on probability of a recession is negative. However, the effects of the two-year and one-year lagged deposit rates are positive. Further, another issue with using the lagged average deposit rate for prediction purposes is that it is heavily influenced by the Federal Funds Effective Rate. A larger magnitude associated with the average deposit rate may be the result of the Fed's response of lowering interest rates when the economy is in a recession (like in 2008).[20]

We further examine the predictive value of lagged standard deviation 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 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.[21]

[20] 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 is mechanical.

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

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. Our least conservative specification, which uses the three-year lagged deposit rate and standard deviation yields an AUC of 0.6950 – above the random coin toss classifier. The inclusion of two-year lagged values increases the AUC to 0.7096. With the inclusion of the one-year lagged values, the AUC increases to 0.7329. The ROC curve associated with this model is presented in Figure 8a. These increases are substantial, considering that even a 0.01 increase in the AUC is noteworthy. 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 quarterly lags of the level and dispersion of state deposit rates can predict state recessions. We calculate the average deposit rate and standard deviation of deposit rates for each state, through aggregation of the county characteristics. Specifically, we construct four measures of the level and dispersion of state deposit rates: *Equal-Weight*, *GDP-Weight*, *Emp-Weight*, and *Pop-Weight*. The Equal-Weight measure calculates the state deposit rate and standard deviation by taking an equal-weighted average of the county deposit rate and standard deviation in each state for the last reporting month of each quarter. The GDP-, Emp-, and Pop-Weight measures are constructed by taking an average of the county deposit rate and standard deviation, weighted by the 2004 county GDP, employment, and population, in each state for the last reporting month of each quarter.

Analogous to the model of Equation 2 we estimate a logit model of a state recession in state s in quarter-year t as a function of the lagged deposit rates at quarter-year t. We consider up to 12 quarterly lags of the standard deviation and average deposit rate within a county. The baseline model is as follows:

$$\begin{aligned} logit(p_{s,t}) = \alpha &+ \beta_1 Rate_{s,t-4} + \beta_2 SD_{s,t-4} + \beta_3 Rate_{s,t-8} + \beta_4 SD_{s,t-8} \\ &+ \beta_5 Rate_{s,t-12} + \beta_6 SD_{s,t-12} + \epsilon_{s,t} \end{aligned} \tag{2}$$

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 3 reports the average marginal effects at the state level. The independent variables across all specifications are the 12-quarter lagged standard deviation and average deposit rate, eight-quarter lagged standard deviation and average deposit rate, and four-quarter lagged standard deviation and deposit rate. Columns 1 through 4 report the results under the equal-, GDP-, employment-, and population-weighted measures, respectively. We account for the time-invariant heterogeneity across states through state fixed effects. We also include lagged values of the average deposit rate in the estimations. Independent variables are standardized for ease of interpretation. Similar to the findings of column 3 of Table 2, the dispersion in the one-year lagged standard deviation remains a significant indicator of economic recessions, after including all lagged values in consideration. Specifically, we find that a one standard deviation increase in the four-quarter lagged standard deviation is associated with an increase in the likelihood of a state recession by 4.79 to 4.97 percentage points. This point estimate is precise, economically meaningful, and statistically significant at the 1% level. We identify the GDP-Weight models of columns 3 and 4 as having the best fit based on the pseudo R^2. 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. The AUC reported in Table 2 indicates that the AUC is extremely high – considerably higher at the state level than the county level. We find that the AUC ranges from 0.8526 to 0.8571. Moreover, we find that the pseudo R^2 is mostly driven by variation in deposit rates rather than state-specific factors.[22] The ROC curve associated with the model of column 2 is presented in Figure 8b.

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 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 Equation 3. The "expected likelihood" of a national recession is then calculated by taking a weighted sum of the

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

predicted state probabilities, weighted by the 2004 state GDPs.[23] 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.[24]

We find that our model predicts 100% of recessions that occurred. Our model also forecasts eight "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 four quarters preceding the Great Recession, two quarters following it, and two quarters 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 COVID-19 hit. 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.[25] The confusion matrix below Table 3 summarizes the number of true positives, false negatives, false positives, and true negatives.

4.4 Robustness

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

We begin by showing that the lagged values of standard deviation are independently accurate predictors of impending recessions. A common conception may be that the standard deviations and average deposit rates are highly correlated – when rates increase, standard deviations also increase – therefore, the standard deviations do not have additional predictive value. However, Figure 4 and Figure 5a demonstrate that the average deposit rate did not increase by as much as the standard deviation of deposit rates prior to the COVID-19 recession.

[23] 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.

[24] We also use the in-sample estimated model parameters and model threshold to forecast whether a recession will occur in 2022Q3, 2022Q4, and 2023Q1 using three-year, two-year, and one-year lagged deposit rate and standard deviation values.

[25] 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.

This implies that there is tremendous heterogeneity in rates across banks despite a low average deposit rate. We study this more rigorously in Appendix Table A.1. Column 1 estimates a logit regression of a county recession as a function of the lagged standard deviations. Column 2 estimates a logit regression of a county recession as a function of the lagged average rates. Column 1 indicates that a one standard deviation increase in the one-year lagged standard deviation of deposit rates is associated with a 3.00 percentage points increase in the likelihood of a recession in the following year in that county. This estimate is statistically significant at the 1% level and is quantitatively similar to the point estimate of 3.49 percentage points, after accounting for the average deposit rate, as reported in Table 2. The point estimates of the average deposit rates reported in column 2 are comparable to that in Table 2. Moreover, we find that the AUC associated with lagged values of the standard deviation is 0.7076 – comparable to the 0.7329 AUC value of our baseline Table 2. Hence, our findings indicate that controlling for the average deposit rates is not necessary to generate a high model predictive value. In unreported regression tables, we consider how the three-year lagged standard deviation performs in predicting county and state recessions. We find that the three-year (12-quarter) lagged standard deviation produces an AUC of 0.6942 (0.6952 to 0.6972) at the county (state) level. The takeaways from these analyses are twofold. First, standard deviations are independently accurate predictors of impending county and state recessions. Second, even by itself, the three-year (12-quarter) lagged standard deviation of deposit rates is a useful heuristic for predicting recessions three years (12-quarters) in advance.

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 lagged values of the Federal Funds Effective Rate to our baseline empirical specifications to control for the macroeconomic environment (Drechsler et al. (2017); Drechsler et al. (2022)). These results are reported at the county level in Appendix Table A.2 and Appendix Table A.3 at the state level. The addition of the lagged values of the Federal Funds Effective Rate does not quantitatively or qualitatively affect the precision of our baseline point estimates reported in Table 2. The addition of the lagged values of the Federal Funds Effective Rate attenuates the point estimates in the state regressions, albeit, the estimates remain economically meaningful and statistically significant. 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 studying the high predictive value of our model in the period between 2011 and 2016 (see Section 8)– a period with little variation in the Federal Funds Effective Rate. These results add reassurance that the lagged standard deviations have predictive value, even after accounting for a key instrument of monetary policy. Our findings show that the second moment of bank deposit rates, which is not as sensitive to monetary policy shocks, is a useful complement to the treasury yield curve data for predicting recessions.[26]

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 3 are robust to the inclusion of time fixed effects. Addition of year fixed effects improves the AUC from 0.7329 to 0.7774 at the county level and from $\sim$0.85 to $\sim$0.92 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.

5 Explaining the Dispersion of Deposit Rates

In the previous sections, we have shown that the dispersion of deposit rates can be used to 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 the deposit rates. The deposit rate changes are computed on a quarterly basis because call report data is available on a quarterly basis. We first compute the average deposit rate across all counties for each bank in each quarter. We then calculate banks' quarterly changes in deposit rates using the quarterly average deposit rates.[27]

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 an impending recession in the next eight quarters, and the interaction of these vari-

[26] In unreported regression tables, we consider how the inclusion of lagged values of the term spread (10-Year Treasury Constant Maturity Minus 3-Month Treasury Constant Maturity) affects the predictive value of our model. Our findings remain robust.

[27] The dispersion in deposit rates is reflected by the quartile indicators for banks' quarterly changes in the deposit rate.

ables. k denotes the lead/lag 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 , and Rec. denotes whether there is a recession within the next eight quarters.

Table 6 presents these 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. Uninsured depositors are typically large depositors such as nonfinancial or financial corporations, wealthy or sophisticated individuals – the vast majority of depositor households have deposits below the insured limit. Our regression specification includes quarter-year fixed effects to control for aggregate shocks.[28] We consider lags and leads of the dependent variable of up to three quarters in columns 1 through 7, respectively.

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 observe a comparable slowing in uninsured deposits. Interestingly, we find that for banks which eventually raise rates to a greater extent, the growth of uninsured deposits declines by a larger amount. In other words, banks that experience greater uninsured deposit withdrawals, raise deposit rates in the following quarter by a larger margin. In addition, as an economy approaches a recession, banks experience additional uninsured deposit withdrawals in the quarter in which rates are raised, as indicated by $\mathbb{1}_{\text{Dep Rate Change}>P75,b,t} \times \text{Rec.}_t$. Unsurprisingly, we also find higher growth in both insured and uninsured deposits in the following quarter after rate changes occur.[29]

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

[28]Quarter-Year fixed effects absorb the *Recession* variable, hence, we omit this from our regression specification.
[29]Unreported, these banks also increase the rate on uninsured deposits.

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 6, 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.[30] 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 6 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 8 investigates these dynamics. Panel A examines the relation between the dynamics of growth in RWA and deposit rate changes. Panel B examines the relation between the dynamics of growth in tier 1 capital and deposit rate changes. We find that during normal periods of economic growth, higher RWA growth precedes higher rate changes. During normal periods of economic growth, banks continue growing their RWA in quarters following rate changes. There is monotonicity in the RWA growth rate and deposit rate changes; during periods of normal economic growth, banks in the fourth quartile experience greater RWA growth compared to banks in the first, second, and third quartiles. Similarly, we find that during normal periods of economic growth, tier 1 capital growth is also 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. Banks in the fourth quartile of deposit rate changes reduce RWA growth by a greater margin than banks in the first, second, and third quartiles.[31] Panel B indicates similar patterns in the growth in tier 1 capital.[32] These findings suggest that during normal periods of economic growth, banks increase rates to expand their balance sheet and the 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 9 indicates that higher lending growth precedes higher rate changes. Specifically, we find that during periods of normal economic growth, banks in

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

[31] In the quarter that the rate changes occur, the net effect of RWA growth is 0.0035 for the fourth quartile. This is the sum of unconditional effect of 0.0065 and the interaction of -0.003.

[32] We also find similar results with tier 2 capital in Appendix Table A.7.

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. [33] 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 attract funds from insured depositors. Thus, the resulting dispersion in deposit rates 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.[34] 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 increased standard deviation of rates. Therefore, an increase in the standard deviation 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

[33] In the quarter before the rate changes occur, the net effect of lending growth is 0.004 for the fourth quartile. This is the sum of unconditional effect of 0.008 and the interaction of -0.004.

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

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.[35]

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 counties 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 standard deviations of deposit rates. We test this hypothesis at the county- and state levels. Appendix Table A.5 presents the results at the county level. Column 1 presents our baseline result from estimating Equation 2 for our entire sample.[36] Column 2 estimates Equation 2 for counties with more than two banks. Column 3 estimates Equation 2 for counties with more than three banks. Column

[35]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.

[36]To measure standard deviation, each county-year must have at least two reporting banks.

4 estimates Equation 2 for counties with more than four banks. As we move from column 1 to column 4, the magnitude of significant point estimates increases, hence, deposit rates and standard deviations are stronger indicators of recessions in areas with more competitive deposit markets. Specifically, in counties with more than four banks, we find that a one standard deviation increase in the one-year lagged standard deviation of deposit rates is associated with a 5.70 percentage points increase in the likelihood of a recession in the following year in that county. These figures are 5.23 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 3.49 percentage points. Moreover, we find that the AUC is higher in markets with a larger number of banks. The model produces an AUC of 0.7329 in counties with at least two banks, 0.7553 in counties with more than two banks, 0.7797 in counties with more than three banks, and 0.8025 in counties with more than four banks. Appendix Table A.6 presents the results at the state level. Similarly, the model produces an AUC of 0.8561 in states with at least two banks per county on average, 0.8570 in states with more than two banks per county on average, 0.8655 in states with more than three banks per county on average, and 0.8825 in states with more than four banks on average.

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 A.5 presents a heatmap of metropolitan, urban, and rural counties. We estimate Equation 2 separately for metropolitan, urban, and rural areas in Appendix Table A.4 and plot the ROC curves in Figure 11a. We find that the point estimates associated with the lagged values of standard deviation 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 in metropolitan counties is 0.8055, compared to 0.6942 in urban counties, and 0.6596 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 to be more competition for funds.[37]

[37] 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 A.6, indicate that the AUC is 0.8228 using deposit rates from stress-tested banks and 0.7319 for all other banks.

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 9 and Figure 10 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 0.619 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 0.647 (s.d. = 0.013) in counties that report greater than two banks, 0.680 (s.d. = 0.019) in counties that report greater than three banks, and 0.705 (s.d. = 0.017) in counties that report greater than four banks. At the state level, we find that the k-fold cross-validated AUC is 0.7870 (s.d. = 0.057). Like in Figure 9, we find that the predictive accuracy increases monotonically with the average number of banks per county in each state. The cross-validated AUC is 0.789 (s.d. = 0.060) in counties that report greater than two banks, 0.811 (s.d. = 0.060) in counties that report greater than three banks, and 0.834 (s.d. = 0.081) 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 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.[38] In other words, can dispersion in deposit rates predict recessions that are not preceded by periods of high credit growth? In this section, first, we show that lagged values of standard deviation can predict recessions, even after accounting for credit growth. Second, we show that the lagged values of standard deviation can predict recessions, even in the absence of credit booms.

