Real activity forecasts using loan portfolio information*

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Abstract

To extend and monitor loans, banks collect detailed and proprietary information about the financial prospects of their customers, many of whom are local businesses and households. Therefore, banks' loan portfolios contain potentially useful information about local economic conditions. We investigate the association between information in loan portfolios and local economic conditions. Using a sample of U.S. commercial banks from 1990:Q1 to 2013:Q4, we document that information in loan portfolios aggregated to the state level is associated with current and future changes in statewide economic conditions. Furthermore, the provision for loan and lease losses contains information incremental to leading indicators of state-level economic activity and recessions. Loan portfolio information also helps to improve predictions of economic conditions at more granular levels, such as at the commuting zone level. We discuss relevance of these findings for economic analysis and forecasting, and the relation of our study to prior work on the informativeness of accounting information about the macroeconomy.

JEL Codes: D82; E02; E32; G01; G21; M41.

Keywords: Banking; coincident index; economic growth; forecasting; loans.

1. Introduction

Economics literature has long recognized the link between the banking system and economic development (Bagehot [1873]; Schumpeter [1912]). Many studies have examined the informativeness of the level of financial intermediation about productivity at the national (e.g., King and Levine [1993]; Levine and Zervos [1998]) and state-level economies (Samolyk [1994]; Driscoll [2004]). In deciding which opportunities to fund, banks collect detailed, and often proprietary, information about their borrowers and monitor them until the loan is repaid. The information about the health and prospects of borrowers is summarized in banks' disclosures about loan portfolios. Since bank lending is concentrated in local markets, by aggregating information about the financial condition of their borrowers, banks can provide insights about local economic activity. We investigate this conjecture and find that banks' loan portfolio information is predictive of state-level economic growth. Importantly, the information embedded in the provision for loan and lease losses is incremental to information contained in other leading state-level economic indicators used for forecasting economic growth.

Banks collect a variety of information about their borrowers throughout the lending relationships. This includes "hard" information that borrowers provide, such as financial statements and tax returns, hard information that banks gather, such as data about borrowers' supply chains and account activities, and "soft" information that banks gather through interactions with borrowers and local community, such as credibility and commitment of the borrowers. Arguably, most of the information banks collect is not easily accessible by the public because the typical borrower is an individual or a privately-held firm. For example, Minnis and Sutherland [2015] report that banks receive nonpublic tax return data from businesses they lend to. Relatedly, Norden and Weber [2010] document that banks use confidential information about credit line usage, limit violations, and checking account activities to adjust lending terms and loan loss provisioning. Moreover, banks use soft information, which is inherently hard to measure objectively and is not readily publicly available, in conjunction with hard information to better evaluate and monitor borrowers (e.g., Petersen and Rajan [1994]; Grunert et al. [2005]).

Bank lending, by its nature, is geographically segmented into local markets as loan monitoring costs increase with distance from the borrower (e.g., Laderman et al. [1991]; Morgan and Samolyk [2003]). Petersen and Rajan [2002] point out the local nature of soft information necessary for credit decisions. Along the same lines, Agarwal and Hauswald [2010] find that in small business lending, a lender's ability to collect proprietary intelligence erodes with its distance from the borrower. Thus, to the extent the hard and soft information banks collect shape loan portfolios, the condition of loan portfolios can provide insights about local economic activity by aggregating information about borrowers. Accordingly, we predict that information in loan portfolios associates with contemporaneous and future growth in local economies. We also predict that, because banks rely significantly on nonpublic information in lending decisions, information in loan portfolios would be incremental to leading economic indicators - which are typically based on publicly available hard information - in predicting local economic activity.

We define local economies as U.S. states since most banks operate in a single state (Morgan and Samolyk [2003]).[1] At the same time, understanding and forecasting economic trends in U.S. states is important because they have a bearing on a wide array of matters ranging from corporate decisions about the location of manufacturing units (Bartik [1985]) to the outcome of political elections (Niemi et al. [1995]) and tax policies (Cornia and Nelson [2010]). Moreover, because of the costs associated with collecting and processing data, most economic indicators are estimated, rather than measured directly, beyond the state level.[2]

[1] In our sample, the average commercial bank collects over 94% of its deposits from a single state.
[2] See Meyer and Yeager [2001] for a discussion of issues in the estimation of labor and income at the county level.

We focus on three aspects of loan portfolios that can impound banks' expectations regarding their borrowers' financial prospects: estimated credit losses, the risk premium on loans, and loan growth. Estimated credit losses reflect information regarding borrowers' repayment ability. Prior research shows that banks are able to assess credit losses ahead of their realization to some extent (e.g., Beatty and Liao [2011]; Balasubramanyan et al. [2014]; Harris et al. [2015]), and that banks realize credit losses at higher rates during economic downturns (Laeven and Majnoni [2003]; Harris et al. [2015]).[3] Therefore, higher estimated credit losses can be indicative of weaker future economic growth. We measure expected credit losses using the provision for loan and lease losses and the change in nonperforming loans. Banks also price protect against greater credit risk by charging a higher interest rate on loans (Morgan and Ashcraft [2003]; Harris et al. [2015]). Therefore, changes in the risk premium on loans can be indicative of trends in future economic activity. Finally, banks are more willing to extend loans during expansionary phases and tighten their lending standards during contractions (Gilchrist and Zakrajsek [2012a]). At the same time, demand for credit increases during expansions and falls during contractions. Therefore, loan growth can be useful in forecasting economic activity.

Our sample is comprised of commercial banks that file Federal Financial Institutions Examination Council (FFIEC)'s Reports of Condition and Income for the 1990:Q1-2013:Q4 period. We calculate state-level values of loan portfolio variables by aggregating the relevant variables for all commercial banks with operations in a given U.S. state. We identify the state(s) a bank operates in using the Summary of Deposits (SOD) data collected by the Federal Deposit Insurance Corporation (FDIC). For banks that operate in more than one state, we adopt the

[3] Prior research provides some evidence consistent with bank managers using loan quality metrics for earnings, capital, and tax management purposes, which may reduce the association between loan quality metrics of the manipulating bank and the economic activity. However, such manipulations are idiosyncratic in nature and when aggregated in a sufficiently large sample they should average out.

approach used in prior literature (e.g., Cetorelli and Strahan [2006]) and estimate the extent of operations in each state based on the proportion of deposits the banks collect in each state.

In our analyses, we use the coincident index as a comprehensive measure of economic activity at the state level. This index is produced monthly by the Federal Reserve Bank of Philadelphia (hereafter FRB) for each of the 50 states and is calculated using models that include four state-level inputs: nonfarm payroll employment, unemployment rate, average hours worked in manufacturing, and wage and salary disbursements deflated by the consumer price index.[4] The trend in each state's index is set to the trend of its gross state product. We focus on the coincident index, rather than the gross state product, because there exists a well-established predictor of changes in the coincident index that we can use as a benchmark (i.e., FRB's leading index). Additionally, the coincident index is available on a timelier basis than the gross state product, which until recently was disclosed annually and with considerable delay.[5] The coincident index has been used as a timely and comprehensive proxy for state-level economic activity (e.g., Massa et al. [2013]; Massa and Zhang [2013]).

We first examine the association between loan portfolio information and current and future changes in the coincident index. We find that the associations between the contemporaneous change in coincident index and measures of loan portfolio information are in predicted directions and statistically significant, except for the change in risk premium which has an insignificant association with changes in coincident index. The economic and statistical significance of the variables gradually decrease as we predict changes in the coincident index farther into the future. Nonetheless, the two measures of expected credit losses, the provision for

[4] The coincident index is not available for the District of Columbia. See Crone and Clayton-Matthews [2005] for more details on the development of the coincident index.
[5] In untabulated tests we find that loan portfolio information is also useful in predicting one-year-ahead changes in gross state product. These tests are available in the internet appendix.

loan and lease losses and change in nonperforming loans, remain predictive of changes in the coincident index up to four quarters ahead. We also find that the provision is more strongly associated with changes in the coincident index when it reflects expected credit losses in a timelier manner.

We then test whether loan portfolios provide information incremental to leading economic indicators in forecasting changes in the coincident index. Controlling for the FRB's prediction of the growth rate of the coincident index and the stock returns of firms headquartered in a state we find that the provision remains statistically and economically significant when forecasting changes in the coincident index. For example, one standard deviation increase in the provision is associated with a 0.135% decrease in the coincident index over the next four quarters. To compare, the median absolute quarterly change in the coincident index is 0.80%. The information content of the remaining loan portfolio measures is subsumed by the leading economic indicators.[6] Using Campbell and Thompson's [2008] out-of-sample R^2 statistic we also confirm that the inclusion of the provision significantly improves out-of-sample forecasts of the coincident index. Moreover, we find that the provision can help in predicting state recessions.

In additional tests, we show that loan portfolio information can be used by forecasters in *real time* to improve their forecasts of statewide economic activity. In particular, we show that loan portfolio data are usually released around the same date as FRB's prediction of the growth rate of the coincident index, and even when the loan portfolio data are available with a lag

[6] In alternative models, we include economic indicators that FRB uses in its calculation of the predicted growth rate of the coincident index individually, and find qualitatively similar results. In these models, we include several lags of changes in coincident index to control for the possibility that observed findings are an artifact of reverse causality such that loan portfolio measures reflect prior economic conditions which are correlated over time. Additionally, in untabulated tests, we regress the provision on eight lags of changes in the coincident index and find that lags of changes in coincident index are not predictive of the provision after controlling for known determinants of the provision.

relative to the FRB's prediction, they could still improve forecasts of the coincident index. We also provide evidence that loan portfolio measures are useful in predicting economic activity at a more granular-level, namely at the commuting zone-level. This suggests that loan portfolio information may be helpful in forecasting economic trends at levels where few other leading indicators are available.

Our study is related to the nascent literature investigating the relation between accounting information and macroeconomic indicators. Gallo et al. [2013] find that aggregate earnings are useful in predicting the Federal Reserve's future monetary policies. Several studies examine informativeness of aggregate earnings with respect to GDP forecasts (e.g., Kalay et al. [2014]; Konchitchki and Patatoukas [2014, 2014]; Nallareddy and Ogneva [2014]). Shivakumar [2007] and Kothari et al. [2013] show that aggregate earnings surprises contain information about future inflation and that macroeconomic forecasters do not fully utilize this information. Aboody, Hughes, and Ozel [2014] and Gkougkousi [2014] examine the concurrent relation between aggregate earnings and bond market returns and show that the relation varies with macro-economic conditions, the use of fair value accounting, and bond ratings. Shivakumar [2007, 2010] calls for additional research to better understand the links between aggregate-level accounting information and the macro economy. We answer his call in two ways.

First, while this literature has focused exclusively on aggregate earnings for investigating links between accounting estimates and macroeconomic conditions we document the predictive content of a previously unexplored set of accounting information, information about the condition of loan portfolios. Second, we extend this literature by focusing on the prediction of economic conditions at the state level rather than at the national level. State economies are important by themselves and national trends can materialize differently across regions depending on the characteristics of the regions (e.g., interstate linkages, industrial composition). Disparities in local economic conditions may be obscured when aggregated at the national level. For example, Figure 1 presents changes in coincident indexes during the third quarter of 2005 and 2008. According to the National Bureau of Economic Research (NBER), the U.S. economy was in an expansionary and a recessionary phase during these periods, respectively. However, there is a wide variation in economic growth across the states during each of these periods.