We examine credit booms at the county level using data on small business lending and mortgage lending. Table 5 runs a horse-race between our lagged measures of standard deviation against lagged measures of credit growth including mortgage lending growth and total lending growth (sum of mortgage and small business lending). Column 1 reports the coefficients estimated from a logit of a county recession on the one-year, two-year, and three-year lagged values of mortgage lending growth. The recent history of a county's' credit growth has predictive value. The associated AUC is 0.6887 and the pseudo R^2 is 0.0795. These values are lower in comparison to our baseline model in which the AUC is reported to be 0.7329 and the pseudo R^2 is 0.1157. In column 2, we add our lagged values of the deposit rate and standard deviation. Columns 3 and 4 report the results with total lending growth instead of mortgage lending growth. The addition of the lagged 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)).[39] Thus, a deterioration in the economic fundamentals 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.7 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 0.7049 and at the state level is 0.7833. 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.

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

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 model that includes up to three year lags of the dispersion of deposit rates across banks within a county (state) is 0.73 (0.86).

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 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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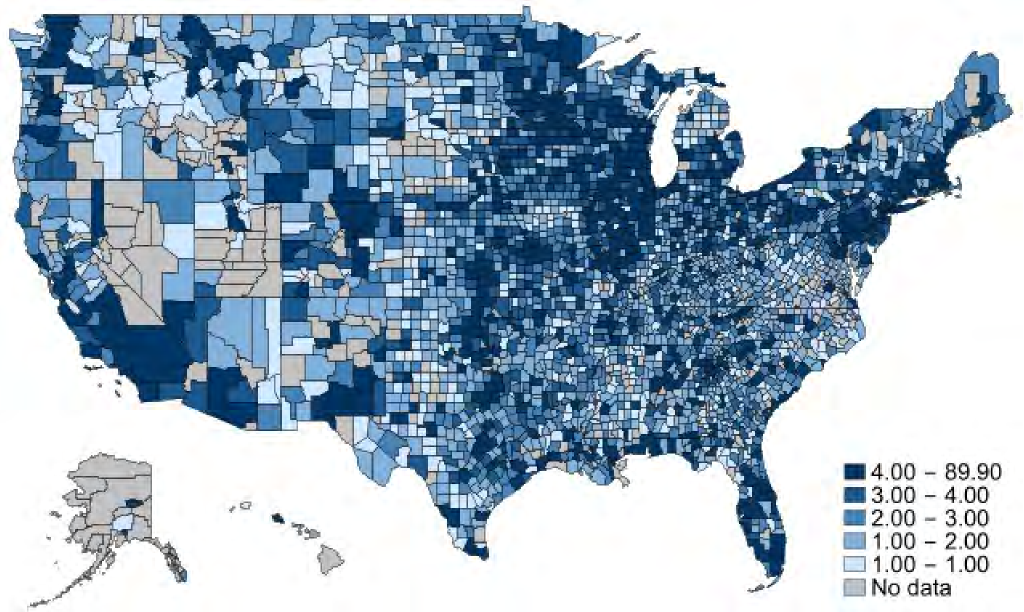
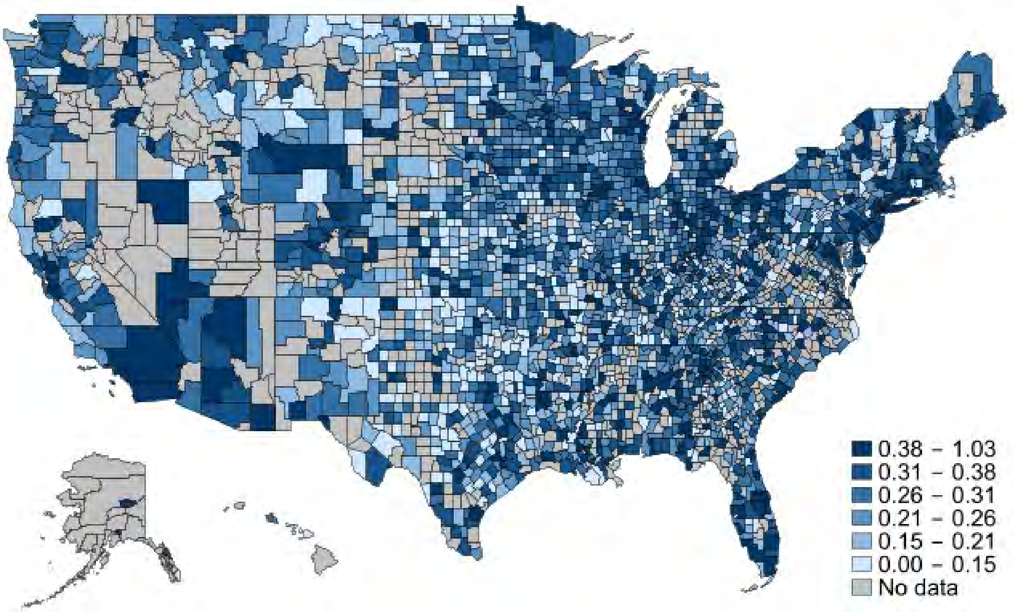
Figures and Tables

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



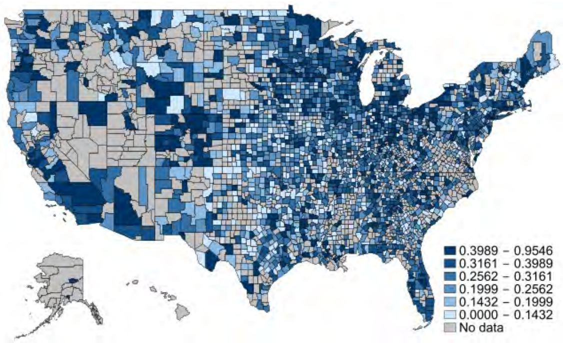
Notes: This figure uses RateWatch data to present a heatmap of the average number of banks that offer 12-month certificates of deposit of at least $10,000 in each county from 2001 to 2020. The intensity of the blue shading represents the number of banks operating in a particular county.

Figure 2: Dispersion of Deposit Rates by County (2001-2020)

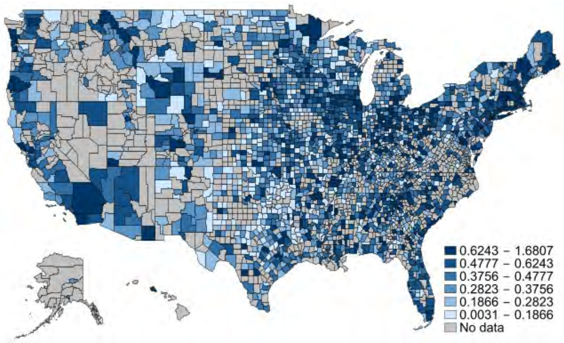


Notes: This figure uses RateWatch data to present a heatmap of the average standard deviation of deposit rates (12-month, $10K CDs) from 2001 to 2020. The deposit rate is the rate on the 12-month certificate of deposit of at least $10,000. The intensity of the blue shading represents the sextile range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

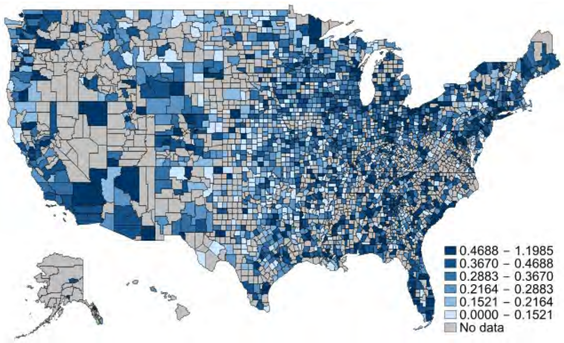
Figure 3: Dispersion of Deposit Rates Over Time