(Insert Figure 1 about here)

Our study is also related to the literature on the relation between local lending and local economic activity. Samolyk [1991, 1994] examines the regional credit view, which posits that bank lending *causally* affects local economic growth.[7] Unlike Samolyk's work, we are interested in not only whether there is a relation between loan portfolios and future economic conditions, but also whether the information available from loan portfolios is *incremental* to leading economic indicators. We also do not take a stance on whether bank lending should causally affect the local economy. Rather, we posit that even in the absence of a causal relation, because banks produce and collect detailed and proprietary information about their borrowers, loan portfolio information could be useful in predicting economic conditions. Additionally, during the sample periods used by Samolyk [1991, 1994], banking and tax regulations provided incentives for systematically misreporting loan quality measures. Most of these incentives were eliminated prior to the beginning of our sample period. Mian and Sufi [2009] and Mian, Rao, and Sufi [2013] examine the effect of household wealth and supply of mortgages on economic activity with a focus on the recent financial crisis. We focus on overall bank lending and examine the relation between bank disclosures and economic activity. Moreover, we do not restrict our

[7] There is mixed evidence on whether such a causal relationship exists. For example, while Samolyk [1991, 1994] finds some evidence of a causal relationship, Driscoll [2004]'s findings do not indicate such a relation.

examination to the recent financial crisis.

The rest of the paper is organized as follows. Section 2 provides institutional details and presents our predictions. Section 3 describes the research design and sample selection. Section 4 presents our findings and Section 5 discusses implementation. Section 6 presents results from additional tests. Section 7 concludes the paper.

2. Background information and empirical predictions

Bank loan portfolios are shaped by the information banks have regarding the financial condition of their borrowers. Banks collect a wide variety of information to screen and monitor borrowers including financial statements, tax returns, credit histories and FICO scores (Berger and Udell [2002]; Minnis and Sutherland [2015]). Much of this information is either confidential or not publicly available because borrowers are typically individuals and privately-held firms who are particularly opaque from an information standpoint. In addition, banks often have access to timely and proprietary information through their role as financial intermediaries. For example, prior research finds that a borrower's checking account activities and credit line usage reveals information about her financial flexibility and debt capacity (Nakamura [1993]; Mester et al. [2007]; Jimenez et al. [2009]). Importantly, banks use this information in adjusting loan terms, credit limits, and loan loss provisioning, and such information is most useful for monitoring borrowers that have opaque information environments (Norden and Weber [2010]). Banks also collect credit risk relevant soft information, such as information about the integrity of borrowers, through repeated contact with borrowers and their local community (e.g., Petersen and Rajan [1994]; Cole [1998]; Berger and Udell [2002]). Soft information aids in the assessment of creditworthiness and in monitoring of borrowers (Grunert et al. [2005]).

When aggregated to the state level, information about loan portfolios can improve existing forecasts of state-level economic growth because banks have information that is often unavailable to forecasters, such as information about private firms, individuals, and bank account activities. Additionally, forecasters typically don't incorporate soft information in their forecasts, rather they rely on publicly available statistical data to predict economic trends. For example, FRB's leading index, which is the state of the art predictor of state coincident index, is estimated based on the realized values of coincident indexes, state-level housing permits, state-level initial unemployment insurance claims, delivery times from the Institute for Supply Management manufacturing survey, and the spread between the ten-year T-bond and the three-month T-bill.[8] Moreover, loan portfolios may incorporate information faster than statistical data. For example, measures like unemployment claims and housing permits reflect realizations whereas estimated credit losses and changes in lending rates partly reflect expectations.

To examine whether loan portfolios are informative about local economic conditions, we focus on three attributes of loan portfolios: estimated credit losses, risk premium on loans, and the growth rate of loans. We conjecture that increases in estimated credit losses and risk premium, and decreases in loan growth are predictive of a slowdown in economic activity.

We use the provision for loan and lease losses and changes in nonperforming loans to measure estimated credit losses. The provision is an estimate of credit losses attributable to originating and holding loans during the relevant fiscal period. Under U.S. GAAP, the provision is determined based on the incurred loss model (ILM) as detailed under SFAS 5 and SFAS 114. The ILM requires banks to record the provision when a loss is incurred and can be reasonably estimated. In practice, banks use "loss emergence periods" to estimate the provision as incurred losses are often not observable until realization. Loss emergence period extends forward from the

[8] http://www.philadelphiafed.org/research-and-data/regional-economy/indexes/leading/

balance sheet date, and if, based on past experience or other information, the bank expects to observe a loss during this period then the loss is considered incurred and must be accrued.[9] Under the current regulatory guidance, banks use a one-year loss emergence period for most loans and record a provision to bring the allowance for loan and lease losses to a level enough to cover loan losses that are projected to occur over the next 12 months (OCC Handbook [1998]). Consistent with the guidance, prior research finds that the provision contains forward-looking information about credit losses (e.g., Liu and Ryan [2006]; Beatty and Liao [2011]; Harris et al. [2015]).[10]

Nonperforming loans refer to loans that lag in scheduled payment and are equal to the sum of nonaccrual loans (i.e., more than 90 days delinquent and not accruing interest) and past due loans (i.e., more than 90 days delinquent and still accruing interest). Nonperforming loans are less discretionary than the provision since their measurement is typically based on more objective criteria (Beaver et al. [1989]; Griffin and Wallach [1991]). Harris et al. [2015] document that both the provision and nonperforming loans contain information relevant for predicting credit losses. Therefore, we use the provision as well as changes in nonperforming loans to capture trends in the credit risk profile of loan portfolios.

Risk premium on loans—the difference between the loan yield and the risk-free rate—

[9] Due to agency problems, loan officers may have incentives to not report the available information in an unbiased manner. However, banks have set up loan review departments and incorporated operational policies such as regular reassignment of loan officers to new borrowers to alleviate incentives of loan officers to hide deteriorating performance (e.g., Udell [1989]; Hertzberg et al. [2010]). Moreover, in our setting this is less of a concern because we aggregate bank-level data to the state level, and idiosyncratic biases due to loan officers' misaligned incentives would average out with aggregation.

[10] The loan loss accruals recorded under SFAS 5 and SFAS 114 do not represent *all* expected losses since ILM leads to some delay in provisioning. However, given the forward-looking approach of loan emergence periods they do reflect the expected losses to some degree. The extent to which individual banks are forward-looking in accounting for their loan losses varies in the cross section (e.g., Nichols et al. [2009]). Since we aggregate the bank-level provisions at the state level, we expect any idiosyncratic differences in the timeliness of the provisions to be diversified.

can provide information relevant for the state of the economy as credit risk is likely to be lower during expansions and increases as the economy contracts. In the face of greater risk of loss due to borrower's default, banks can price protect themselves. Consistent with this notion, Morgan and Ashcraft [2003] and Harris et al. [2015] find that higher yields are associated with weaker future loan performance. Similarly, prior research reports that credit spreads on corporate bonds (Gilchrist et al. [2009]; Gilchrist and Zakrajsek [2012b]) and the spread between commercial paper and the T-bill rate (Friedman and Kuttner [1992]) has information about future economic activity. However, the market for bank lending does not operate like other markets where prices do most of the adjustment in response to changes in risk for the market to clear. Rather than raising interest rates, banks may tighten lending standards and reduce credit to the marginal borrowers that do not meet the standards (Lown et al. [2000]; Lown and Morgan [2006]).

The final attribute of loan portfolio quality that we examine is loan growth. Firms demand more credit during economic expansions and banks are more willing to lend during such times. On the contrary, during economic contractions, demand for credit falls and banks tighten their lending standards (e.g., Lown et al. [2000]; Lown and Morgan [2006]). Gilchrist and Zakrajsek [2012a] report that bank lending is highly cyclical. Therefore, we conjecture that the growth rate of bank lending is informative about economic activity and that loan growth is higher when the economy is expected to expand.

3. Research design and sample selection

3.1. Research design

3.1.1. Does banks' loan portfolio information predict future economic activity?

We investigate whether information about loan portfolios aggregated at a local economy level is informative about contemporaneous and future conditions of the local economy. We use U.S. states as the unit of aggregation since measures and benchmark predictors of economic activity are available at the state level and it is possible to identify commercial banks operating in a given state with good precision. Moreover, credit markets tend to be segmented along regional dimensions and lending is usually concentrated in local areas because it is more costly to monitor performance of risky projects out of the local sphere (Samolyk [1989]; Adams et al. [2007]). For example, Morgan and Samolyk [2003] report that bank holding companies are typically not geographically diversified, and at the end of 2001, the average bank holding company was operating in only 1.7 markets, which they define as a Metropolitan Statistical Area or all rural counties in a state. Despite significant deregulation of interstate banking and branching, they find that the share of bank holding companies operating in a single market fell from 85% to only about 75% from 1994 to 2001. In our setting, the diversification across markets is even less because we conduct our tests using data from commercial banks, which often operate as local subsidiaries of bank holding companies. In our sample, the average commercial bank collects over 94% of its deposits in a single state (see Table 1).

Forecasting local economic conditions is important as they influence a variety of decisions ranging from locations of corporate establishments (Bartik [1985]) to labor demand (Tokle and Huffman [1991]) and political election outcomes (Niemi et al. [1995]). It is also an area that remains relatively under researched. Moreover, national economic trends can materialize differently across local economies depending on individual areas' characteristics. For example, during our sample period, only 56% of state recessions coincide with a national recession, when a state recession is defined as two or more consecutive quarters of declines in the coincident index. Along these lines, Ang and Longstaff [2013] analyze CDS spreads for ten states and find that the systemic credit risk represents only about 12% of total credit risk of U.S. states.

We use the coincident index published by the FRB to measure economic activity at the state level. The coincident index combines nonfarm payroll employment, average hours worked in manufacturing, unemployment rate, and wage and salary disbursements deflated by the consumer price index, to summarize state-level economic conditions in a single measure. The trend for a state's coincident index is set to the trend of the state's gross state product, which is available on an annual frequency. The coincident index is calculated monthly for 50 states and serves as a comprehensive and timely measure of economic activity at the state level. For example, Mattoon et al. [2010] find that the coincident index could be used as a timely trigger for starting and stopping countercyclical aid to state governments. Similarly, Cornia and Nelson [2010] show that the index is helpful for state governments in formulating tax policies.

To examine the association between information about loan portfolios and changes in coincident index we estimate the following least squares regression model:

$$\begin{aligned}\Delta COINDEX_{s,t+i} &= \alpha + \beta_1 xPLLTL_{s,t} + \beta_2 x\Delta NPLTL_{s,t} + \beta_3 x\Delta EXYIELD_{s,t} + \beta_4 xLGROWTH_{s,t} \\ &+ \beta_5 xALLTL_{s,t-1} + \sum_{m=1}^{M} \beta_{5+m} xFE_s + \sum_{q=1}^{Q} \beta_{5+M+q} xFE_t + \varepsilon_{s,t+i} \quad ,\end{aligned} \tag{1}$$

where $\Delta COINDEX_{s,t+i}$ is the quarterly growth rate in coincident index for state *s* in quarter *t*. Since the coincident index is disclosed on a monthly frequency, we use the last monthly value for each calendar quarter to calculate the quarterly growth rate in the coincident index. Our forecasting horizon *i* varies from one to four quarters ahead. $PLLTL_{s,t}$ is the ratio of state-level provision for loan and lease losses to the average of beginning and end of quarter state-level total loans. $\Delta NPLTL_{s,t}$ is the change in the ratio of state-level nonperforming loans to end of quarter state-level total loans. $\Delta EXYIELD_{s,t}$ is the change in the difference between the ratio of state-level interest and fee income on loans to average state-level total loans and the three-year T-bond rate. $LGROWTH_{s,t}$ is the quarterly percentage growth in state-level total loans. $ALLTL_{s,t-1}$ is the one-quarter-lagged value of state-level allowance for loan and lease losses scaled by end of quarter state-level total loans. We provide detailed definitions of all variables in Appendix A.