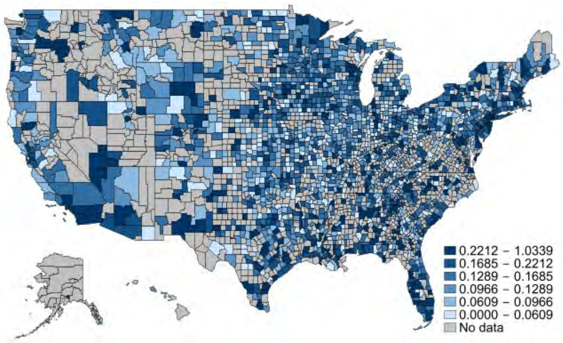
(a) 2001-2004



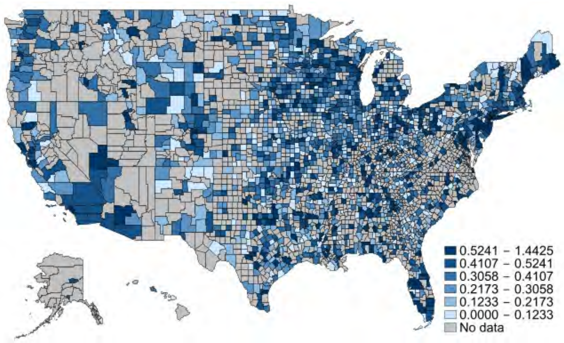
(b) 2005-2007



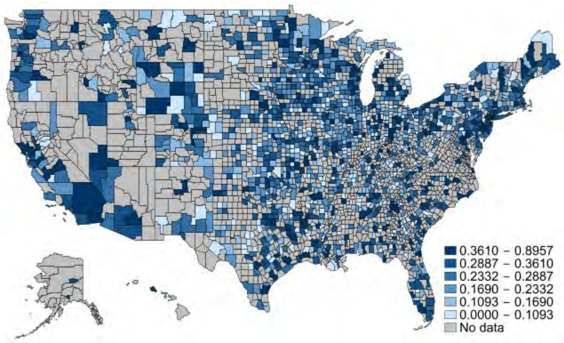
(c) 2008-2010



(d) 2011-2016



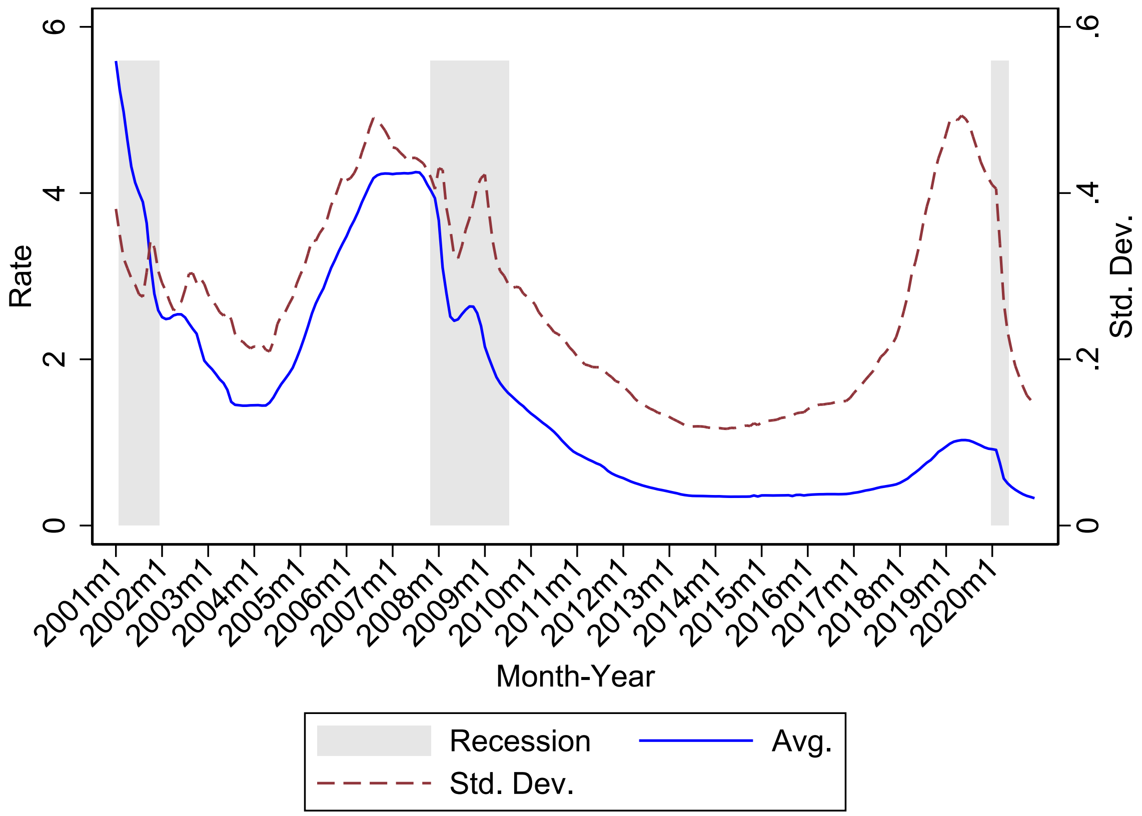
(e) 2017-2019



(f) 2020

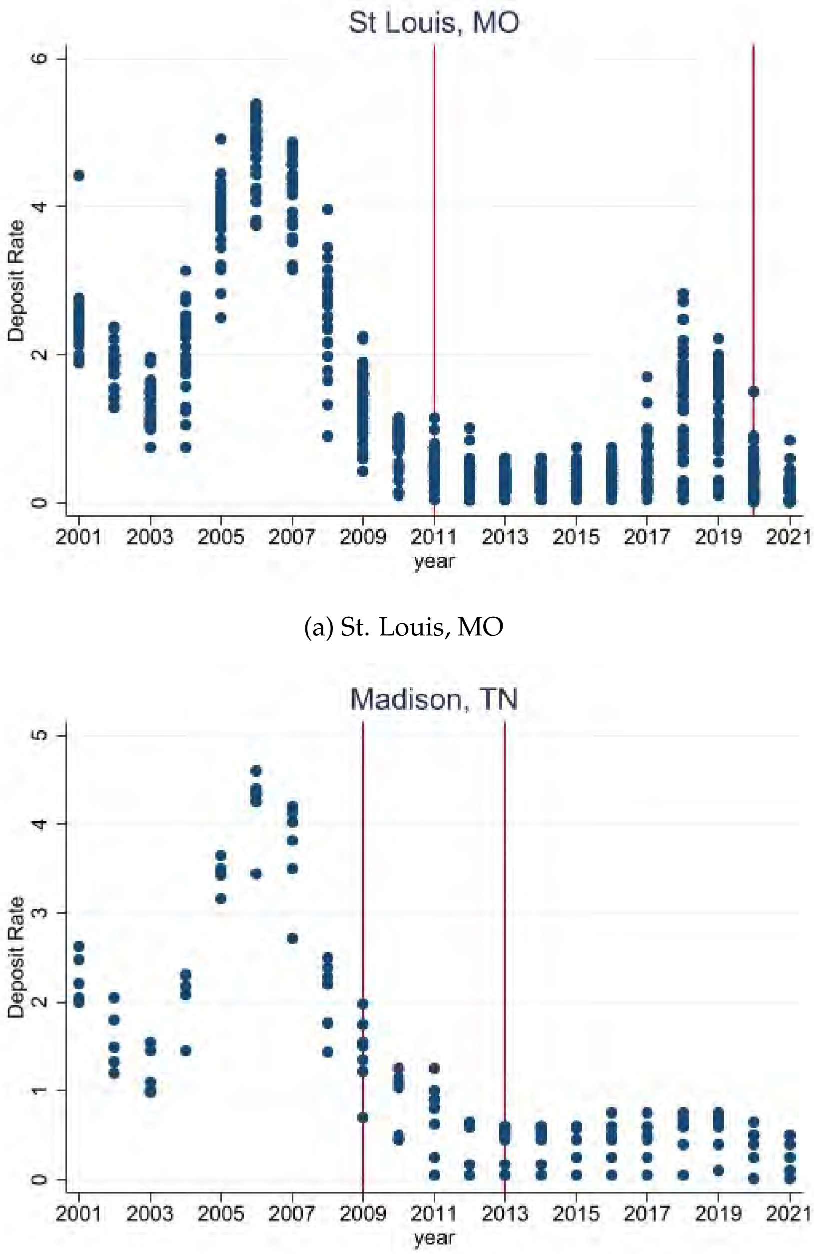
Notes: This figure uses RateWatch data to present a heatmap of the average standard deviation of deposit rates (12-month, $10K CDs). Figure 3a presents the time-series average of the standard deviation of deposit rates from 2001-2004; Figure 3b presents the time-series average of the standard deviation of deposit rates from 2005-2007; Figure 3c presents the time-series average of the standard deviation of deposit rates from 2008 to 2010; Figure 3d presents the time-series average of the standard deviation of deposit rates from 2011 to 2016; Figure 3e presents the time-series average of the standard deviation of deposit rates from 2017 to 2019; and Figure 3f 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 4: 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 5: Dispersion of Deposit Rates and County Recessions

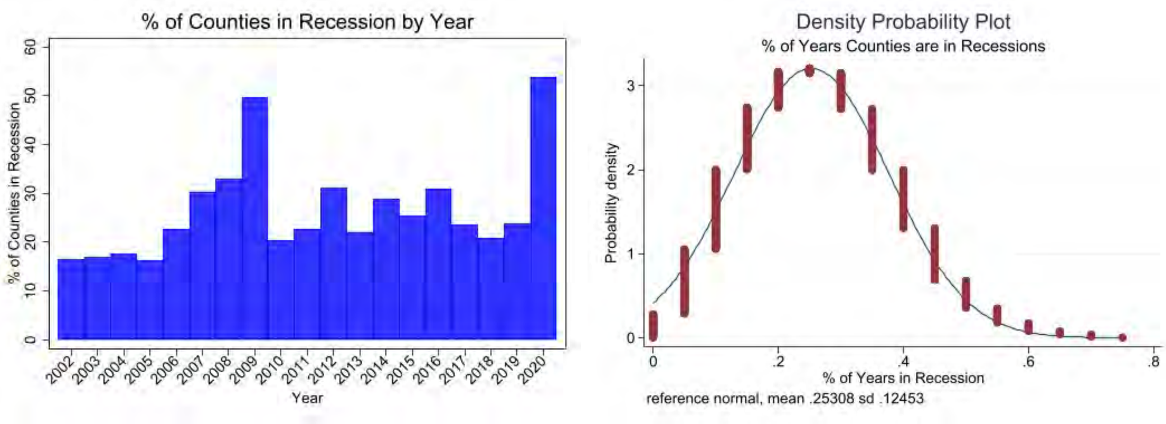


(a) St. Louis, MO

(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 6: Recessions Across Counties and Time

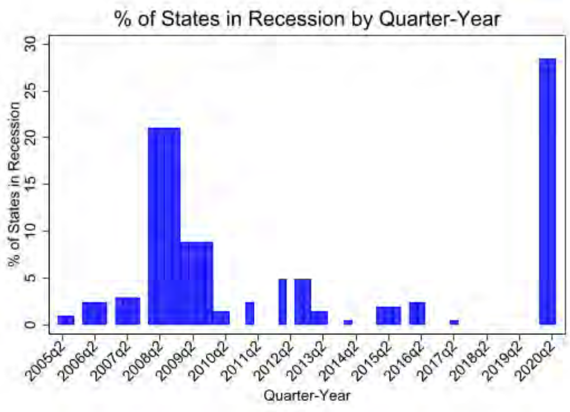


(a) % of Counties in Recession

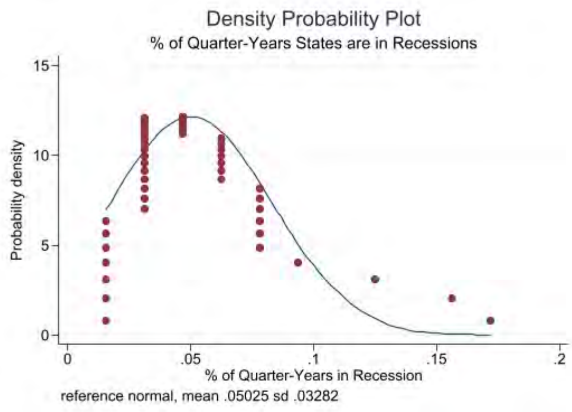
(b) % of Recessions within Counties

Notes: This figure presents the percentage of counties in recessions by year in Figure 6a, and a density probability plot of the percent of year counties are in recessions in Figure 6b 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 7: Recessions Across States and Time



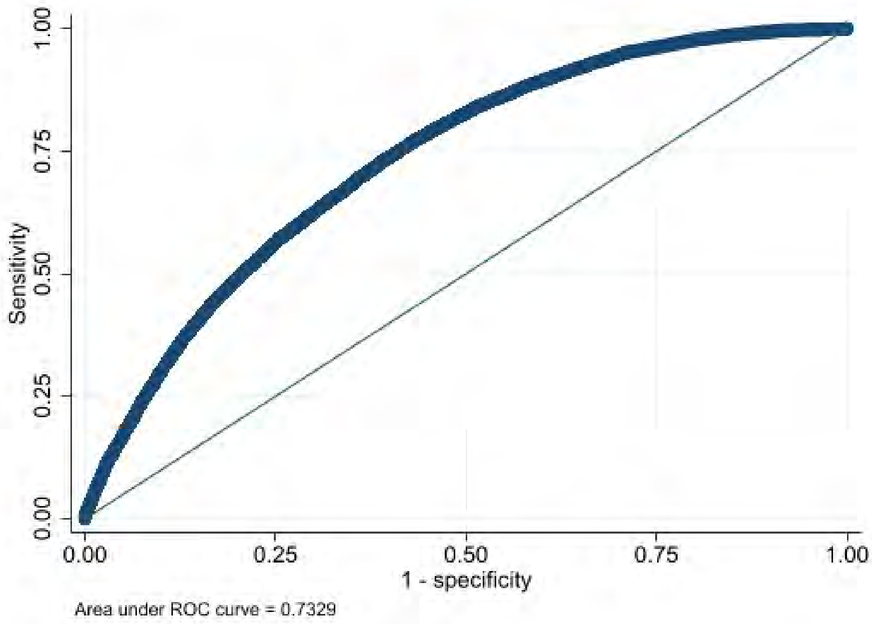
(a) % of States in Recession



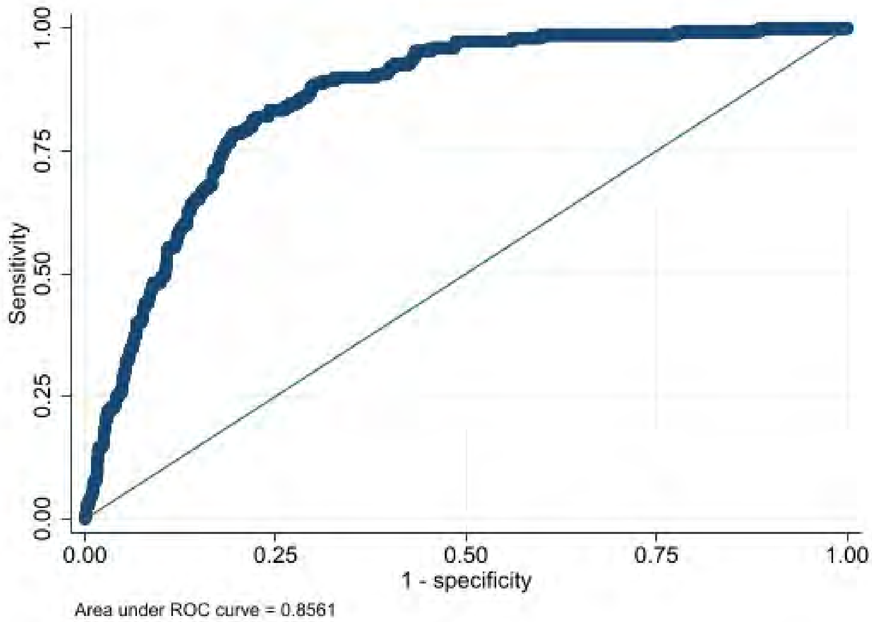
(b) % of Recessions within States

Notes: This figure presents the percentage of states in recessions by quarter-year in Figure 6a, and a density probability plot of the percent of quarter-years states are in recessions in Figure 6b based on State GDP data from the Bureau of Economic Analysis. State GDP data is available at the quarterly frequency from 2005. A county is in a recession if its GDP growth between two consecutive quarters is below -2%.

Figure 8: Dispersion of Deposit Rates Predicts Recessions



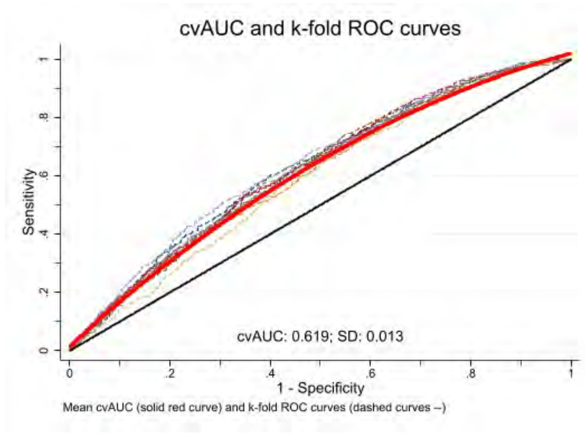
(a) County



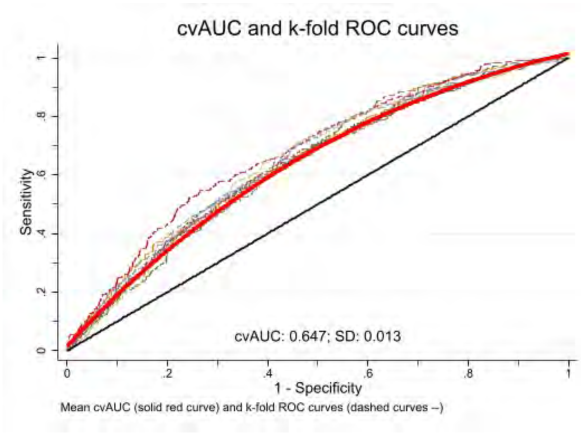
(b) State

Notes: This figure plots the Receiver Operating Characteristic (ROC) curves. Figure 8a presents the ROC curve associated with the model of column 6 in Table 2. Figure 8b presents the ROC curve associated with the model of column 4 in Table 3.