The state-level aggregate values of accounting data items are calculated by summing the relevant items over all commercial banks with operations in a given state for a given quarter. For banks that operate in more than one state, we weigh accounting variables by the percentage of their operations attributable to each state that the bank operates in. We estimate the extent to which a bank operates in any state as the proportion of its deposits that originate in that state using the SOD data collected by the FDIC. This approach is also used in prior studies to identify local regions of operation for banks (e.g. Cetorelli and Strahan [2006]; Daly et al. [2008]).[11]

In this model we predict β_1, β_2, and β_3 to be negative and β_4 to be positive since higher provision, change in nonperforming loans, and risk premium and lower loan growth imply weaker economic conditions. We include $ALLTL_{s,t-1}$ as a control variable following Wahlen [1994] and Beatty et al. [1995], who explain that over (under) reserving in prior periods would lead to lower (higher) current period provisions. Given that the dependent variable is measured in changes whereas $ALLTL_{s,t-1}$ is a stock variable, we do not have a prediction for β_5. We also include state and time fixed effects to control for state and time specific common factors. We cluster standard errors on time and state dimensions to control for dependence in the regression residuals over time or across states not accounted for by state and time fixed effects.

3.1.2. How useful is the information about loan portfolios in predicting future economic activity?

[11] While a measure based on the percentage of loans rather than deposits would be more appropriate, such data are not publicly available. If the percentage of deposits is not a good indicator of the bank's lending operations in that state, estimates of banks' operations in the different states will be noisy. To address this concern, in tests reported in the internet appendix, we remove all observations of banks operating in more than one state in a given quarter from our sample and redo our tests. While this treatment eliminates potentially noisy information about multi-state banks, it also restricts the information gathered about economic activity to a subset of relatively smaller banks, which could potentially induce a bias against our findings. Nonetheless, our findings remain qualitatively similar.

To assess the usefulness of loan portfolio information in predicting economic activity, we ask: does the information about loan portfolios merely reflect factors captured by other indicators of current and future economic activity? Or, does it also embed other factors incremental to known leading indicators of state-level economic conditions?

We use two measures as leading indicators of state-level economic conditions: concurrent and one-quarter-lagged values of the leading index (*LEADINDEX*), which is published by the FRB specifically as a predictor of the six-month growth rate of the coincident index, and value-weighted stock return of publicly-traded firms ($VWRET_{s,t}$) headquartered in a given state, which Korniotis and Kumar [2013] find vary with state-business cycles.[12] Prior studies (e.g., Patatoukas [2014]; Konchitchki and Patatoukas [2014]) provide evidence that the predictive ability of stock returns for future economic activity stretches over one year. Accordingly, we measure $VWRET_{s,t}$ over the 12-month period ending with quarter *t*. To examine the incremental usefulness of loan portfolio information we estimate the following linear model:

$$\begin{aligned} \Delta COINDEX_{s,t+i} = \alpha &+ \beta_1 xPLLTL_{s,t} + \beta_2 x\Delta NPLTL_{s,t} + \beta_3 x\Delta EXYIELD_{s,t} + \beta_4 xLGROWTH_{s,t} \\ &+ \beta_5 xALLTL_{s,t-1} + \beta_6 xLEADINDEX_{s,t} + \beta_7 xLEADINDEX_{s,t-1} + \beta_8 xVWRET_{s,t} \\ &+ \sum_{m=1}^{M} \beta_{8+m} xFE_s + \sum_{q=1}^{Q} \beta_{8+M+q} xFE_t + \varepsilon_{s,t+i} \end{aligned} \qquad (2)$$

where we expect β_1- β_3 to be negative and β_4 to be positive.

We also estimate an alternative model where we replace *LEADINDEX* and its lagged value with indicators that are incorporated into the leading index. This specification accounts for the possibility that the information available from the individual indicators may not be fully incorporated in the summary measure. In particular, the alternative model includes the

[12] We include one-quarter-lagged value of the leading index because the leading index is a predictor of six-month growth rate in the coincident index. Therefore its lagged value may contain information about future, especially one-quarter-ahead, growth rates of the coincident index. Our findings are not sensitive to the inclusion of each of the five monthly lags of the leading index instead, or of up to four quarterly lags of the leading index.

concurrent and lagged changes in the coincident index, as well as the concurrent growth rate in state's total personal income ($PIGROWTH_{s,t}$) and concurrent changes in the state's all transactions housing price index ($\Delta HOUSING_{s,t,}$) and unemployment rate ($\Delta UNRATE_{s,t}$):

$$\begin{aligned}\Delta COINDEX_{s,t+i} = {} & \gamma + \delta_1 xPLLTL_{s,t} + \delta_2 x\Delta NPLTL_{s,t} + \delta_3 x\Delta EXYIELD_{s,t} + \delta_4 xLGROWTH_{s,t} \\ & + \delta_5 xALLTL_{s,t-1} + \sum_{r=0}^{r=3} \delta_{6+r} x\Delta COINDEX_{s,t-r} + \delta_{10} x\Delta HOUSING_{s,t} + \delta_{11} xPIGROWTH_{s,t} \\ & + \delta_{12} x\Delta UNRATE_{s,t} + \delta_{13} xVWRET_{s,t} + \sum_{m=1}^{M} \delta_{13+m} xFE_s + \sum_{q=1}^{Q} \delta_{13+M+q} xFE_t + \varepsilon_{s,t+i}\end{aligned} \tag{3}$$

where we expect δ_1-δ_3 to be negative and δ_4 to be positive.[13]

3.2. *Sample selection and descriptive statistics*

In the United States, whether privately-held or publicly-traded, every national, state-member, and insured nonmember commercial bank is required by the FFIEC to file Reports of Condition and Income (also known as "call reports") as of the close of business on the last day of each calendar quarter. Our sample is comprised of U.S. commercial banks that file these reports. We begin our sample selection with 914,862 bank-quarter observations which span 96 quarters from 1990:Q1 to 2013:Q4. Our sample period begins with the first quarter of 1990 because accounting and tax rules regarding loan quality measures were not stable before then. For example, Kim and Kross [1998] show that change in bank capital standards in 1989 largely eliminated banks' incentives to use provisions and charge-offs for capital management. To keep our sample consistent over time we exclude savings and loan associations and federal savings banks, both of which were not required to file call reports until 2012:Q1.

To eliminate observations with missing/invalid data items, we impose the following data filters at the bank level: (i) total assets (call report item: *RCFD2170*) and total gross loans

[13] As we report in the internet appendix, our inferences about the predictive ability of banks' loan portfolio information remain unchanged if we estimate a single model that combines Equations (2) and (3).

(*RCFD1400*) are positive and total loans are less than total assets, (ii) allowance for loan and lease losses (*RCFD3123*) and nonperforming loans (*RCFD1403* plus *RCFD1407*) are nonnegative and less than end of quarter total loans, (iii) absolute value of the provision for loan and lease losses (*RIAD4230*) is less than the average balance of total loans, and (iv) interest income (*RIAD4010*) is nonnegative and is smaller than the average balance of total loans. These filters eliminate 68,157 observations with missing/invalid data. Even after these filters, some observations exhibit extreme loan growth. To ensure our results are not driven by these outliers – which could be data errors– we eliminate 8,466 observations that are in the top and bottom half-percentile based on loan growth rate. Our conclusions are not sensitive to this screen.

We use the SOD data from the FDIC to estimate the proportion of each bank's operations in a given state. The SOD dataset provides branch-level data on the deposits for a given bank as of June 30th of each year starting in 1994. We aggregate this data by state for each bank-year and use the bank's percentage of deposits in a given state as our measure of the bank's operations in that state during that year. For years prior to 1994, we assume that each bank operates only in the state that it was headquartered since prior to Riegle-Neal Interstate Banking and Branching Efficiency Act of 1994, with some exceptions, banks were only permitted to establish branches in the state in which they are headquartered. Consistent with these restrictions, according to the 1994 SOD file, 99% of the banks operate in only one state. 2,253 bank-quarters that have missing/invalid data on deposits and 2,616 quarters that belong to credit card companies (*specdesc="credit-card"*) that operate from a single main office or few locations rather than through branches (e.g., Nordstrom fsb, JCPenney National Bank, Discover Bank) are excluded from the analysis. Our final sample contains 833,370 bank-quarters from 16,009 unique banks.

Table 1 provides the distribution of bank-quarter observations in our sample across the states.[14] The state of Texas (Alaska) has the most (fewest) number of bank-quarter observations. The average percentage of operations of banks in a given state based on the SOD data is also provided in Table 1. Over our sample period, the average bank has over 94% of its operations in a single state and over three quarters of the banks in our sample collect deposits from a single state during the entire period that they appear in the sample. This suggests bank-level variables aggregated to the state level are likely to provide information about the local economy in a representative manner.

(Insert Table 1 about here)

Table 2 reports descriptive statistics at the bank level for our sample. The average bank has \$835 million in total assets and \$475 million in total loans. The 75th percentile values for total assets and total loans are \$199 million and \$126 million, respectively, which suggests that most of the banks in our sample are relatively small. The median loan growth is 1.57% per quarter and the median provision for loan and lease losses is 0.05% of average total loans. The median allowance is about 1.36% of end of quarter total loans which is larger than 0.81%, the median of nonperforming loans. On average, the annualized yield on loans is about 8.47%.

(Insert Table 2 about here)

Table 3 presents the descriptive statistics for the variables used in the state-level analyses. Variables are calculated for 50 states and 95 quarters. At the state level, the median quarterly loan growth (*LGROWTH*) is around 1.7%. This is comparable to the national median of 1.5% for the same period as reported in the Federal Reserve Economic Data. The average *PLLTL* is 0.20% whereas the average *ΔNPLTL* is close to zero. The Pearson (Spearman) correlation coefficient between these two variables is only 0.47 (0.23) suggesting that there are significant differences

[14]Since some banks operate in more than one state, we include these banks in the count for each state they operate in. Hence, the total number of observations in Table 1 is greater than that reported in Table 2.

in the attributes of credit risk captured by each of the variables.

(Insert Table 3 about here)

The correlations between state-level loan portfolio variables and changes in coincident index are in the expected directions and statistically significant. The Pearson correlation coefficients between *ΔCOINDEX* and *LGROWTH*, *PLLTL*, *ΔNPLTL*, and *ΔEXYIELD* are 0.14,-0.52, -0.50, and -0.04, respectively. Moreover, these loan portfolio variables also have significant correlations with *LEADINDEX* which is a forecast of economic conditions. Overall, the univariate results suggest that loan portfolio information is associated with current and future economic conditions, raising the prospect that it may be useful for predicting economic activity.

4. Results

4.1. Does loan portfolio information predict future economic activity?

We begin our multivariate analysis by examining whether loan portfolio data aggregated at the state level are associated with current and future statewide economic activity. We measure future economic activity using cumulative and marginal changes in the coincident index, where cumulative and marginal changes are calculated as in Equations (4) and (5), respectively:

$$\Delta COINDEX_{s,t,t+i} = (100/i) \times ((COINDEX_{s,t+i} - COINDEX_{s,t}) / COINDEX_{s,t}), \qquad (4)$$

$$\Delta COINDEX_{s,t+i-1,\,t+i} = 100 \times ((COINDEX_{s,t+i} - COINDEX_{s,t+i-1}) / COINDEX_{s,t+i-1}) \qquad (5)$$

Cumulative change is the average change in the coincident index over several periods. Hence it would likely provide more precise information on how far into the future loan portfolio information can predict economic activity.

In Table 4 we present least squares regression estimates of Equation (1). Consistent with our predictions, a decline (improvement) in aggregate loan portfolio quality is associated with concurrent and future deterioration (improvement) in state-level economic conditions. The concurrent association between the coincident index and loan portfolio information is statistically significant in the predicted direction for all measures of loan portfolio quality, except *ΔEXYIELD*. The insignificance of *ΔEXYIELD* could be because banks reduce lending to the marginal borrowers rather than charging them higher interest rates. Alternatively, it could be because *ΔEXYIELD* captures changes in risk premium due to not only loan originations but also maturing loans.