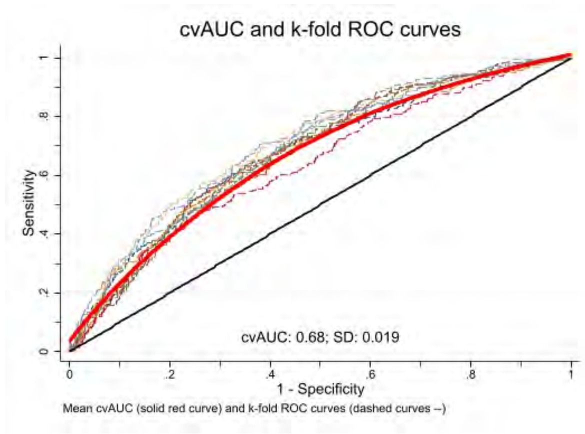
Figure 9: Out-of-Sample Estimation: Dispersion of Deposit Rates Predicts Recessions Recessions Better in Counties with More Banks



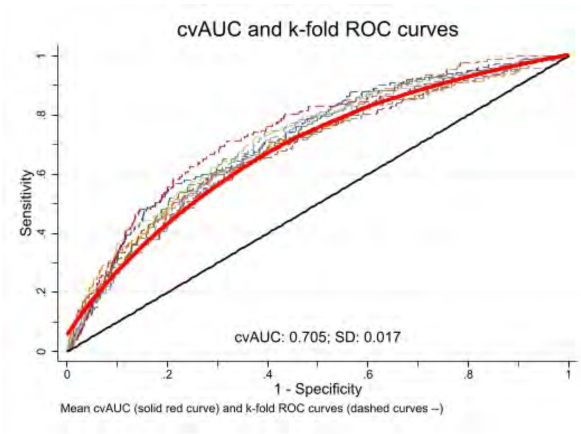
(a) All



(b) >2 Banks



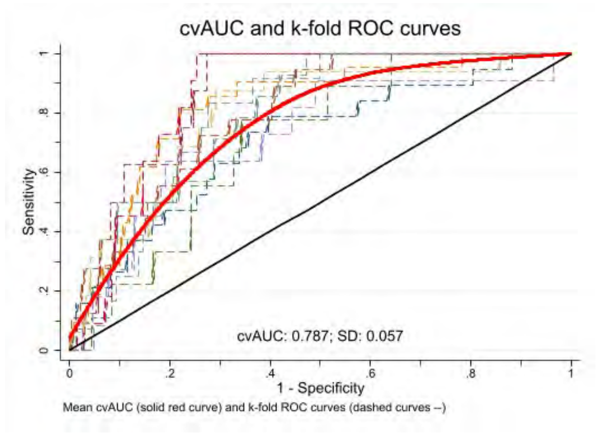
(c) >3 Banks



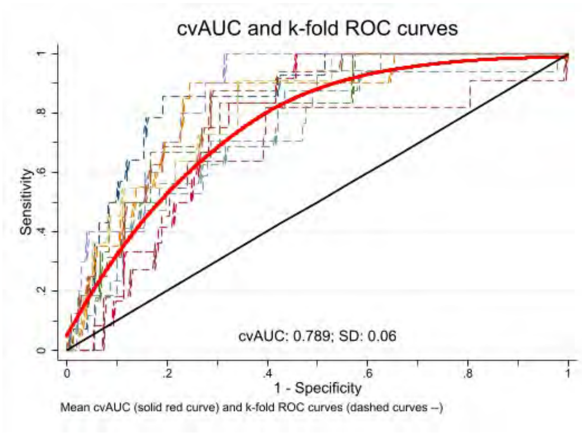
(d) >4 Banks

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 6 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 9a presents the cross-validated results for all counties. Figure 9b presents the cross-validated results for counties with more than two banks; Figure 9c presents the cross-validated results for counties with more than three banks; Figure 9d presents the cross-validated results for counties with more than four banks.

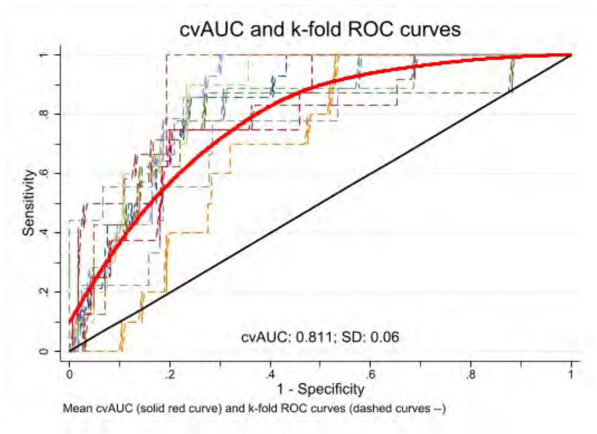
Figure 10: Out-of-Sample Estimation: Dispersion of Deposit Rates Predicts Recessions Recessions Better in States with More Banks



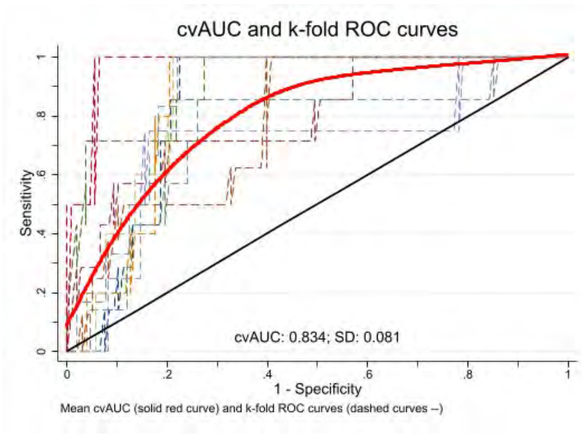
(a) All



(b) >2 Banks



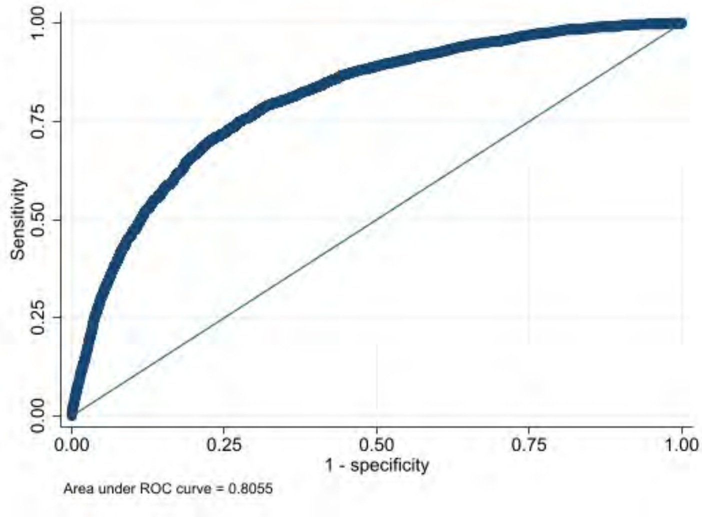
(c) >3 Banks



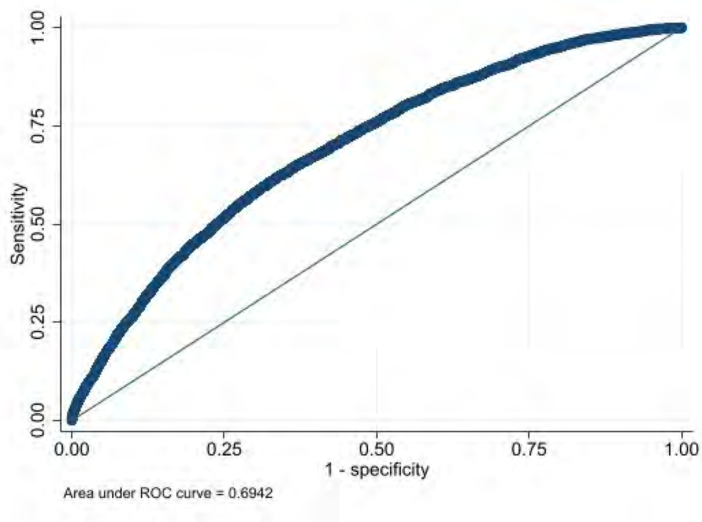
(d) >4 Banks

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 4 in Table 3 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 states. Figure 10b presents the cross-validated results for states with more than two banks per county on average; Figure 10c presents the cross-validated results for states with more than three banks per county on average; Figure 10d states with more than four banks per county on average.

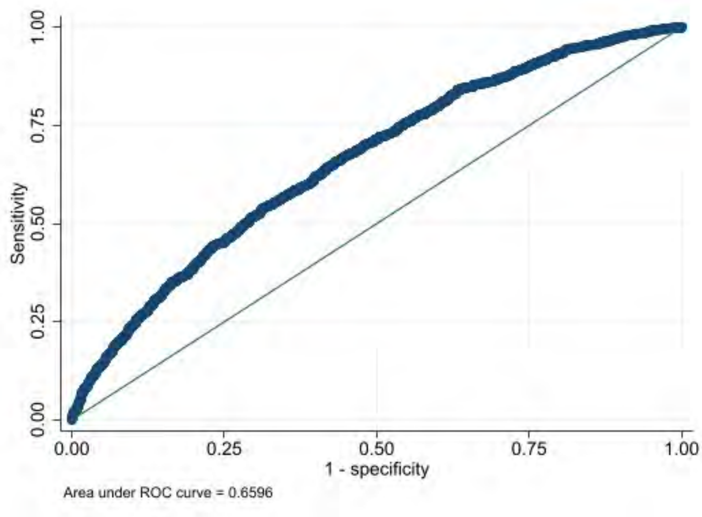
Figure 11: Dispersion of Deposit Rates Predicts Recessions Recessions in Metro, Urban, and Rural Counties



(a) Metro



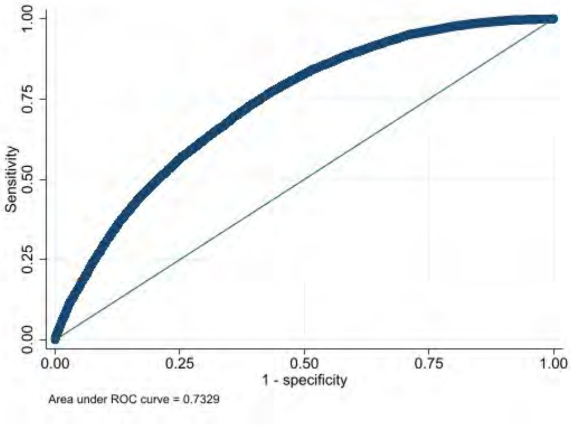
(b) Urban



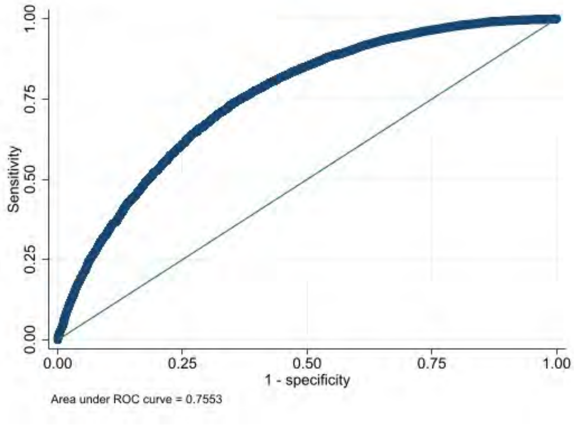
(c) Rural

Notes: This figure plots the Receiver Operating Characteristic (ROC) curves. The figures plot the ROC curves associated with the model of column 6 in Table 2. Figure 11a estimates the model separately for metropolitan counties. Figure 11b estimates the model separately for urban counties. Figure 11c 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 A.5 note for more details.

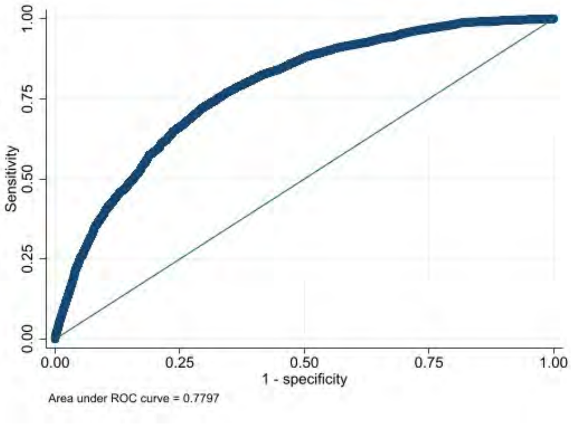
Figure 12: Dispersion of Deposit Rates Predicts Recessions Recessions Better in Counties with More Banks



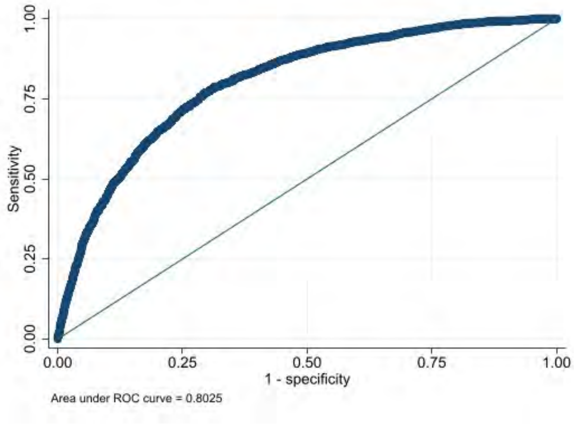
(a) All



(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 6 in Table 2. Figure 12a estimates the model for all counties. Figure 12b estimates the model separately for counties with more than two counties. Figure 12c estimates the model separately for counties with more than three counties. Figure 12d estimates the model separately for counties with more than four counties.