(Insert Table 4 about here)

The economic and statistical significance of variables gradually decrease as we predict economic activity farther in the future. Nonetheless, the provision for loan and lease losses (*PLLTL*) and changes in nonperforming loans (*ΔNPLTL*) continue to predict changes in the coincident index up to four quarters ahead. The estimated coefficient on *PLLTL* ranges between -0.813 and -0.657 (-0.466) and that on *ΔNPLTL* ranges between -0.351 and -0.309 (-0.280), when the dependent variables is the cumulative (marginal) change in the coincident index ranging from one quarter to four quarters ahead. Their contribution to the prediction of coincident index is economically significant as well. For example, all else equal, if the provision for loan and lease losses as a percentage of average total loans increases by one standard deviation (0.205) then the last column in cumulative change analysis shows that coincident index decreases by 0.54% ((0.205 x -0.657) x 4) from quarter t to quarter t+4. Similarly, one standard deviation increase in the change in nonperforming loans as a percentage of total loans (0.247) is associated with 0.31% ((0.247 x -0.309) x 4) decline in coincident index during the same cumulative period. Considering that the absolute value of quarterly change in the coincident index has a median of 0.80% (untabulated), these effects are not trivial.

4.2. How useful is information about loan portfolios in predicting future economic activity?

In this section, we examine whether information about loan portfolios is incremental to that contained in leading economic indicators for the prediction of state-level economic activity. We estimate the two linear models introduced in Equations (2) and (3) for this analysis. Table 5 presents the results from this analysis.

In Table 5, Panel A, the known leading state-level economic indicators include concurrent and one-quarter-lagged values of leading index (*LEADINDEX*) and value-weighted stock returns of firms headquartered in the state (*VWRET*). Controlling for these variables, the provision is negative and statistically significant when predicting one-quarter-ahead changes in coincident index. The remaining loan portfolio variables are statistically insignificant, suggesting that these variables are not incrementally informative. The provision remains statistically significant in the prediction of up to four (three)-quarter-ahead cumulative (marginal) changes in the coincident index. The estimated coefficient on the provision ranges between -0.130 and -0.176 (-0.232) when the dependent variable is the cumulative (marginal) change in coincident index. The ability of the provision in predicting changes in economic activity is consistent with the fact that the provision incorporates information about loan losses that are projected to occur over the next four quarters for most loan pools (OCC Handbook [1998]). The contribution of the provision is economically significant as well. For example, all else equal, if the provision increases by one standard deviation, the four-quarter-ahead column in the cumulative changes regression implies that the state coincident index would decline by 0.034% (=0.205 x -0.165) on average each quarter over the next four quarters or about 0.135% ((=0.205 x -0.165) x 4) in total.

(Insert Table 5 about here)

In Panel B, we replace the leading index with seven other variables including the concurrent value and three lags of the quarterly change in coincident index, and each state's percentage change in all transactions housing price index (Δ*HOUSING*), growth rate in total personal income (*PIGROWTH*) and change in unemployment rate (Δ*UNRATE*). Here, the statistical and economic significance of the provision are stronger than those in Panel A and our conclusions remain similar. In addition, the coefficient on change in nonperforming loans has the predicted sign and it becomes statistically significant in this specification. With the exception of Δ*UNRATE*, coefficients on control variables are in the predicted directions and mostly significant. While the positive coefficient on Δ*UNRATE* is unexpected, this is driven by the inclusion of changes in the coincident index, which explicitly incorporate the state-level unemployment rate, along with the change in unemployment rate in the model. In untabulated tests we confirm that the coefficient on Δ*UNRATE* is negative and statistically significant when the concurrent and lagged values of coincident index are not included.

To summarize, the evidence presented in Table 5 suggests that at the state level, the provision for loan and lease losses, a forward-looking estimate of expected credit losses on a bank's loan portfolio, is not only a robust leading indicator of the economic conditions, but also incremental to other known leading indicators in predicting changes in the economic conditions. Change in nonperforming loans also contains information about future state-level economic activity, but its usefulness is not robust to alternative specifications. The information content of the other loan portfolio measures is subsumed by the other known leading economic indicators.

As an extension of the analysis in Table 5, we also examine whether loan portfolio information can help predict drastic changes in economic activity, namely state-level recessions. To explore this possibility we estimate the following logistic regressions that relate an indicator variable for state-level recessions to the lagged loan portfolio information, controlling for the other leading economic indicators used in Table 5.

$$\begin{aligned}\Pr(STREC_{s,t+2}) = \Lambda(&\alpha + \beta_1 xPLLTL_{s,t} + \beta_2 x\Delta NPLTL_{s,t} + \beta_3 x\Delta EXYIELD_{s,t} + \beta_4 xLGROWTH_{s,t} \\ &+ \beta_5 xALLTL_{s,t-1} + \beta_6 xSTREC_{s,t} + \beta_7 xSTREC_{s,t-1} + \beta_8 xLEADINDEX_{s,t} \\ &+ \beta_9 xLEADINDEX_{s,t-1} + \beta_{10} xVWRET_{s,t} + \sum_{m=1}^{M} \beta_{10+m} xFE_s + \varepsilon_{s,t+2}) \quad ,\end{aligned} \tag{6}$$

$$\begin{aligned}\Pr(STREC_{s,t+2}) = \Lambda(&\gamma + \delta_1 xPLLTL_{s,t} + \delta_2 x\Delta NPLTL_{s,t} + \delta_3 xEXYIELD_{s,t} + \delta_4 xLGROWTH_{s,t} \\ &+ \delta_5 xALLTL_{s,t-1} + \delta_6 xSTREC_{s,t} + \delta_7 xSTREC_{s,t-1} + \sum_{r=0}^{r=3} \delta_{8+r} x\Delta COINDEX_{s,t-r} \\ &+ \delta_{12} x\Delta HOUSING_{s,t} + \delta_{13} xPIGROWTH_{s,t} + \delta_{14} x\Delta UNRATE_{s,t} + \delta_{15} xVWRET_{s,t} \\ &+ \sum_{m=1}^{M} \delta_{15+m} xFE_s + \varepsilon_{s,t+2})\end{aligned} \tag{7}$$

where the dependent variable, $STREC_{s,t+2}$ is equal to one if quarter t+2 is a recession quarter for state *s*, and zero otherwise. For parsimony, we report results for quarter t+2 but in untabulated analyses we find that the provision is a robust predictor of one-quarter-ahead but not three- or four-quarter-ahead recessions.[15]

Unlike national business cycles, state-level business cycles are not dated by a committee of experts. Accordingly, we define state-level recessions as two or more consecutive quarters of declines in the coincident index. This definition is analogous to the conventional way of determining national recessions as two consecutive quarters of declines in GDP (e.g., Estrella and Hardouvelis [1991]; Fair [1993]). Based on this definition, there are 164 unique state recessions (843 state-quarters) with an average length of 5.1 quarters. During the sample period, Michigan is the most recession prone state whereas North Dakota has spent no time in recessions. Accordingly, North Dakota had to be dropped out from this analysis. 56% of the state recession quarters overlap with a national recession as defined by the NBER, which suggests that state recessions often do not coincide with national recessions.

To account for common factors that may affect the economy of all states, we also

[15] As we report in the internet appendix, our inferences about the predictive ability of banks' loan portfolio information for state-level recessions remain unchanged if we estimate a single model that combines Equations (6) and (7).

estimate specifications that include the following macroeconomic factors: quarterly change in one-year T-bill rates and Moody's BAA-rated corporate bond yield index; quarterly CRSP value-weighted stock market returns; mean one- and two-quarter-ahead real GDP growth prediction from the survey of professional forecasters; and seasonally differenced quarterly aggregate earnings scaled by aggregate beginning total assets.[16]

We present estimates from the models defined in Equations (6) and (7) in Table 6. The results indicate that the provision has incremental explanatory power in predicting state recessions. The coefficient on *PLLTL* is statistically significant and its effect is economically large. For example, in the full model reported in column (4) the average marginal effect of the *PLLTL* is 0.09 (untabulated). In other words, one percent increase in *PLLTL* is associated with a nine percent increase in the odds of a recession in two quarters. In comparison the average marginal effect of *LEADINDEX* is about -0.08. Similar to Table 5, the remaining loan portfolio measures are not consistently significant across specifications. *ΔNPLTL* is significant in some specifications. *LGROWTH* and Δ*EXYIELD* are significant in columns (2), (4), and (6) but not in other columns, which appears to be due to the correlation between these variables and macroeconomic controls. *ALLTL* is significant but negative in all specification which is likely because *ALLTL* is a stock variable that responds slowly to economic changes (Harris et al. 2015). That is, it starts increasing but remains relatively low for a while at the beginning of recessions and decreases but remains relatively high for a while after the end of recessions. Overall, these results once again indicate that the provision is a robust incremental predictor of state-level economic activity.

[16] We do not include time fixed effects as doing so will remove all quarters without any variation in the dependent variable from the analyses, effectively inducing a look-ahead bias. That is, time fixed effects will perfectly (almost perfectly) predict the dependent variable when none/all (few/most) of the states are heading into recession. Our findings in Table 5 also remain qualitatively similar if we replace time fixed effects with macroeconomic factors.

(Insert Table 6 about here)

4.3. How well does the provision for loan and lease losses perform out-of-sample?

In this section, we assess the out-of-sample performance of the provision for loan and lease losses in forecasting future changes in statewide economic activity. In the in-sample tests, we find that while both the provision and changes in nonperforming loans help predict future economic activity; the provision is the only loan portfolio variable that consistently and robustly provides incremental explanatory power beyond other predictors of state-level economic activity. Estrella and Mishkin [1998] show that parsimonious models work best for out-of-sample predictions, so in the out-of-sample tests we limit our analyses to the usefulness of the provision for predicting statewide economic activity. However, in untabulated tests, we find that inclusion of changes in nonperforming loans in out-of-sample tests generally strengthens our findings.

For this analysis we estimate the following model by each state separately:

$$\begin{aligned}\Delta COINDEX_{t+i} = {} & \alpha + \beta_1 xPLLTL_t + \beta_2 xALLTL_{t-1} + \beta_3 xLEADINDEX_t + \beta_4 xLEADINDEX_{t-1} \\ & + \beta_5 xVWRET_t + \varepsilon_{t+i} \quad ,\end{aligned} \tag{8}$$

and compare its forecasting power with the following benchmark model:

$$\Delta COINDEX_{t+i} = \alpha + \beta_1 xLEADINDEX_t + \beta_2 xLEADINDEX_{t-1} + \beta_3 xVWRET_t + \varepsilon_{t+i} \quad . \tag{9}$$

As an alternative, we also run these models by replacing *LEADINDEX* and its lag with the concurrent value and three lags of *ΔCOINDEX*, as well as *ΔHOUSING, PIGROWTH*, and *ΔUNRATE*. Similar to our main analysis, we run these regressions using both the cumulative and marginal changes in coincident index as the dependent variable.

Specifically, we estimate Equations (8) and (9) for each state separately over expanding hold-out windows with the first estimation being based on 20 observations per state.[17] The out-

[17] Our findings remain qualitatively similar when we use 30 observations for the first estimation window.

of-sample forecasting power of the full model defined in Equation (8) is then compared against the benchmark models using Campbell and Thompson [2008] out-of-sample R^2 statistic:

$$R_{os}^2 = 1 - \frac{\sum_{t=1}^{T} (\Delta COINDEX_{s,t+i} - \Delta COINDEX_{s,t+i}^{FULL})^2}{\sum_{t=1}^{T} (\Delta COINDEX_{s,t+i} - \Delta COINDEX_{s,t+i}^{BENCHMARK})^2} \tag{10}$$

where *i* ranges from one to four, $\Delta COINDEX$ is the actual quarterly change in the coincident index, $\Delta COINDEX^{FULL}$ is the fitted value from the full predictive regressions specified in Equation (8) estimated through quarter t, and $\Delta COINDEX^{BENCHMARK}$ is the fitted value from the benchmark predictive regressions specified in Equation (9) estimated through quarter t. The numerator and the denominator of the ratio in Equation (10) are the mean squared errors from full and benchmark regressions, respectively. Thus, out-of-sample R^2 measures the contribution of the provision to the out-of-sample prediction of quarterly changes in the coincident index beyond the variables used in the benchmark models. Additionally, we use a t-test to compare the mean absolute errors from the full and benchmark models.

(Insert Table 7 about here)

The results of the out-of-sample forecasting power tests are reported in Table 7. In both Panel A and Panel B, the evidence suggests that the provision for loan and lease losses improves the out-of-sample prediction of quarterly changes in the coincident index up to four quarters ahead. The out-of-sample R^2 statistic is positive in all specifications and ranges from 13.3% to 20.0% in Panel A, and from 18.4% to 29.5% in Panel B. The comparison of mean absolute errors also indicates that the mean absolute error is significantly smaller in the model that includes the provision compared to the benchmark models. The contribution of the provision beyond the benchmark models increases as the horizon for the prediction of the change in the coincident index becomes longer consistent with the forecasting horizon of the benchmark variables being shorter than that of the provision. These findings hold irrespective of whether the dependent variable is the cumulative or marginal change in the coincident index.

5. Implementation

One of our objectives is to demonstrate that *real time* forecasts of statewide economic activity can be improved by incorporating information in loan portfolios relevant for current and future state-level economic activity that is not embedded in other leading indicators. Accordingly, next, we discuss timing of data releases and how forecasters can incorporate loan information from bank call reports in real time to improve forecasts of coincident indexes. The primary benchmark used in our analysis, the leading index, is calculated monthly and usually released within five weeks after the end of the reference month.[18] For reference, we provide the release schedule of the leading indexes for 2015 in Appendix B.

FFIEC's instructions require that banks submit the call reports (Forms 031/041) within 30 calendar days of the end of the quarter. Submitted forms are generally made publicly available during the same day. In particular, since 2005, the year FFIEC completed modernization of the data collection process through the Central Data Repository (CDR) project, the call reports are made publicly available approximately six hours after being submitted.[19] Badertscher et al. (2015) track the release of call reports from January 1, 2012 to March 31, 2014 and report that 92% of call reports are made publicly available within 31 days after quarter end. Thus, the

[18] The release of the January leading index is an exception as it is usually not issued until March. This is because, the coincident index, which is an input to the leading index, is released a few days after the release of the Current Employment Statistics (CES) survey and the CES estimates are released by the Bureau of Labor Statistics (BLS) around the third Friday of the month following the reference month (http://www.bls.gov/lau/laufaq.htm#Q07). CES survey estimates for the month of January become available only in March because they are compared to the comprehensive counts of employment using state unemployment insurance tax records which become available in March. Thus, the release of the January leading index is delayed until March.

[19] Instructions are available at https://www.ffiec.gov/pdf/FFIEC_forms/FFIEC031_FFIEC041_201412_i.pdf. According to FFIEC, prior to the implementation of CDR, call reports were made publicly available several days after their receipt (FFIEC 2006). Information about public release of call reports under CDR is available at https://cdr.ffiec.gov/public/HelpFileContainers/WelcomeAdditionalInfo.aspx

availability of call report data to bank regulators approximately corresponds to the FRB's scheduled releases of the leading indexes.

Given this timeline, third parties who rely on the leading index to forecast state-level economic activity can incorporate call report data to improve their forecasts often with little or no delay. The FRB, on the other hand, may or may not be able to incorporate call report data in its estimates of the leading index in the same month. In Figure 2, we provide a timeline of the availability of data relevant for the prediction of 2015:Q2 coincident index which demonstrates a quarter where the leading index is released shortly before the call report deadlines. In this case, as a practical expedient, the FRB can incorporate aggregate information in call reports into the forecasts of state economic activity in a timely manner if either a representative set of banks file call reports within 28 days after the quarter end, or the leading index can be revised after initial release or the initial release schedule can be altered to accommodate call report filing deadline.

(Insert Figure 2 about here)

We also consider the case where neither of the above conditions are met. In particular, we consider a setting where call report data can only be measured with a one month lag compared to the coincident and leading index. To fix ideas, in this alternative specification the call report data for the January-March quarter would be used to predict the changes in the coincident index for the May-July period instead of April-June. This alternative measurement ensures that the call report data are available before leading index for the month of April is scheduled to be released, and hence can be incorporated into the forecasts of economic activity for the May-July quarter. For example, the call report data for 2015:Q1 becomes available to bank regulators by April 30th and, the leading index for April is scheduled to be released on June 2, 2015 (see Appendix B).

We replicate our analysis in this setting and report the in-sample and out-of-sample results in Table 8.[20] As shown in Panel A and Panel B, we continue to find that the provision is a robust leading indicator of local economic activity after controlling for other known leading economic indicators. Overall, we conclude that even if call report data available to forecasters is one month old, it can still be used to improve forecasts of economic activity.

(Insert Table 8 about here)

6. Extensions

6.1. Does the timeliness of the provision affect its association with future economic activity?

In this section we extend our analysis to examine whether the timeliness of provision for loan and lease losses affects the association between the provision and future economic activity. In particular, timelier provisions incorporate changes in the credit conditions of loan portfolios sooner (Beatty and Liao [2011]), and therefore can reflect expectations about future economic activity on a timelier basis.

We follow Beatty and Liao [2011] and define timeliness of the provision as the additional explanatory power of current and future nonperforming loans beyond that of past nonperforming loans in explaining the current provision. Specifically, our timeliness measure is the difference in adjusted R^2 of the following two regressions ((12)-(11)) that are estimated for each state quarter using expanding windows, where the first estimation is based on 20 observations per state:[21]

$$PLLTL_t = \alpha + \beta_1 x\Delta NPLTL_{t-1} + \beta_2 x\Delta NPLTL_{t-2} + \beta_3 xEBP_t + \beta_4 xCR_t + \varepsilon_t \qquad (11)$$

$$PLLTL_t = \alpha + \beta_1 x\Delta NPLTL_{t+1} + \beta_2 x\Delta NPLTL_t + \beta_3 x\Delta NPLTL_{t-1} + \beta_4 x\Delta NPLTL_{t-2} + \beta_5 xEBP_t + \beta_6 xCR_t + \varepsilon_t \qquad (12)$$

where $PLLTL_{s,t}$ and $\Delta NPLTL_{s,t}$ are defined as above, $EBP_{s,t}$ is equal to the aggregate pre-provision earnings before income taxes scaled by the average of beginning and ending aggregate

[20] For brevity, we do not tabulate results using the alternative model that includes other leading state-level economic indicators. However, our conclusions remain unchanged when we use the alternative model to conduct these tests.
[21] Our findings remain qualitatively similar when we use 30 observations for the first estimation window.

total assets of banks in state s and quarter t; and $CR_{s,t}$ is the ratio of beginning aggregate total equity to beginning aggregate total assets of banks in state s and quarter t.

For each state, we classify quarters into high (low) timeliness category if one-quarter-lagged value of the additional R^2 is above (below) the state's median additional R^2 over the sample period. This yields balanced clusters/panels and allows us to compare the performance of each state's loan portfolio information in periods of relatively high or low timeliness.

We report the results from our analyses of the association between loan portfolio information and future changes in the coincident index for low and high timeliness periods separately in Table 9. For brevity, we only report results where the dependent variable is four-quarter-ahead cumulative changes in coincident index. Our conclusions continue to hold when we use one-, two-, or three-quarter ahead values or when we use marginal changes as the dependent variable.

(Insert Table 9 about here)

The results in the first column for each subsample indicate that the provision is statistically significant in the high but not in the low timeliness subsample when other loan quality measures are not included. Consistent with forecasting power increasing in timeliness of the provision, the coefficient on the provision as well as the explanatory power of the regression is larger in the high timeliness subsample. The explanatory power in the high timeliness subsample is around 79 percent while it is around 74 percent for low timeliness subsample. In column (2), we include the remaining loan portfolio variables and in columns (3) and (4) we turn our attention to the incremental information content tests. In columns (3) and (4), the coefficient on *PLLTL* is statistically significant only in the high timeliness subsample. Overall, the evidence is consistent with the conjecture that the provision associates more strongly with economic activity when it reflects the changes in the credit risk of the underlying loan portfolios in a timelier manner.[22]

6.2. *Is loan portfolio information useful in predicting economic activity at a more granular level?*

Our main findings indicate that information about loan portfolios can help predict economic conditions at the state level. In this section we extend our tests to examine the usefulness of loan portfolio information at a finer delineation of the local economy, namely the commuting zones. From an economic point of view, state boundaries do not necessarily constrain local economies. Commuting zones (CZs) were developed by the Department of Agriculture in the 1980s for the purpose of delineating local labor markets and economies (see Tolbert and Sizer 1996). Each CZ is composed of several counties and each county belongs to one CZ. The Department of Agriculture publishes definitions of commuting zones every ten years since 1980. We use year 2000 definitions of CZs since this year is approximately the midpoint of our sample period. There are 709 CZs covering the entire United States and each CZ is defined by the ability of a worker living in that region to transit easily somewhere else in that region for employment. Assuming that banks are also more likely to lend in the CZ from which their branches are obtaining deposits, we re-run our main tests using CZs as the unit of analysis.

Since there is no measure that is analogous to GDP or coincident index at the county or CZ level, we measure CZ-level economic activity using unemployment rates. To measure the unemployment rate at the CZ level, we sum the number of unemployed people over all counties in a given CZ and divide it by the total number of people in the labor force in these counties.

[22] Arguably, due to regulatory capital incentives banks can manipulate the provision when capital ratios are low. This could in turn reduce the association between the provision and future economic activity. In tests tabulated in the internet appendix, we compare state quarters where the aggregate capital ratio is low with those where the aggregate capital ratio is high and find weak support for this conjecture.

Because of the seasonal patterns in unemployment, we use seasonally differenced unemployment rates in these tests. Similar to the main analysis, we calculate our independent variables by aggregating bank-level accounting information over all banks operating in a given CZ each quarter. When a bank operates in more than one CZ, we allocate weights to the accounting variables based on the bank's percentage of deposits originating in a given CZ. We begin our sample period with the first quarter of 1994 as branch location data from FDIC became available then.[23] Data on other control variables used in the state-level tests are not available at the CZ level, and therefore these variables are not included in the analysis. Similar to our main tests, we include CZ and time fixed effects and cluster standard errors by CZ and time.

(Insert Table 10 about here)

Table 10 reports the results of this analysis. Consistent with our findings at the state level, we find that the provision for loan and lease losses and changes in nonperforming loans are both positively and significantly associated with future changes in CZ-level unemployment rates. The results remain unchanged after controlling for the lagged change in the unemployment rate. Also, consistent with our findings at the state level, change in risk premium and loan growth are insignificant in the prediction of four-quarter-ahead unemployment rate at the CZ level. Overall, based on the findings in Table 10 we conclude that loan portfolio information is also informative about local economic conditions at the CZ level.

7. Conclusion

We investigate whether information about loan portfolios is associated with the current and future local economic activity. We find that at the state level, information about expected

[23] Branching regulations that were in place prior to 1994 restricted banks' operations to the state they are headquartered but each state has several commuting zones. Therefore, we need actual branch location data for this analysis and accordingly begin the analysis from 1994.

credit losses as reflected in the provision for loan and lease losses and changes in nonperforming loans is associated with contemporaneous and future changes in statewide economic activity measured using the coincident index. More importantly, we find that the provision, a forward-looking estimate of credit losses attributable to originating and holding loans during a period, contains information incremental to the leading state-level economic indicators in predicting changes in coincident index and state recessions. The out-of-sample analysis suggests that prediction models that include state-level provisions outperform benchmark models that exclude such information. Taken together, our results have practical implications as they suggest that economic forecasts of the coincident index can be improved by using accounting information about loan portfolios. In additional tests, we show that loan portfolio information is also useful in predicting economic conditions at the commuting zone level.