Table 1: Summary Statistics (2001-2020)

	N	P25	Median	P75	Mean	SD
Monthly Bank Deposit Rate	585,096	0.4500	1.1520	2.4500	1.6017	1.3679
Monthly Bank Dep. Rate SD	422,045	0.1061	0.2121	0.3754	0.2709	0.2287
Annual County Deposit Rate	54,327	0.3667	0.8632	2.1500	1.3892	1.2657
Annual County Dep. Rate SD	37,904	0.0995	0.1945	0.3585	0.2595	0.2277
Annual County GDP Growth	59,127	-0.0230	0.0122	0.0455	0.0128	0.0908
Quarterly State Deposit Rate (UW)	3,247	0.3877	0.6715	1.9748	1.3165	1.2868
Quarterly State Dep. Rate SD (UW)	3,247	0.1535	0.2481	0.3961	0.2909	0.1707
Quarterly State Deposit Rate (GDP)	3,247	0.3859	0.6785	1.9781	1.3270	1.3099
Quarterly State Dep. Rate SD (GDP)	3,247	0.1959	0.3067	0.4862	0.3525	0.1846
Quarterly State Deposit Rate (Pop)	3,247	0.3855	0.6757	1.9857	1.3253	1.3050
Quarterly State Dep. Rate SD (Pop)	3,247	0.1880	0.2968	0.4697	0.3420	0.1805
Quarterly State Deposit Rate (Emp)	3,247	0.3844	0.6766	1.9790	1.3247	1.3077
Quarterly State Dep. Rate SD (Emp)	3,247	0.1921	0.3030	0.4779	0.3482	0.1826
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)	(2)	(3)
L3.SD	0.0139***	-0.0012	-0.0008
	(0.0033)	(0.0036)	(0.0036)
L3.Rate	0.0150***	-0.0394***	-0.1314***
	(0.0032)	(0.0048)	(0.0068)
L2.SD		0.0374***	0.0275***
		(0.0035)	(0.0038)
L2.Rate		0.0554***	0.2571***
		(0.0045)	(0.0108)
L1.SD			0.0349***
			(0.0035)
L1.Rate			-0.1556***
			(0.0071)
County FIPS FE	✓	✓	✓
N	28,614	27,660	26,838
pseudo R^2	0.0826	0.0947	0.1157
AUC	0.6950	0.7096	0.7329
Overall test statistic, χ^2	2359.6318	2797.7889	3362.5720
p-value	0.0000	0.0000	0.0000

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: $logit(p_{c,t}) = \alpha + \beta_1 Rate_{c,t-1} + \beta_2 SD_{c,t-1} + \beta_3 Rate_{c,t-2} + \beta_4 SD_{c,t-2} + \beta_5 Rate_{c,t-3} + \beta_6 SD_{c,t-3} + \epsilon_{c,t}$ 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. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 3: Dispersion of Deposit Rates Predicts State Recessions

$\mathbb{1}_{Recession}$	(1) Equal-Weight	(2) GDP-Weight	(3) Emp-Weight	(4) Pop-Weight
L12.SD	0.0072	0.0049	0.0065	0.0071
	(0.0111)	(0.0115)	(0.0116)	(0.0116)
L12.Rate	-0.0411***	-0.0339***	-0.0356***	-0.0366***
	(0.0138)	(0.0130)	(0.0132)	(0.0132)
L8.SD	-0.0050	0.0021	0.0009	0.0003
	(0.0085)	(0.0080)	(0.0080)	(0.0080)
L8.Rate	0.0494**	0.0341*	0.0360*	0.0379*
	(0.0207)	(0.0206)	(0.0206)	(0.0204)
L4.SD	0.0497***	0.0479***	0.0479***	0.0485***
	(0.0075)	(0.0073)	(0.0073)	(0.0073)
L4.Rate	-0.0106	0.0005	-0.0008	-0.0025
	(0.0140)	(0.0144)	(0.0143)	(0.0142)
State FE	✓	✓	✓	✓
N	2,633	2,633	2,633	2,633
pseudo R^2	0.1999	0.2142	0.2128	0.2129
AUC	0.8526	0.8561	0.8569	0.8571
Overall test statistic, χ^2	266.6281	278.7751	278.4658	279.5087
p-value	0.0000	0.0000	0.0000	0.0000

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) t: $logit(p_{s,t}) = \alpha + \beta_1 Rate_{s,t-4} + \beta_2 SD_{s,t-4} + \beta_3 Rate_{s,t-8} + \beta_4 SD_{s,t-8} + \beta_5 Rate_{s,t-12} + \beta_6 SD_{s,t-12} + \epsilon_{s,t}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, *Rate* denotes the average bank deposit rate, and *SD* denotes the standard deviation of bank deposit rates. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Dispersion of Deposit Rates Forecasts National Recessions

Year	Quarter	Forecast	Actual
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	1	0
2007	1	1	0
2007	2	1	0
2007	3	1	0
2007	4	1	1
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	1	0
2009	4	1	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	0	0
2019	4	1	1
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	
2023	1	0	

Prediction Outcome

		p	**n**	**Total**
Actual Value	**p′**	True Positive = 10	False Negative =0	8′
	n′	False Positive = 8	True Negative =56	66′
	Total	18	56	

Notes: This table indicates our model-generated forecast of a recession and whether a recession actually occurred according to the NBER's Business Cycle Dating Committee. The model-generated forecast is constructed in several steps. First, the likelihood of a state recession is predicted based on Equation 3. Then. "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 indicates a recession if this expected likelihood is below the 25^{th} percentile of values. The in-sample estimated model parameters and model threshold are used to forecast whether a recession will occur in 2022Q3, 2022Q4, and 2023Q1 using three-year, two-year, and one-year lagged deposit rate and standard deviation values. We summarize the number of true positives, false negatives, false positives, and true negatives in a confusion matrix below.

Table 5: Dispersion of Deposit Rates Predicts County Recessions controlling for Credit Growth

$\mathbb{1}_{Recession}$	(1)	(2)	(3)	(4)
L3.SD		-0.0023		-0.0019
		(0.0038)		(0.0038)
L3.Rate		-0.1201***		-0.1241***
		(0.0071)		(0.0071)
L2.SD		0.0314***		0.0318***
		(0.0040)		(0.0040)
L2.Rate		0.2506***		0.2553***
		(0.0111)		(0.0112)
L1.SD		0.0323***		0.0317***
		(0.0036)		(0.0036)
L1.Rate		-0.1565***		-0.1578***
		(0.0073)		(0.0073)
L1.Δln(Mtg)	0.0029	-0.0109***		
	(0.0024)	(0.0030)		
L2.Δln(Mtg)	0.0232***	0.0166***		
	(0.0026)	(0.0032)		
L3.Δln(Mtg)	-0.0076***	-0.0027		
	(0.0023)	(0.0030)		
L1.Δln(Total)			0.0013	-0.0130***
			(0.0024)	(0.0030)
L2.Δln(Total)			0.0256***	0.0191***
			(0.0025)	(0.0030)
L3.Δln(Total)			-0.0076***	0.0019
			(0.0023)	(0.0030)
County FIPS FE	✓	✓	✓	✓
N	36,226	25,083	36,252	25,083
pseudo R^2	0.0795	0.1188	0.0799	0.1193
AUC	0.6887	0.7536	0.6894	0.7363
Overall test statistic, χ^2	2948.5147	3251.5828	2970.911	3255.8926
p-value	0.0000	0.0000	0.0000	0.0000

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: $logit(p_{c,t}) = \alpha + \beta_1 Rate_{c,t-1} + \beta_2 SD_{c,t-1} + \beta_3 CB_{c,t-1} + \beta_4 Rate_{c,t-2} + \beta_5 SD_{c,t-2} + \beta_6 CB_{c,t-2} + \beta_7 Rate_{c,t-3} + \beta_8 SD_{c,t-3} + \beta_9 CB_{c,t-3} + \epsilon_{s,t}$ 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 CB denotes credit growth (mortgage lending in columns 1 and 2 and sum of mortgage lending and small business lending in columns 3 and 4). The independent variables are standardized. Mortgage lending data comes from HMDA and small business lending data comes from the CRA. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

Panel A: Insured Deposit Growth

Δln(Insured Deposits)	(1) t-3	(2) t-2	(3) t-1	(4) t	(5) t+1	(6) t+2	(7) t+3
$\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ × 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)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ × 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)
$\mathbb{1}_{\text{Dep Rate Change}>P75}$ × 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

Δln(Uninsured Deposits)	(1) t-3	(2) t-2	(3) t-1	(4) t	(5) t+1	(6) t+2	(7) t+3
$\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ × 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)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ × 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)
$\mathbb{1}_{\text{Dep Rate Change}>P75}$ × 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

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

$\Delta ln(\frac{\text{Insured}}{\text{Uninsured}})$	(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.	-0.0028	-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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Balance Sheet Growth and Deposit Rate Changes

Panel A: RWA Growth

Δln(RWA)	(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.	-0.0021	-0.0020*	-0.0036**	-0.0029	-0.0031***	-0.0015	-0.0011
	(0.0015)	(0.0011)	(0.0014)	(0.0018)	(0.0010)	(0.0016)	(0.0008)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75} \times$ Rec.	0.0004	-0.0001	-0.0020	-0.0012	-0.0015	-0.0003	-0.0007
	(0.0012)	(0.0012)	(0.0013)	(0.0012)	(0.0011)	(0.0012)	(0.0011)
$\mathbb{1}_{\text{Dep Rate Change}>P75} \times$ Rec.	-0.0021	-0.0032**	-0.0033**	-0.0035**	-0.0031**	-0.0030***	-0.0021**
	(0.0013)	(0.0014)	(0.0013)	(0.0014)	(0.0012)	(0.0011)	(0.0010)
$\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$	0.0007	0.0017***	0.0026***	0.0033***	0.0024***	0.0021***	0.0019***
	(0.0008)	(0.0005)	(0.0008)	(0.0008)	(0.0006)	(0.0007)	(0.0005)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$	-0.0001	0.0006	0.0027***	0.0028***	0.0023***	0.0019**	0.0017*
	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0007)	(0.0008)	(0.0009)
$\mathbb{1}_{\text{Dep Rate Change}>P75}$	0.0027***	0.0041***	0.0055***	0.0065***	0.0045***	0.0041***	0.0038***
	(0.0008)	(0.0009)	(0.0009)	(0.0009)	(0.0008)	(0.0007)	(0.0007)
Quarter-Year FE	✓	✓	✓	✓	✓	✓	✓
N	237,335	240,356	243,582	245,445	243,911	242,596	241,355
R^2	0.0144	0.0137	0.0138	0.0138	0.0134	0.0132	0.0131

Panel B: Tier 1 Growth

Δln(Tier 1 Cap.)	(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.	-0.0015	-0.0020**	-0.0019*	-0.0018	-0.0021**	-0.0010	0.0001
	(0.0011)	(0.0010)	(0.0011)	(0.0013)	(0.0010)	(0.0011)	(0.0009)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75} \times$ Rec.	-0.0010	-0.0009	-0.0004	-0.0001	-0.0008	-0.0014	0.0018*
	(0.0011)	(0.0010)	(0.0011)	(0.0012)	(0.0013)	(0.0012)	(0.0010)
$\mathbb{1}_{\text{Dep Rate Change}>P75} \times$ Rec.	-0.0016*	-0.0033***	-0.0020*	-0.0042***	-0.0024**	-0.0010	-0.0029***
	(0.0009)	(0.0011)	(0.0010)	(0.0009)	(0.0010)	(0.0010)	(0.0009)
$\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$	0.0012	0.0014**	0.0024***	0.0019**	0.0022***	0.0018**	0.0003
	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0007)	(0.0006)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$	0.0013**	0.0015*	0.0019***	0.0003	0.0010**	0.0013	0.0003
	(0.0006)	(0.0008)	(0.0006)	(0.0007)	(0.0005)	(0.0009)	(0.0007)
$\mathbb{1}_{\text{Dep Rate Change}>P75}$	0.0025***	0.0030***	0.0041***	0.0039***	0.0021***	0.0023***	0.0030***
	(0.0007)	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0006)	(0.0008)
Quarter-Year FE	✓	✓	✓	✓	✓	✓	✓
N	238,560	242,959	247,598	250,878	249,330	248,002	246,748
R^2	0.0080	0.0081	0.0083	0.0081	0.0080	0.0080	0.0081

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 risk-weighted assets (Panel A) and tier 1 capital (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 risk-weighted assets and tier 1 capital comes from S&P Market Intelligence. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table 9: Lending Growth and Deposit Rate Changes

Panel A: Loan Growth							
Δln(Loans)	(1) t-3	(2) t-2	(3) t-1	(4) t	(5) t+1	(6) t+2	(7) t+3
$\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ × 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)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ × 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)
$\mathbb{1}_{\text{Dep Rate Change}>P75}$ × 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							
Δln(NPL)	(1) t-3	(2) t-2	(3) t-1	(4) t	(5) t+1	(6) t+2	(7) t+3
$\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$ × 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)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$ × 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)
$\mathbb{1}_{\text{Dep Rate Change}>P75}$ × 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

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

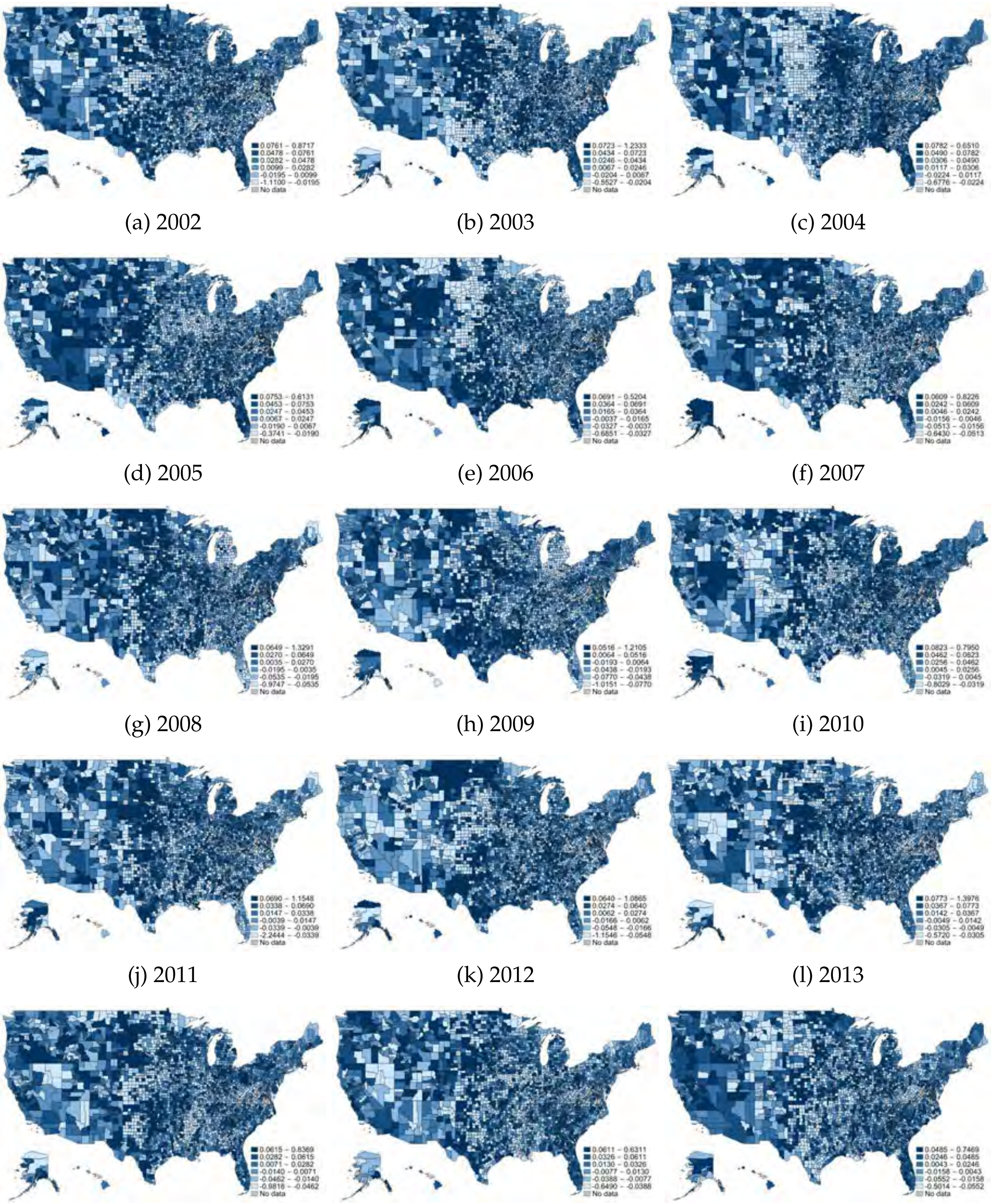
Notes: The table presents the coefficients estimated from the following regression for bank b at time t (quarter-year): $\Delta ln(y)_{b,t+k} = \beta_0 + \beta_1 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} \times \text{Rec.}_t + \beta_2 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} \times \text{Rec.}_t + \beta_3 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} \times \text{Rec.}_t + \beta_4 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} + \beta_5 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} + \beta_6 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} + \alpha_t + \epsilon_{b,t}$ 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. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Online Appendix for:

Predicting Recessions

Appendix A Figures and Tables

Figure A.1: Variation in GDP Growth at County Level



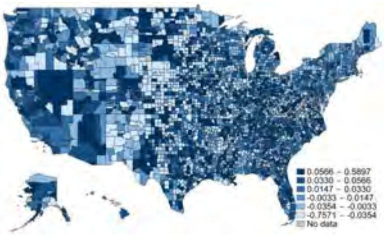
(a) 2002 (b) 2003 (c) 2004

(d) 2005 (e) 2006 (f) 2007

(g) 2008 (h) 2009 (i) 2010

(j) 2011 (k) 2012 (l) 2013

(m) 2014 (n) 2015 (o) 2016



(p) 2017

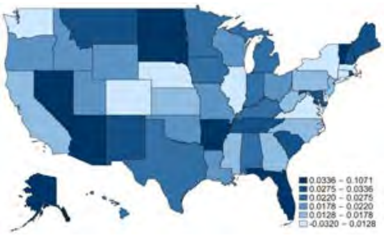
(q) 2018

(r) 2019

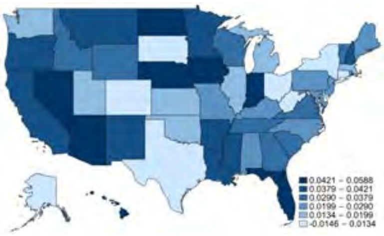
(s) 2020

Notes: This figure uses Bureau of Economic Analysis data to present a heatmap of GDP growth across counties at the annual frequency from 2002 through 2020. The intensity of the blue shading indicates higher GDP growth.

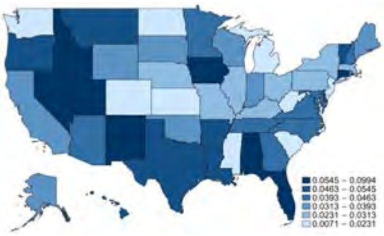
Figure A.2: Variation in State GDP Growth



(a) 2002

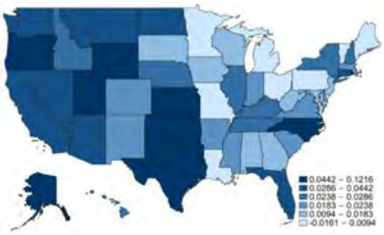


(b) 2003

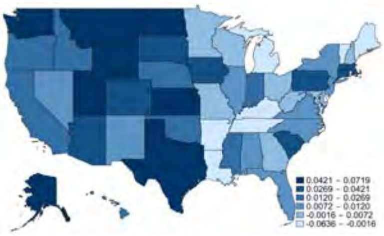


(c) 2004

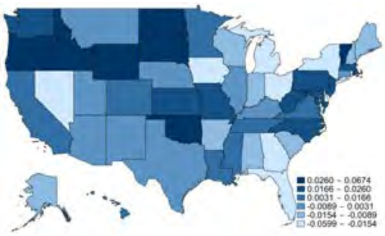
(d) 2005



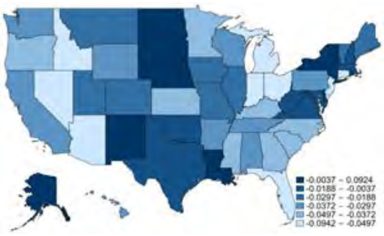
(e) 2006



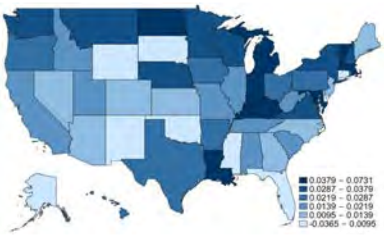
(f) 2007



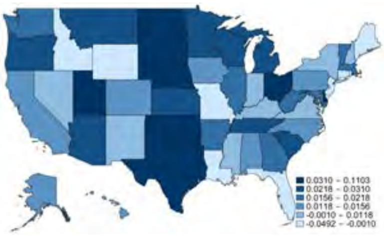
(g) 2008



(h) 2009

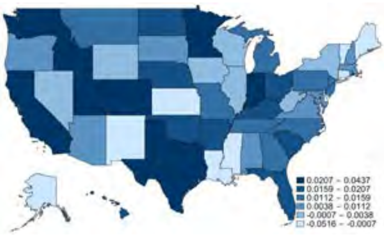


(i) 2010

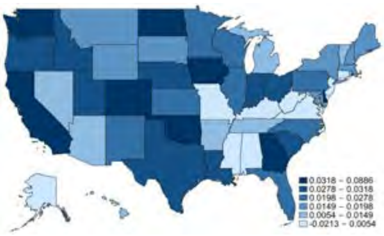


(j) 2011

(k) 2012

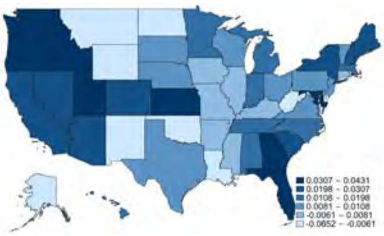


(l) 2013



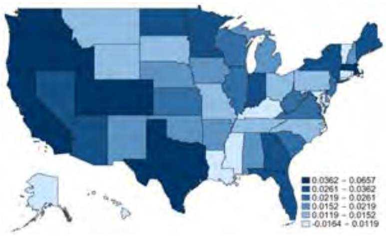
(m) 2014

(n) 2015



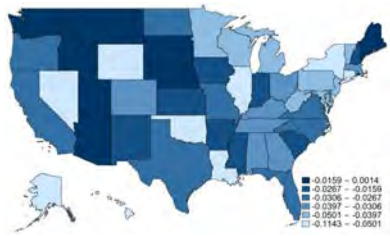
(o) 2016

(p) 2017



(q) 2018

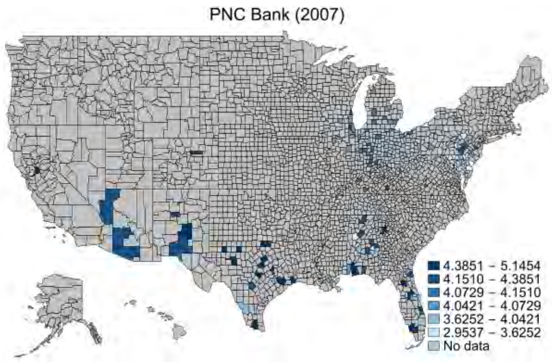
(r) 2019



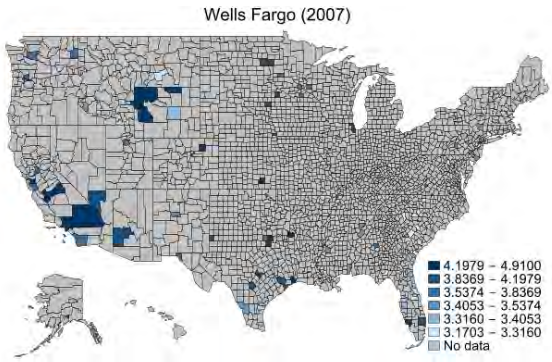
(s) 2020

Notes: This figure uses Bureau of Economic Analysis data to present a heatmap of GDP growth across states at the annual frequency from 2002 through 2020. The intensity of the blue shading indicates higher GDP growth.

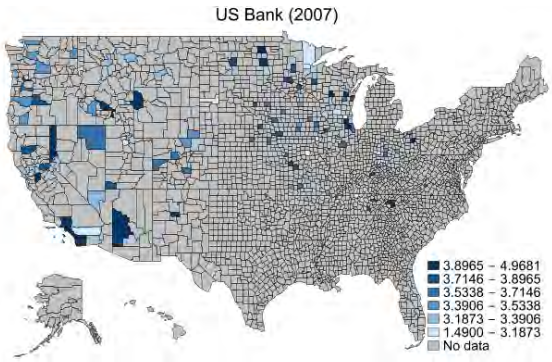
Figure A.3: Average Deposit Rates in 2007



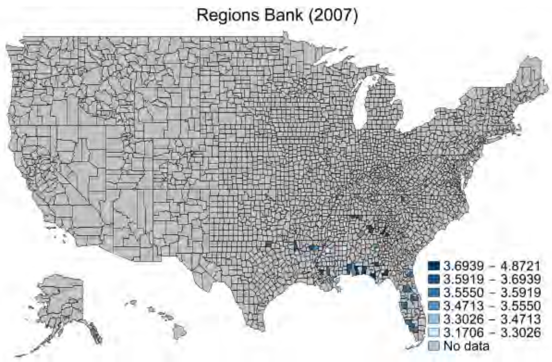
(a) PNC Bank



(b) Wells Fargo



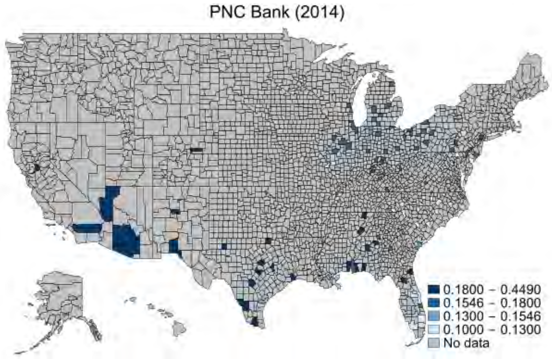
(c) US Bank



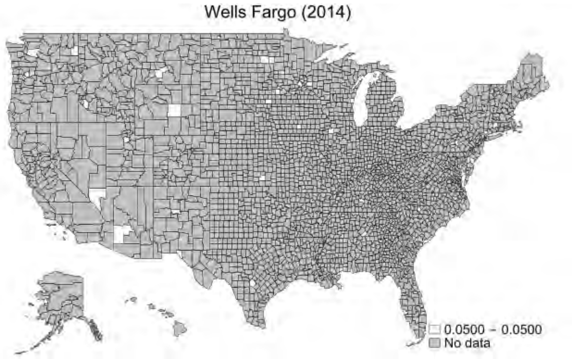
(d) Regions Bank

Notes: This figure uses RateWatch data to present a heatmap of the deposit rates of PNC Bank (Figure A.3a), Wells Fargo Bank (Figure A.3b), US Bank (Figure A.3c), and Regions Bank (Figure A.3d) 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.