Our paper contributes to the literature studying the informativeness of aggregate accounting information for the economy. We document the usefulness of the loan portfolio information for predicting local economic trends. Our findings are also relevant to research that studies forecasting of economic trends. Importantly, we contribute to the literature that examines the prediction of local economic conditions, a topic that remains relatively under researched.

Appendix A: Variable definitions

Variable	**Description** (Data source is listed in parenthesis)
Table 4 (subscripts *s* and *t* stand for state s and quarter t)	
$COINDEX_{s,t}$	Value of the Federal Reserve Bank of Philadelphia's coincident index for state *s* as of the last month of calendar quarter *t*. Coincident indexes are calculated for 50 U.S. states using a system of models that include four state-level inputs: nonfarm payroll employment, average hours worked in manufacturing, unemployment rate, and wage and salary disbursements deflated by consumer price index. The trend in each state's index is set to the trend of its gross state product. (https://www.philadelphiafed.org/research-and-data/regional-economy/).
$PLLTL_{s,t}$	Aggregate provision for loan and leases losses divided by the average balance of aggregate total loans (Bank Regulatory Database).
$\Delta NPLTL_{s,t}$	Quarterly change in the ratio of aggregate nonperforming loans to aggregate total loans (Bank Regulatory Database).
$\Delta EXYIELD_{s,t}$	Quarterly change in the difference between annualized ratio of aggregate net interest income to the average balance of aggregate total loans and three-year constant maturity T-bond rate (Bank Regulatory Database).
$LGROWTH_{s,t}$	Quarterly growth rate in aggregate total loans (Bank Regulatory Database).
$ALLTL_{s,t}$	Aggregate allowance for loan and lease losses divided by aggregate total loans (Bank Regulatory Database).
Table 5 (subscripts *s* and *t* stand for state s and quarter t)	
$LEADINDEX_{s,t}$	Value of the Federal Reserve Bank of Philadelphia's leading index -a forecast of six-month growth rate in coincident index- for state *s* as of the last month of calendar quarter *t*. The leading indexes are constructed using current and prior values of the coincident indexes, state-level housing permits, state-level initial unemployment insurance claims, delivery times from the Institute for Supply Management manufacturing survey and the interest rate spread between the ten-year T-bond and three-month T-bill (https://www.philadelphiafed.org/research-and-data/regional-economy/).
$\Delta HOUSING_{s,t}$	Quarterly percentage change in all transactions housing price index of the Federal Housing Finance Agency for state *s* (http://www.fhfa.gov/).
$PIGROWTH_{s,t}$	Quarterly growth rate in state-level total personal income (http://www.bea.gov/).
$\Delta UNRATE_{s,t}$	Quarterly change in state-level unemployment rate (http://www.bea.gov/).
$VWRET_{s,t}$	Value-weighted stock return of firms headquartered in state *s* over the 12-month period ending with quarter *t*. (CRSP).
Table 6 (subscripts *s* and *t* stand for state s and quarter t)	
$STREC_{s,t}$	An indicator variable that is equal to one if state *s* is in recession during the calendar quarter *t* and zero otherwise. State recessions are defined as two or more consecutive quarters of declines in the coincident index.
Macroeconomic controls	Quarterly change in one-year T-bill rates and Moody's BAA-rated corporate bond yield index (https://research.stlouisfed.org/fred2/); value-weighted stock market returns (CRSP); mean one- and two-quarters ahead real GDP growth prediction from the survey of professional forecasters (https://www.philadelphiafed.org/research-and-data/real-time-center/survey-of-professional-forecasters/); and seasonally-differenced quarterly aggregate earnings scaled by aggregate beginning total assets (Compustat).
Table 10 (subscripts *cz* and *t* stand for commuting zone cz and quarter t)	
$\Delta UNRATE_{cz,t,t+4}$	Change in the unemployment rate of commuting zone *cz* between calendar quarters *t* and *t+4*. Unemployment rate at the CZ level is calculated by summing the number of unemployed people over all counties in a given CZ and dividing it by the total number of people in the labor force in these counties. Data on unemployment and labor force are obtained from the Bureau of Economic Analysis (http://www.bea.gov/).
$PLLTL_{cz,t}$	Aggregate provision for loan and leases losses divided by the average balance of aggregate total loans (Bank Regulatory Database).

$\Delta NPLTL_{cz,t}$	Quarterly change in the ratio of aggregate nonperforming loans to aggregate total loans (Bank Regulatory Database).
$\Delta EXYIELD_{cz,t}$	Quarterly change in the difference between annualized ratio of aggregate net interest income to the average balance of aggregate total loans and three-year constant maturity T-bond rate (Bank Regulatory Database).
$LGROWTH_{cz,t}$	Quarterly growth rate in aggregate total loans (Bank Regulatory Database).
$ALLTL_{cz,t}$	Aggregate allowance for loan and lease losses divided by aggregate total loans (Bank Regulatory Database).

Appendix B: Leading index release schedule for 2015

2015 Leading Index Release Dates	
Report Period	**Release Date**
January 2015	*March 25, 2015*
February 2015	*April 1, 2015*
March 2015	*April 28, 2015*
April 2015	*June 2, 2015*
May 2015	*June 26, 2015*
June 2015	*July 29, 2015*
July 2015	*August 28, 2015*
August 2015	*September 28, 2015*
September 2015	*October 29, 2015*
October 2015	*November 30, 2015*
November 2015	*December 28, 2015*
December 2015	*February 3, 2016*

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Table 1: Number of banks by state

	Total Number of Bank-Quarters	Average Quarterly Number of Banks	Average Bank's % of Operations in the State
AK	764	8.0	85.1%
AL	16,555	172.4	93.6%
AR	17,949	187.0	96.5%
AZ	4,573	47.6	74.5%
CA	30,624	319.0	95.8%
CO	20,186	210.3	92.7%
CT	6,787	70.7	89.2%
DE	2,467	25.7	77.9%
FL	28,625	298.2	91.8%
GA	31,456	327.7	96.1%
HI	1,078	11.2	90.1%
IA	41,162	428.8	97.6%
ID	2,508	26.1	64.5%
IL	73,723	767.9	97.3%
IN	18,055	188.1	90.4%
KS	37,706	392.8	96.5%
KY	23,562	245.4	94.8%
LA	15,528	161.8	97.3%
MA	19,534	203.5	96.4%
MD	8,786	91.5	79.9%
ME	2,999	31.2	93.9%
MI	16,613	173.1	94.3%
MN	46,120	480.4	97.6%
MO	37,954	395.4	95.1%
MS	10,069	104.9	93.4%
MT	8,733	91.0	97.3%
NC	9,780	101.9	87.2%
ND	10,894	113.5	95.7%
NE	27,024	281.5	97.9%
NH	3,508	36.5	84.6%
NJ	11,064	115.3	85.9%
NM	5,828	60.7	92.0%
NV	2,711	28.2	76.1%
NY	17,808	185.5	90.0%
OH	22,110	230.3	94.1%
OK	28,664	298.6	98.0%
OR	4,576	47.7	77.7%
PA	23,647	246.3	93.5%
RI	1,218	12.7	71.5%
SC	7,631	79.5	90.2%
SD	9,040	94.2	95.9%
TN	20,759	216.2	92.7%
TX	74,349	774.5	97.5%
UT	4,813	50.1	88.3%
VA	14,287	148.8	86.4%
VT	2,080	21.7	84.4%
WA	9,593	99.9	86.5%
WI	32,248	335.9	97.4%
WV	9,684	100.9	88.4%
WY	4,767	49.7	92.7%
Total	882,199	9,189.6	94.3%

Table 2: Bank-level descriptive statistics

This table provides descriptive statistics for variables at the bank level. Panel A reports summary statistics and Panel B reports pairwise correlation coefficients (Pearson below diagonal, Spearman above diagonal), where p-values are reported in parentheses. Data are obtained from the quarterly Reports of Condition and Income filings for the sample period starting with the first quarter of 1990 and ending with the last quarter of 2013. *Total assets* and *Total loans* are self-explanatory and are measured in millions of dollars. The remaining variables are reported in percentages and are defined as follows: *Loan growth* is the quarter-over-quarter percentage growth in *Total loans; Provision for loan losses* is the quarterly provision for loan and lease losses scaled by the average of beginning and ending balance of total loans; *Allowance for loan losses* is end of quarter allowance for loan and lease losses scaled by the end of quarter total loans; *Nonperforming loans* is end of quarter nonperforming loans scaled by the end of quarter total loans; and *Yield* is the annualized value of the ratio of quarterly net interest income to the average of beginning and ending balance of total loans.

Panel A: Summary statistics

	Obs. Count	Mean	St. Dev	25%	50%	75%
Total assets	833,370	835	18,438	40	85	199
Total loans	833,370	475	8,957	22	50	126
Loan growth	833,370	2.53	7.62	-1.05	1.57	4.58
Provision for loan losses	833,370	0.13	0.41	0.00	0.05	0.13
Allowance for loan losses	833,370	1.62	1.15	1.07	1.36	1.84
Nonperforming loans	833,370	1.51	2.31	0.26	0.81	1.86
Yield	833,370	8.47	2.02	6.99	8.55	9.69

Panel B: Correlations

		(1)	(2)	(3)	(4)	(5)
(1)	Loan growth	-	0.02	-0.21	-0.24	0.08
			(0.00)	(0.00)	(0.00)	(0.00)
(2)	Provision for loan losses	-0.02	-	0.07	0.23	0.03
		(0.00)		(0.00)	(0.00)	(0.00)
(3)	Allowance for loan losses	-0.14	0.19	-	0.32	0.08
		(0.00)	(0.00)		(0.00)	(0.00)
(4)	Nonperforming loans	-0.18	0.27	0.44	-	0.01
		(0.00)	(0.00)	(0.00)		(0.00)
(5)	Yield	0.09	0.03	0.08	-0.06	-
		(0.00)	(0.00)	(0.00)	(0.00)	

Table 3: State-level descriptive statistics

This table provides descriptive statistics for variables at the state level. Panel A reports summary statistics and Panel B reports pairwise correlation coefficients (Pearson below diagonal, Spearman above diagonal), where p-values are reported in parentheses. State-level aggregates of accounting items are calculated as the sum of values over all banks operating in a given state in a quarter. For banks that operate in more than one state, each item is weighted by the percentage of the bank's operations in the given state, where the percentage of operations is measured using summary of deposits data. *LGROWTH* is equal to the quarterly growth rate in aggregate total loans; *PLLTL* is equal to aggregate provision for loan and leases losses divided by the average of beginning and ending balance of aggregate total loans; *ALLTL* is equal to aggregate allowance for loan and lease losses divided by aggregate end of quarter total loans; *ΔNPLTL* is equal to the quarterly change in the ratio of aggregate nonperforming loans to aggregate end of quarter total loans; *ΔEXYIELD* is equal to the quarterly change in the difference between annualized ratio of aggregate net interest income to the average beginning and ending balance of aggregate total loans and three-year constant maturity T-bond rate; *ΔCOINDEX* and *LEADINDEX* are equal to the quarterly growth rate in the Federal Reserve Bank of Philadelphia's coincident index and the predictor of six-month growth rate in the coincident index (i.e., the leading index), respectively; *ΔHOUSING* is the quarterly percentage change in the all transactions housing price index of the Federal Housing Finance Agency; *PIGROWTH* is the quarterly growth rate in total personal income; *ΔUNRATE* is the quarterly change in state-level unemployment rate; and *VWRET* is the value-weighted stock returns of firms headquartered in the given state over the 12-months ending with the current quarter. All variables are reported in percentages.