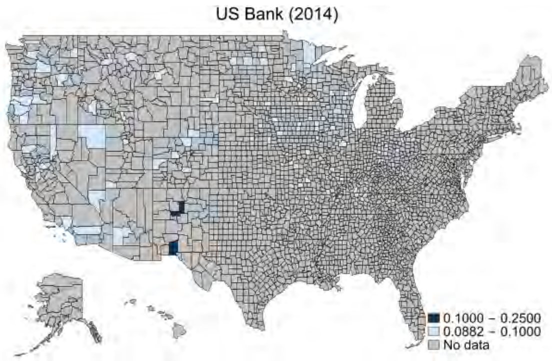
Figure A.4: Average Deposit Rates in 2014



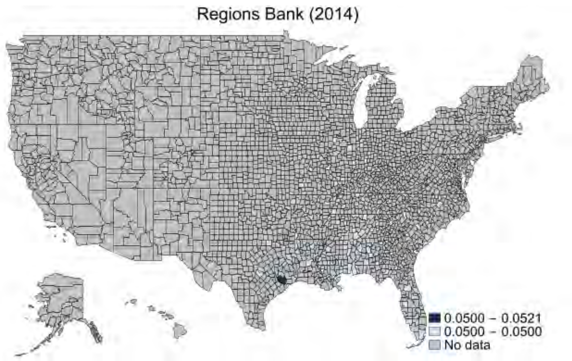
(a) PNC Bank



(b) Wells Fargo



(c) US Bank



(d) Regions Bank

Notes: This figure uses RateWatch data to present a heatmap of the deposit rates of PNC Bank (Figure A.4a), Wells Fargo Bank (Figure A.4b), US Bank (Figure A.4c), and Regions Bank (Figure A.4d) in 2012. 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.

Table A.1: Predicting County Recessions using Dispersion and Average Deposit Rates separately

$\mathbb{1}_{Recession}$	(1)	(2)
L3.SD	0.0018	
	(0.0034)	
L3.Rate		-0.1118***
		(0.0055)
L2.SD	0.0355***	
	(0.0037)	
L2.Rate		0.2225***
		(0.0087)
L1.SD	0.0300***	
	(0.0032)	
L1.Rate		-0.1133***
		(0.0055)
County FIPS FE	✓	✓
N	26,838	38,998
pseudo R^2	0.0935	0.0957
AUC	0.7076	0.7094
Overall test statistic, χ^2	2698.6252	3985.5952
p-value	0.0000	0.0000

Notes: The table presents the average marginal effects of the covariates estimated from the following logit models of a county recession in county c at time (year) t: $logit(p_{c,t}) = \alpha + \beta_1 Rate_{c,t-1} + \beta_2 Rate_{c,t-2} + \beta_3 Rate_{c,t-3} + \epsilon_{c,t}$ (columns 1 and 2) and $logit(p_{c,t}) = \alpha + \beta_1 SD_{c,t-1} + \beta_2 SD_{c,t-2} + \beta_3 SD_{c,t-3} + \epsilon_{c,t}$ (columns 3 and 4) 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 in columns 1 and 2. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Dispersion of Deposit Rates Predicts County Recessions controlling for Fed Funds Rates

$\mathbb{1}_{Recession}$	(1)	(2)	(3)
L3.SD	0.0138***	0.0011	-0.0017
	(0.0033)	(0.0036)	(0.0037)
L3.Rate	-0.0145*	0.0580***	-0.0374***
	(0.0075)	(0.0107)	(0.0124)
L2.SD		0.0251***	0.0311***
		(0.0035)	(0.0038)
L2.Rate		-0.1729***	0.0048
		(0.0103)	(0.0159)
L1.SD			0.0228***
			(0.0035)
L1.Rate			-0.0313***
			(0.0112)
L3.Fed Funds	0.0308***	-0.0609***	-0.0885***
	(0.0068)	(0.0080)	(0.0082)
L2.Fed Funds		0.2136***	0.2259***
		(0.0080)	(0.0106)
L1.Fed Funds			-0.1003***
			(0.0109)
County FIPS FE	✓	✓	✓
N	28,614	27,660	26,838
pseudo R^2	0.0832	0.1198	0.1323
AUC	0.6958	0.7399	0.7522
Overall test statistic, χ^2	2435.2473	3576.4666	3727.1528
p-value	0.0000	0.0000	0.0000

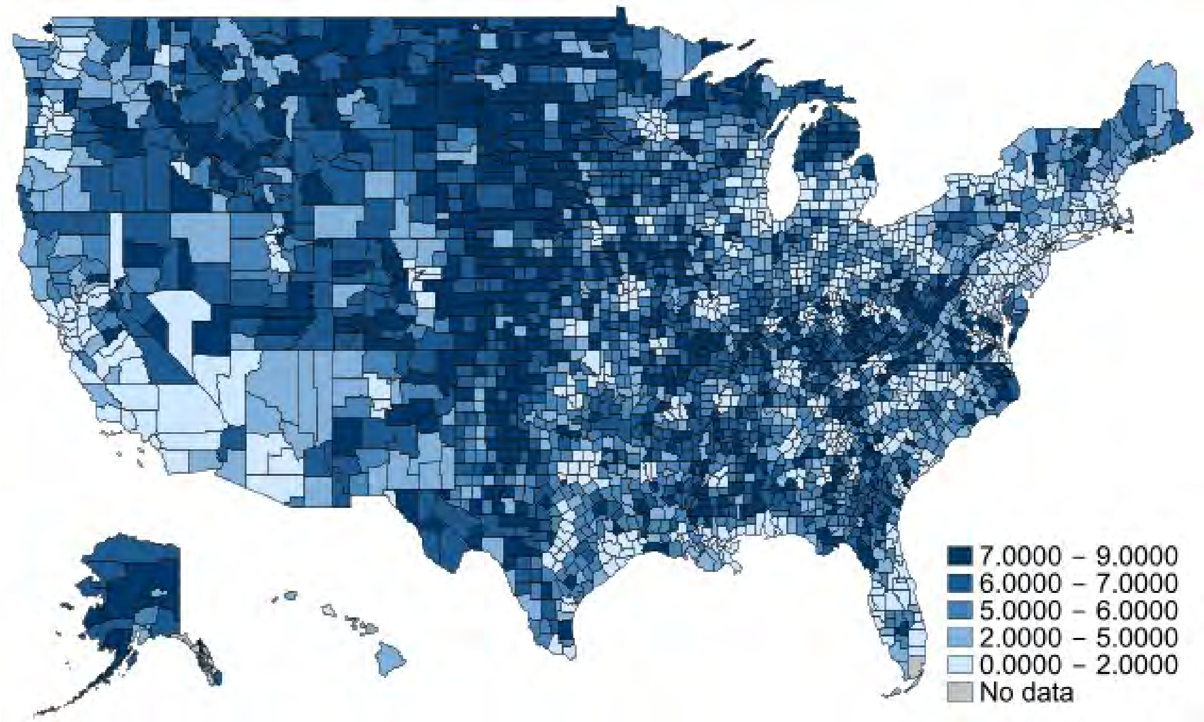
Notes: The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county c at time (year) t: $logit(p_{c,t}) = \alpha + \beta_1 Rate_{c,t-1} + \beta_2 SD_{c,t-1} + \beta_3 FF_{c,t-1} + \beta_4 Rate_{c,t-2} + \beta_5 SD_{c,t-2} + \beta_6 FF_{c,t-2} + \beta_7 Rate_{c,t-3} + \beta_8 SD_{c,t-3} + \beta_9 FF_{c,t-3} + \epsilon_{s,t}$ 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 *FF* denotes the Federal Funds Effective Rate. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.3: Dispersion of Deposit Rates Predicts State Recessions controlling for Fed Funds Rates

$\mathbb{1}_{Recession}$	(1) Equal-Weight	(2) GDP-Weight	(3) Emp-Weight	(4) Pop-Weight
L12.SD	0.0170*	0.0127	0.0145	0.0149
	(0.0099)	(0.0111)	(0.0111)	(0.0111)
L12.Rate	0.0288	0.0250	0.0246	0.0213
	(0.0384)	(0.0393)	(0.0390)	(0.0392)
L8.SD	-0.0047	0.0007	-0.0003	-0.0008
	(0.0082)	(0.0083)	(0.0082)	(0.0082)
L8.Rate	-0.0291	-0.0304	-0.0295	-0.0237
	(0.0442)	(0.0467)	(0.0464)	(0.0464)
L4.SD	0.0221**	0.0279***	0.0271***	0.0279***
	(0.0089)	(0.0090)	(0.0089)	(0.0090)
L4.Rate	-0.0860***	-0.0618**	-0.0651**	-0.0666***
	(0.0257)	(0.0253)	(0.0255)	(0.0254)
L12.Fed Funds	0.0161	0.0076	0.0083	0.0093
	(0.0309)	(0.0312)	(0.0309)	(0.0309)
L8.Fed Funds	0.0230	0.0246	0.0242	0.0212
	(0.0308)	(0.0315)	(0.0313)	(0.0312)
L4.Fed Funds	0.0973***	0.0752***	0.0780***	0.0778***
	(0.0218)	(0.0195)	(0.0198)	(0.0198)
State FE	✓	✓	✓	✓
N	2,633	2,633	2,633	2,633
pseudo R^2	0.2264	0.2294	0.2288	0.2284
AUC	0.8582	0.8596	0.8597	0.8597
Overall test statistic, χ^2	280.4339	278.6817	278.8644	281.1473
p-value	0.0000	0.0000	0.0000	0.0000

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) t: $logit(p_{s,t}) = \alpha + \beta_1 Rate_{s,t-4} + \beta_2 SD_{s,t-4} + \beta_3 FF_{s,t-4} + \beta_4 Rate_{s,t-8} + \beta_5 SD_{s,t-8} + \beta_6 FF_{s,t-12} + \beta_7 Rate_{s,t-12} + \beta_8 SD_{s,t-12} + \beta_9 FF_{s,t-12} + \epsilon_{s,t}$ 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 *FF* denotes the Federal Funds Effective Rate. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A.5: Metro, Urban, and Rural Counties (1993)



Notes: This figure uses the USDA ERS's Rural-Urban Continuum Codes from 1993 to present a heatmap of metropolitan, urban, an rural counties.

Metropolitan counties have the following codes and definitions.

- 0: Central counties of metropolitan areas of 1 million population or more.
- 1: Fringe counties of metropolitan areas of 1 million population or more.
- 2: Counties in metropolitan areas of 250,000 to 1 million population.
- 3: Counties in metropolitan areas of fewer than 250,000 population.

Urban counties have the following codes and definitions.

- 4: Urban population of 20,000 or more, adjacent to a metropolitan area.
- 5: Urban population of 20,000 or more, not adjacent to a metropolitan area.
- 6: Urban population of 2,500 to 19,999, adjacent to a metropolitan area.
- 7: Urban population of 2,500 to 19,999, not adjacent to a metropolitan area.

Rural counties have the following codes and definitions.

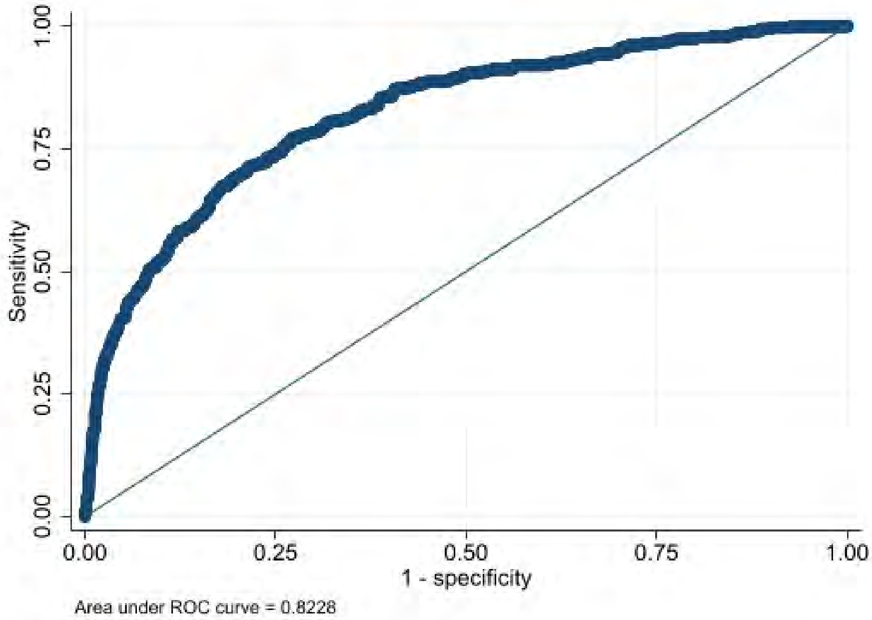
- 8: Completely rural or less than 2,500 urban population, adjacent to a metropolitan area.
- 9: Completely rural or less than 2,500 urban population, not adjacent to a metropolitan area

Table A.4: Dispersion of Deposit Rates Predicts County Recessions for Metro, Urban, and Rural Counties