Panel A: Summary statistics

	Obs. Count	Mean	St. Dev	25%	50%	75%
$LGROWTH_{s,t}$	4,750	1.819	5.269	0.147	1.743	3.340
$PLLTL_{s,t}$	4,750	0.195	0.205	0.073	0.125	0.232
$ALLTL_{s,t-1}$	4,750	1.770	0.584	1.383	1.634	2.026
$\Delta NPLTL_{s,t}$	4,750	0.007	0.247	-0.101	-0.016	0.063
$\Delta EXYIELD_{s,t}$	4,750	-0.176	1.461	-0.454	-0.038	0.469
$\Delta COINDEX_{s,t}$	4,750	0.564	0.901	0.207	0.705	1.089
$LEADINDEX_{s,t}$	4,750	1.181	1.567	0.464	1.385	2.111
$\Delta HOUSING_{s,t}$	4,750	0.797	1.583	0.126	0.889	1.522
$PIGROWTH_{s,t}$	4,750	1.193	1.165	0.653	1.191	1.762
$\Delta UNRATE_{s,t}$	4,750	0.011	0.340	-0.200	0.000	0.100
$VWRET_{s,t}$	4,750	12.069	25.563	-1.406	12.284	24.732

Panel B: Correlations

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	$LGROWTH_{s,t}$	-	-0.25	-0.26	-0.07	0.21	0.23	0.17	0.22	0.13	-0.09	0.02
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.13)
(2)	$PLLTL_{s,t}$	-0.11	-	0.37	0.23	0.10	-0.44	-0.34	-0.39	-0.21	0.30	-0.18
		(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(3)	$ALLTL_{s,t-1}$	-0.12	0.41	-	-0.32	-0.04	0.01	0.13	-0.27	-0.08	-0.12	0.08
		(0.00)	(0.00)		(0.00)	(0.00)	(0.39)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(4)	$\Delta NPLTL_{s,t}$	-0.14	0.47	-0.16	-	0.07	-0.35	-0.39	-0.09	-0.15	0.40	-0.23
		(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(5)	$\Delta EXYIELD_{s,t}$	0.18	0.00	-0.03	0.01	-	-0.11	-0.13	0.01	-0.13	0.07	-0.03
		(0.00)	(0.92)	(0.02)	(0.61)		(0.00)	(0.00)	(0.72)	(0.00)	(0.00)	(0.03)
(6)	$\Delta COINDEX_{s,t}$	0.14	-0.52	-0.02	-0.50	-0.04	-	0.88	0.30	0.47	-0.61	0.30
		(0.00)	(0.00)	(0.25)	(0.00)	(0.01)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(7)	$LEADINDEX_{s,t}$	0.11	-0.44	0.08	-0.49	-0.03	0.90	-	0.25	0.37	-0.58	0.32
		(0.00)	(0.00)	(0.00)	(0.00)	(0.07)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
(8)	$\Delta HOUSING_{s,t}$	0.11	-0.43	-0.29	-0.23	0.01	0.36	0.33	-	0.20	-0.09	0.07
		(0.00)	(0.00)	(0.00)	(0.00)	(0.40)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)
(9)	$PIGROWTH_{s,t}$	0.03	-0.24	-0.05	-0.23	-0.08	0.47	0.40	0.19	-	-0.22	0.18
		(0.03)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)
(10)	$\Delta UNRATE_{s,t}$	-0.08	0.40	-0.08	0.47	0.00	-0.74	-0.69	-0.18	-0.29	-	-0.27
		(0.00)	(0.00)	(0.00)	(0.00)	(0.88)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
(11)	$VWRET_{s,t}$	0.05	-0.16	0.08	-0.25	-0.02	0.34	0.37	0.09	0.19	-0.33	-
		(0.00)	(0.00)	(0.00)	(0.00)	(0.29)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	

Table 4: Predicting state-level economic conditions using loan portfolio information

This table presents linear regression analysis of the association between changes in economic conditions and information about loan portfolios at the state level. The dependent variables are the concurrent and future cumulative and marginal changes in coincident index (*ΔCOINDEX*), defined as:

$$\textit{Cumulative change: } \Delta COINDEX_{s,t,,t+i} = (100/i) \text{ x } ((COINDEX_{s,t+i} - COINDEX_{s,t}) / COINDEX_{s,t}),$$

$$\textit{Marginal change: } \Delta COINDEX_{s,t+i-1,\, t+i} = 100 \text{ x } ((COINDEX_{s,t+i} - COINDEX_{s,t+i-1}) / COINDEX_{s,t+i-1}).$$

Definitions of all other variables are available in Appendix A. All models include time and state fixed effects and standard errors are clustered by time and state. *, **, and *** denote significance at a two-sided 10%, 5%, and 1% level, respectively.

		ΔCOINDEX $_{t}$	Cumulative ΔCOINDEX $_{t,t+i}$				Marginal ΔCOINDEX $_{t+i-1,t+i}$			
	Pred.		i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4
$PLLTL_{s,t}$	-	-0.824 ***	-0.813 ***	-0.779 ***	-0.718 ***	-0.657 ***	-0.813 ***	-0.748 ***	-0.589 ***	-0.466 ***
		(-4.24)	(-4.36)	(-4.34)	(-4.25)	(-4.12)	(-4.36)	(-4.29)	(-3.87)	(-3.08)
$\Delta NPLTL_{s,t}$	-	-0.332 ***	-0.351 ***	-0.339 ***	-0.323 ***	-0.309 ***	-0.351 ***	-0.332 ***	-0.304 ***	-0.280 ***
		(-3.48)	(-3.87)	(-3.46)	(-3.28)	(-3.27)	(-3.87)	(-3.02)	(-2.87)	(-3.19)
$\Delta EXYIELD_{s,t}$	-	0.005	0.013	0.011	0.008	0.010	0.013	0.008	0.004	0.016
		(0.43)	(1.24)	(0.98)	(0.72)	(0.95)	(1.24)	(0.68)	(0.31)	(1.38)
$LGROWTH_{s,t}$	+	0.003 **	0.002 *	0.002 *	0.002	0.001	0.002 *	0.001	0.002	0.000
		(2.10)	(1.71)	(1.86)	(1.60)	(0.89)	(1.71)	(1.43)	(1.08)	(0.18)
$ALLTL_{s,t-1}$		-0.077	-0.039	-0.022	-0.009	0.004	-0.039	-0.008	0.012	0.033
		(-1.22)	(-0.61)	(-0.34)	(-0.13)	(0.05)	(-0.61)	(-0.11)	(0.16)	(0.42)
State FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.67	0.68	0.69	0.70	0.71	0.68	0.68	0.68	0.67
Obs. Count		4,750	4,700	4,650	4,600	4,550	4,700	4,650	4,600	4,550

Table 5: Predicting state-level economic conditions using loan portfolio information and leading economic indicators

This table presents linear regression analysis of the association between changes in economic conditions and information about loan portfolios at the state level, controlling for other known predictors of economic conditions. The dependent variables are the concurrent and future cumulative and marginal changes in the coincident index (*ΔCOINDEX*), defined as:

$$\textit{Cumulative change: } \Delta COINDEX_{s,t,t+i} = (100/i) \text{ x } ((COINDEX_{s,t,t+i} - COINDEX_{s,t}) / COINDEX_{s,t}),$$

$$\textit{Marginal change: } \Delta COINDEX_{s,t+i-1,\, t+i} = 100 \text{ x } ((COINDEX_{s,t+i} - COINDEX_{s,t+i-1}) / COINDEX_{s,t+i-1}).$$

Definitions of all other variables are available in Appendix A. All models include time and state fixed effects and standard errors are clustered by time and state. *, **, and *** denote significance at a two-sided 10%, 5%, and 1% level, respectively.

Panel A: Controlling for leading index

		Cumulative ΔCOINDEX $_{t,t+i}$				Marginal ΔCOINDEX $_{t+i-1,t+i}$			
	Pred.	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4
$PLLTL_{s,t}$	-	-0.130 ***	-0.176 ***	-0.174 ***	-0.165 **	-0.130 ***	-0.232 ***	-0.184 **	-0.142
		(-2.81)	(-3.13)	(-2.88)	(-2.60)	(-2.81)	(-3.30)	(-2.41)	(-1.51)
$\Delta NPLTL_{s,t}$	-	0.006	-0.027	-0.047	-0.061	0.006	-0.065	-0.099	-0.119
		(0.15)	(-0.49)	(-0.80)	(-1.01)	(0.15)	(-0.86)	(-1.26)	(-1.63)
$\Delta EXYIELD_{s,t}$	-	0.000	-0.001	0.000	0.003	0.000	-0.001	-0.002	0.011
		(0.02)	(-0.08)	(-0.05)	(0.48)	(0.02)	(-0.15)	(-0.19)	(1.39)
$LGROWTH_{s,t}$	+	0.001	0.001	0.001	0.000	0.001	0.001	0.001	0.000
		(1.30)	(1.09)	(1.01)	(0.50)	(1.30)	(0.67)	(0.73)	(-0.13)
$ALLTL_{s,t-1}$		0.008	0.019	0.024	0.032	0.008	0.028	0.037	0.053
		(0.36)	(0.69)	(0.76)	(0.85)	(0.36)	(0.85)	(0.81)	(0.91)
$LEADINDEX_{s,t}$		0.428 ***	0.366 ***	0.321 ***	0.286 ***	0.428 ***	0.304 ***	0.226 ***	0.173 ***
		(30.55)	(27.77)	(23.74)	(18.24)	(30.55)	(14.82)	(10.07)	(6.52)
$LEADINDEX_{s,t-1}$		0.054 ***	0.057 ***	0.056 ***	0.055 ***	0.054 ***	0.058 ***	0.055 ***	0.052 **
		(3.59)	(4.18)	(4.06)	(3.96)	(3.59)	(3.16)	(2.78)	(2.55)
$VWRET_{s,t}$		0.000	0.000	0.000	0.000	0.000	0.001 **	0.001 *	0.000
		(0.70)	(1.49)	(1.62)	(1.42)	(0.70)	(1.95)	(1.76)	(0.80)
State FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.91	0.88	0.86	0.85	0.91	0.81	0.76	0.73
Obs. Count		4,700	4,650	4,600	4,550	4,700	4,650	4,600	4,550