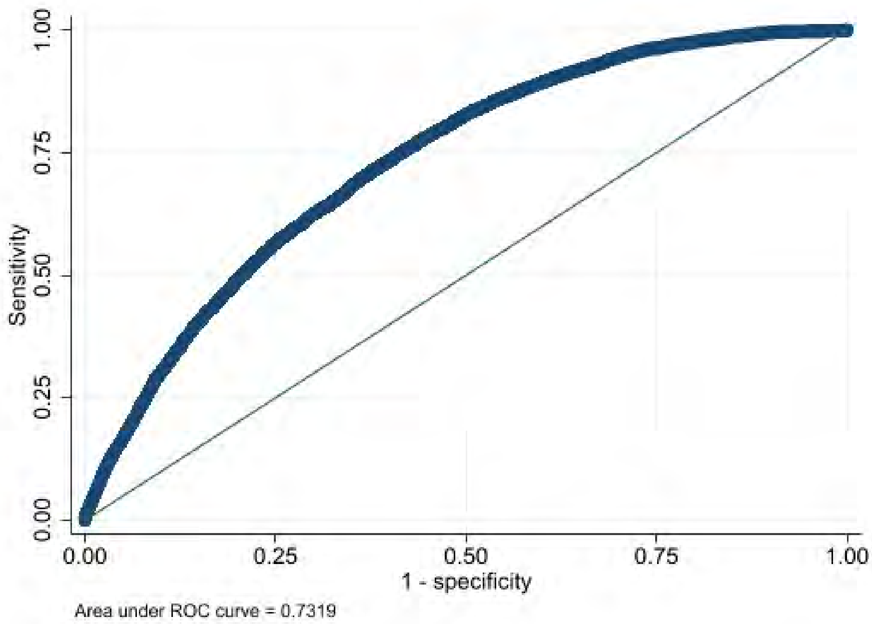
$1_{Recession}$	(1) Metro	(2) Urban	(3) Rural
L3.SD	0.0129**	-0.0119**	0.0035
	(0.0051)	(0.0053)	(0.0126)
L3.Rate	-0.1887***	-0.1246***	-0.0411**
	(0.0109)	(0.0099)	(0.0205)
L2.SD	0.0385***	0.0198***	-0.0107
	(0.0052)	(0.0056)	(0.0129)
L2.Rate	0.3732***	0.2366***	0.0492
	(0.0184)	(0.0155)	(0.0314)
L1.SD	0.0380***	0.0292***	0.0020
	(0.0047)	(0.0051)	(0.0126)
L1.Rate	-0.2317***	-0.1403***	-0.0197
	(0.0123)	(0.0101)	(0.0203)
County FIPS FE	✓	✓	✓
N	9,948	13,839	3,034
pseudo R^2	0.1953	0.0833	0.0596
AUROC	0.8055	0.6942	0.6596
Overall test statistic, χ^2	1616.2122	1243.4547	207.7088
p-value	0.0000	0.0000	0.9879

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: $logit(p_{c,t}) = \alpha + \beta_1 Rate_{c,t-1} + \beta_2 SD_{c,t-1} + \beta_3 Rate_{c,t-2} + \beta_4 SD_{c,t-2} + \beta_5 Rate_{c,t-3} + \beta_6 SD_{c,t-3} + \epsilon_{c,t}$ 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. The independent variables are standardized. 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 Figure A.5 note for more details. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A.6: Dispersion of Deposit Rates Predicts County Recessions for Stress-tested Banks and Other Banks



(a) Stress-tested



(b) Other Banks

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: $logit(p_{c,t}) = \alpha + \beta_1 Rate_{c,t-1} + \beta_2 SD_{c,t-1} + \beta_3 Rate_{c,t-2} + \beta_4 SD_{c,t-2} + \beta_5 Rate_{c,t-3} + \beta_6 SD_{c,t-3} + \epsilon_{c,t}$ 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. Stress-tested banks are banks which participated in the 2018 and 2022 Federal Reserve Stress Tests (superset of both lists). Other banks are all other banks. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.5: Dispersion of Deposit Rates Predicts Recessions Better in Counties with More Banks

$\mathbb{1}_{Recession}$	(1) All	(2) >2 Banks	(3) >3 Banks	(4) >4 Banks
L3.SD	-0.0008	0.0015	0.0042	0.0013
	(0.0036)	(0.0045)	(0.0055)	(0.0068)
L3.Rate	-0.1314***	-0.1547***	-0.1721***	-0.2039***
	(0.0068)	(0.0085)	(0.0103)	(0.0125)
L2.SD	0.0275***	0.0279***	0.0346***	0.0339***
	(0.0038)	(0.0047)	(0.0058)	(0.0067)
L2.Rate	0.2571***	0.3050***	0.3367***	0.4066***
	(0.0108)	(0.0136)	(0.0167)	(0.0207)
L1.SD	0.0349***	0.0437***	0.0523***	0.0570***
	(0.0035)	(0.0043)	(0.0050)	(0.0058)
L1.Rate	-0.1556***	-0.1925***	-0.2151***	-0.2603***
	(0.0071)	(0.0090)	(0.0112)	(0.0139)
County FIPS FE	✓	✓	✓	✓
N	26,838	18,347	12,396	8,833
pseudo R^2	0.1157	0.1358	0.1623	0.1924
AUC	0.7329	0.7553	0.7797	0.8025
Overall test statistic, χ^2	3362.5720	2531.2738	1938.7934	1498.7670
p-value	0.0000	0.0000	0.0000	0.0000

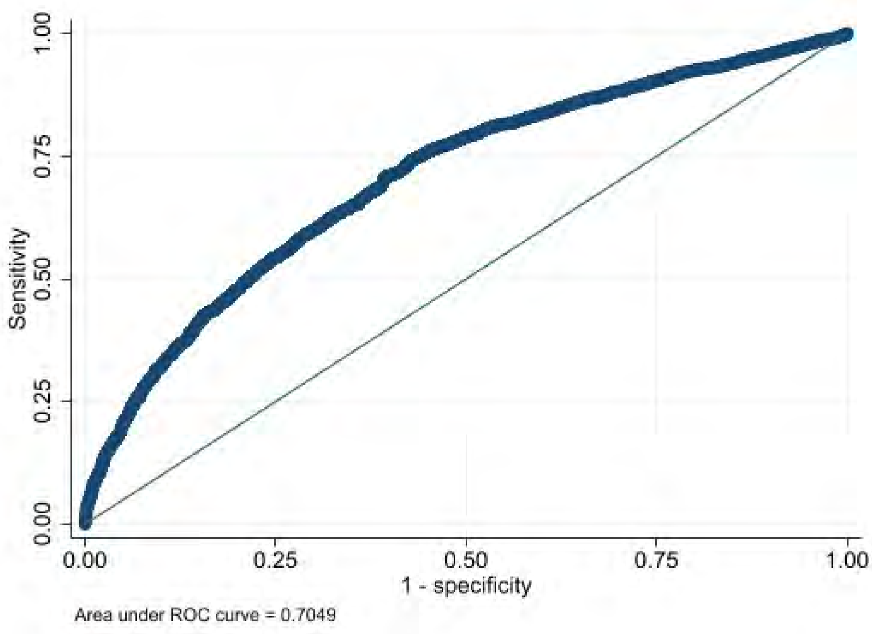
Notes: The table presents the average marginal effects of the covariates estimated from the following logit model of a county recession in county c at time (year) t: $logit(p_{c,t}) = \alpha + \beta_1 Rate_{c,t-1} + \beta_2 SD_{c,t-1} + \beta_3 Rate_{c,t-2} + \beta_4 SD_{c,t-2} + \beta_5 Rate_{c,t-3} + \beta_6 SD_{c,t-3} + \epsilon_{c,t}$ 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. Column 1 presents the estimation for all counties. Column 2 presents the estimation for counties with more than two banks. Column 3 presents the estimation for counties with more than three banks. Column 4 presents the estimation for counties with more than four banks. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Table A.6: Dispersion of Deposit Rates Predicts Recessions Better in States with More Banks

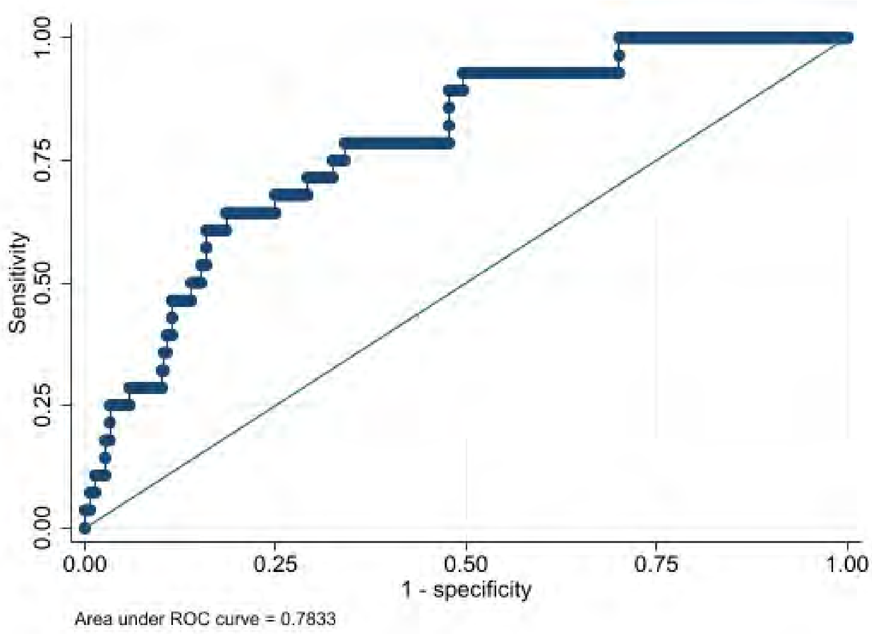
	(1)	(2)	(3)	(4)
$\mathbb{1}_{Recession}$	All Banks	>2 Banks	>3 Banks	>4 Banks
L12.SD	0.0049	0.0047	-0.0103	-0.0149
	(0.0115)	(0.0114)	(0.0122)	(0.0142)
L12.Rate	-0.0339***	-0.0338***	-0.0275*	-0.0257
	(0.0130)	(0.0130)	(0.0143)	(0.0212)
L8.SD	0.0021	0.0019	0.0056	0.0009
	(0.0080)	(0.0080)	(0.0097)	(0.0115)
L8.Rate	0.0341*	0.0337	0.0431*	0.0462
	(0.0206)	(0.0207)	(0.0234)	(0.0327)
L4.SD	0.0479***	0.0477***	0.0494***	0.0463***
	(0.0073)	(0.0074)	(0.0089)	(0.0106)
L4.SD	0.0005	0.0013	-0.0096	-0.0059
	(0.0144)	(0.0144)	(0.0161)	(0.0217)
State FE	✓	✓	✓	✓
N	2,633	2,605	1,983	1,131
pseudo R^2	0.2142	0.2148	0.2316	0.2553
AUC	0.8561	0.8570	0.8655	0.8825
Overall test statistic, χ^2	278.7751	279.5856	203.888	114.3129
p-value	0.0000	0.0000	0.0000	0.0000

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) t: $logit(p_{s,t}) = \alpha + \beta_1 Rate_{s,t-4} + \beta_2 SD_{s,t-4} + \beta_3 Rate_{s,t-8} + \beta_4 SD_{s,t-8} + \beta_5 Rate_{s,t-12} + \beta_6 SD_{s,t-12} + \epsilon_{s,t}$ where $logit(p) = ln(\frac{p}{1-p})$ denotes the log of the odds ratio, $Rate$ denotes the average bank deposit rate, and SD denotes the standard deviation of bank deposit rates. Column 1 presents the estimation for all states. Column 2 presents the estimation for states with more than two banks per county on average. Column 3 presents the estimation for counties with more than three banks per county on average. Column 4 presents the estimation for counties with more than four banks per county on average. The independent variables are standardized. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Figure A.7: 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.7a presents the ROC curve associated with the model of column 6 in Table 2 for the period 2011-2016. Figure A.7b presents the ROC curve associated with the model of column 4 in Table 3 for the period 2011-2016.

Table A.7: Bank Tier 2 Capital Growth and Deposit Rate Changes

Δln(Tier 2 Cap.)	(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.	-0.0025	-0.0005	-0.0008	-0.0034**	-0.0040**	-0.0035	0.0006
	(0.0020)	(0.0018)	(0.0023)	(0.0015)	(0.0017)	(0.0021)	(0.0018)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75} \times$ Rec.	0.0023	0.0003	-0.0022	-0.0014	-0.0031	-0.0025	-0.0006
	(0.0022)	(0.0021)	(0.0022)	(0.0014)	(0.0019)	(0.0021)	(0.0020)
$\mathbb{1}_{\text{Dep Rate Change}>P75} \times$ Rec.	-0.0023	-0.0026	-0.0017	-0.0043**	-0.0037**	-0.0051**	-0.0003
	(0.0021)	(0.0024)	(0.0021)	(0.0018)	(0.0016)	(0.0021)	(0.0016)
$\mathbb{1}_{P25<\text{Dep Rate Change}\leq P50}$	0.0006	0.0002	0.0023**	0.0039***	0.0016*	0.0031***	0.0007
	(0.0012)	(0.0011)	(0.0011)	(0.0007)	(0.0009)	(0.0011)	(0.0012)
$\mathbb{1}_{P50<\text{Dep Rate Change}\leq P75}$	-0.0009	-0.0008	0.0021	0.0033***	0.0020*	0.0032***	0.0010
	(0.0013)	(0.0011)	(0.0013)	(0.0007)	(0.0010)	(0.0009)	(0.0013)
$\mathbb{1}_{\text{Dep Rate Change}>P75}$	0.0017	0.0037***	0.0046***	0.0068***	0.0038***	0.0048***	0.0021**
	(0.0011)	(0.0011)	(0.0012)	(0.0010)	(0.0009)	(0.0011)	(0.0009)
Quarter-Year FE	✓	✓	✓	✓	✓	✓	✓
N	257,842	260,943	264,255	263,196	258,659	254,368	250,180
R^2	0.0048	0.0057	0.0057	0.0056	0.0052	0.0051	0.0050

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

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

The table presents the coefficients estimated from the following regression for bank b at time t (quarter-year): $\Delta ln(Tier2)_{b,t+k} = \beta_0 + \beta_1 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} \times \text{Rec.}_t + \beta_2 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} \times \text{Rec.}_t + \beta_3 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} \times \text{Rec.}_t + \beta_4 \mathbb{1}_{P25<\text{Dep Rate Change}\leq P50,b,t} + \beta_5 \mathbb{1}_{P50<\text{Dep Rate Change}\leq P75,b,t} + \beta_6 \mathbb{1}_{\text{Dep Rate Change}>P75,b,t} + \alpha_t + \epsilon_{b,t}$ where $\Delta ln(RWA/Tier1)_{b,t+k}$ denotes growth in risk-weighted assets (Panel A) and tier 1 capital (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 tier 2 capital comes from S&P Market Intelligence. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$