Panel B: Controlling for other leading state-level economic indicators

		Cumulative ΔCOINDEX $_{t,t+i}$				Marginal ΔCOINDEX $_{t+i-1,t+i}$			
	Pred.	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4
$PLLTL_{s,t}$	-	-0.167 ***	-0.219 ***	-0.214 ***	-0.202 ***	-0.167 ***	-0.275 ***	-0.218 ***	-0.161 *
		(-4.03)	(-3.80)	(-3.55)	(-3.06)	(-4.03)	(-3.58)	(-3.15)	(-1.67)
$\Delta NPLTL_{s,t}$	-	-0.081 **	-0.088 **	-0.096 **	-0.096 **	-0.081 **	-0.100 *	-0.117 **	-0.115 *
		(-2.05)	(-2.01)	(-2.23)	(-2.19)	(-2.05)	(-1.77)	(-2.25)	(-1.95)
$\Delta EXYIELD_{s,t}$	-	0.006	0.005	0.005	0.008	0.006	0.005	0.003	0.014
		(1.06)	(0.67)	(0.56)	(0.91)	(1.06)	(0.43)	(0.23)	(1.43)
$LGROWTH_{s,t}$	+	0.000	0.000	0.000	0.000	0.000	0.000	0.000	-0.001
		(-0.53)	(-0.20)	(0.00)	(-0.39)	(-0.53)	(0.00)	(0.30)	(-0.34)
$ALLTL_{s,t-1}$		0.021	0.042	0.058	0.071	0.021	0.062	0.091 *	0.106 *
		(0.99)	(1.36)	(1.50)	(1.58)	(0.99)	(1.56)	(1.76)	(1.68)
$\Delta COINDEX_{s,t}$		1.016 ***	0.821 ***	0.715 ***	0.621 ***	1.016 ***	0.620 ***	0.493 ***	0.326 ***
		(20.69)	(16.48)	(15.06)	(13.49)	(20.69)	(10.50)	(8.61)	(5.31)
$\Delta COINDEX_{s,t-1}$		-0.374 ***	-0.242 ***	-0.217 ***	-0.193 ***	-0.374 ***	-0.107 **	-0.164 ***	-0.122 **
		(-7.02)	(-5.17)	(-5.13)	(-4.77)	(-7.02)	(-2.01)	(-3.41)	(-2.33)
$\Delta COINDEX_{s,t-2}$		0.197 ***	0.094 ***	0.079 ***	0.108 ***	0.197 ***	-0.013	0.044	0.195 ***
		(4.84)	(2.86)	(2.59)	(3.70)	(4.84)	(-0.30)	(0.90)	(4.45)
$\Delta COINDEX_{s,t-3}$		-0.086 ***	-0.024	0.005	-0.016	-0.086 ***	0.041	0.068	-0.075 *
		(-2.96)	(-0.87)	(0.18)	(-0.58)	(-2.96)	(1.14)	(1.49)	(-1.94)
$\Delta HOUSING_{s,t}$		0.033 ***	0.040 ***	0.041 ***	0.041 ***	0.033 ***	0.045 ***	0.041 **	0.042 **
		(4.22)	(3.63)	(3.25)	(3.01)	(4.22)	(3.13)	(2.48)	(2.30)
$PIGROWTH_{s,t}$		0.006	0.020 *	0.026 **	0.031 ***	0.006	0.033 **	0.039 **	0.041 ***
		(0.65)	(1.80)	(2.29)	(2.88)	(0.65)	(2.28)	(2.51)	(3.63)
$\Delta UNRATE_{s,t}$		0.253 ***	0.302 ***	0.298 ***	0.277 ***	0.253 ***	0.345 ***	0.278 ***	0.208 ***
		(5.61)	(5.01)	(4.84)	(4.87)	(5.61)	(4.42)	(4.08)	(3.67)
$VWRET_{s,t}$		0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001 **	0.001
		(2.33)	(2.30)	(2.40)	(2.14)	(2.33)	(2.50)	(2.43)	(1.37)
State FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.88	0.85	0.84	0.83	0.88	0.78	0.75	0.72
Obs. Count		4,550	4,500	4,450	4,400	4,550	4,500	4,450	4,400

Table 6: Predicting state-level recessions using loan portfolio and other information

This table presents logistic regression analysis of the association between state recessions and information about loan portfolios at the state level, controlling for other known predictors of economic conditions. The dependent variable is equal to one if quarter t+2 is a recession quarter for a given state, and zero otherwise. Recessions are defined as two or more consecutive quarters of negative changes in the coincident index. The definitions of all other variables are available in Appendix A. All models include state fixed effects and standard errors are clustered by state and time. *, **, and *** denote significance at a two-sided 10%, 5%, and 1% level, respectively.

	Pred.	(1)	(2)	(3)	(4)	(5)	(6)
$PLLTL_{s,t}$	+	4.998 ***	3.960 ***	1.284 *	1.460 **	2.006 **	1.674 **
		(5.93)	(4.51)	(1.72)	(2.10)	(2.16)	(2.12)
$\Delta NPLTL_{s,t}$	+	1.961 ***	2.580 ***	0.262	1.136 **	0.494	1.474 ***
		(3.19)	(4.50)	(0.57)	(2.10)	(1.02)	(2.62)
$\Delta EXYIELD_{s,t}$	+	-0.102	-0.238 ***	-0.159 *	-0.223 ***	0.229 *	-0.118
		(-1.02)	(-5.22)	(-1.92)	(-4.43)	(1.79)	(-0.80)
$LGROWTH_{s,t}$	-	-0.006	0.025 **	0.023	0.036 ***	-0.003	0.031 ***
		(-0.42)	(2.36)	(1.42)	(3.00)	(-0.19)	(2.81)
$ALLTL_{s,t-1}$		-2.139 ***	-1.494 ***	-1.128 ***	-0.778 **	-1.807 ***	-1.319 ***
		(-4.43)	(-3.37)	(-3.28)	(-2.58)	(-4.32)	(-3.75)
$STREC_{s,t}$				0.395	0.443	1.190 ***	1.093 ***
				(1.24)	(1.32)	(2.91)	(2.81)
$STREC_{s,t-1}$				-0.399	-0.299	-0.316	-0.279
				(-1.54)	(-1.31)	(-1.23)	(-1.21)
$LEADINDEX_{s,t}$				-1.576 ***	-1.274 ***		
				(-6.13)	(-5.55)		
$LEADINDEX_{s,t-1}$				0.047	-0.194		
				(0.37)	(-1.48)		
$\Delta COINDEX_{s,t}$						-2.906 ***	-2.517 ***
						(-4.43)	(-4.00)
$\Delta COINDEX_{s,t-1}$						1.337 ***	0.814 ***
						(3.53)	(2.77)
$\Delta COINDEX_{s,t-2}$						-0.452	-0.300
						(-1.00)	(-0.87)
$\Delta COINDEX_{s,t-3}$						0.341	0.176
						(1.01)	(0.65)
$\Delta HOUSING_{s,t}$						-0.111	-0.256 ***
						(-0.96)	(-2.65)
$PIGROWTH_{s,t}$						0.159	0.172
						(1.30)	(1.29)
$\Delta UNRATE_{s,t}$						-1.536 ***	-2.019 ***
						(-2.97)	(-3.95)
$VWRET_{s,t}$				-0.012 **	-0.008 **	-0.017 ***	-0.012 ***
				(-2.43)	(-2.28)	(-2.98)	(-2.87)
Macro. Controls		No	Yes	No	Yes	No	Yes
State FE		Yes	Yes	Yes	Yes	Yes	Yes
Pseudo R-squared		0.26	0.41	0.51	0.56	0.46	0.52
Log Pseudolikelihood		-1,574	-1,257	-1,033	-938	-1,073	-945
Obs. Count		4,457	4,557	4,557	4,557	4,410	4,410

Table 7: Out-of-sample predictive power of provision for loan and lease losses

This table presents out-of-sample tests of predictive power of provision for loan and lease losses for state-level economic conditions. Panel A presents comparison of the predictive power of the full model defined in Equation (8) against the benchmark model defined in Equation (9). Panel B presents the same analysis using an alternative specification where $LEADINDEX_{s,t}$ and its lag are replaced with $\Delta COINDEX_{s,t}$ and its three lags, $\Delta HOUSING_{s,t}$, $PIGROWTH_{s,t}$, and $\Delta UNRATE_{s,t}$. The dependent variables are the future cumulative and marginal future changes in state coincident index ($\Delta COINDEX$), defined as:

$$\textit{Cumulative change: } \Delta COINDEX_{s,t,t+i} = (100/i) \times ((COINDEX_{s,t,t+i} - COINDEX_{s,t}) / COINDEX_{s,t}),$$

$$\textit{Marginal change: } \Delta COINDEX_{s,t+i-1,\, t+i} = 100 \times ((COINDEX_{s,t+i} - COINDEX_{s,t+i-1}) / COINDEX_{s,t+i-1}).$$

Definitions of all other variables are available in Appendix A. All models are estimated for each state separately using expanding hold-out windows where the first estimation window is based on 20 observations per state. R^2_{os} is Campbell and Thompson's [2008] out-of-sample R^2 measure, calculated as $1 - (MSE_{Full} / MSE_{Benchmark})$, where MSE stands for mean squared error from estimations. Δ|Error| column shows the difference in the mean absolute errors between the full and the benchmark models. *, **, and *** denote significance at a two-sided 10%, 5%, and 1% level, respectively.

Panel A: Benchmark based on leading index

	Cumulative ΔCOINDEX $_{t,t+i}$			Marginal ΔCOINDEX $_{t+i-1,t+i}$		
i	Obs. Count	R^2_{os}	Δ|Error|	Obs. Count	R^2_{os}	Δ|Error|
1	3,750	13.3%	-0.010***	3,750	13.3%	-0.010***
2	3,700	12.3%	-0.010***	3,700	12.3%	-0.012***
3	3,650	13.9%	-0.012***	3,650	16.1%	-0.021***
4	3,600	16.9%	-0.016***	3,600	20.0%	-0.031***

Panel B: Benchmark based on other leading state-level economic indicators

	Cumulative ΔCOINDEX $_{t,t+i}$			Marginal ΔCOINDEX $_{t+i-1,t+i}$		
i	Obs. Count	R^2_{os}	Δ|Error|	Obs. Count	R^2_{os}	Δ|Error|
1	3,600	18.4%	-0.020***	3,600	18.4%	-0.020***
2	3,550	23.0%	-0.032***	3,550	23.7%	-0.043***
3	3,500	26.2%	-0.042***	3,500	25.6%	-0.057***
4	3,450	29.5%	-0.049***	3,450	28.9%	-0.063***

Table 8: Changes in timing of the measurement of economic activity

This table presents the in-sample (Panel A) and out-of-sample (Panel B) analysis of the association between changes in economic conditions and information about loan portfolios at the state level. The dependent variables are the concurrent and future cumulative and marginal changes in state coincident index (*ΔCOINDEX*), calculated as:

$$\text{Cumulative change: } \Delta COINDEX_{s,t,t+i} = (100/i) \times ((COINDEX_{s,t,t+i} - COINDEX_{s,t}) / COINDEX_{s,t}),$$

$$\text{Marginal change: } \Delta COINDEX_{s,t+i-1,\, t+i} = 100 \times ((COINDEX_{s,t+i} - COINDEX_{s,t+i-1}) / COINDEX_{s,t+i-1}).$$

Changes in coincident index, leading index, and value weighted returns are measured starting one month after the end of calendar quarters (e.g., when bank data are for the quarter ended on March, $LEADINDEX_{s,t}$ is measured for April). The remaining variables are measured over calendar quarters and their definitions are available in Appendix A. In-sample tests include state and time fixed effects and standard errors are clustered by state and time.*, **, and *** denote significance at a two-sided 10%, 5%, and 1% level, respectively.

Panel A: In-sample tests

		Cumulative ΔCOINDEX $_{t,t+i}$				Marginal ΔCOINDEX $_{t+i-1,t+i}$			
	Pred.	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4
$PLLTL_{s,t}$	-	-0.167 ***	-0.185 ***	-0.183 ***	-0.177 ***	-0.167 ***	-0.207 ***	-0.180 ***	-0.163 *
		(-3.49)	(-3.47)	(-3.51)	(-3.10)	(-3.49)	(-3.19)	(-2.61)	(-1.69)
$\Delta NPLTL_{s,t}$	-	-0.021	-0.050	-0.072	-0.078	-0.021	-0.085	-0.127 *	-0.110
		(-0.54)	(-0.93)	(-1.28)	(-1.40)	(-0.54)	(-1.12)	(-1.88)	(-1.62)
$\Delta EXYIELD_{s,t}$	-	-0.006	-0.005	-0.004	0.000	-0.006	-0.004	0.000	0.010
		(-0.97)	(-0.71)	(-0.48)	(-0.03)	(-0.97)	(-0.46)	(-0.01)	(1.30)
$LGROWTH_{s,t}$	+	0.000	0.000	0.000	0.000	0.000	0.001	0.000	0.000
		(0.18)	(0.53)	(0.31)	(0.14)	(0.18)	(0.69)	(-0.05)	(-0.31)
$ALLTL_{s,t-1}$		0.010	0.018	0.024	0.033	0.010	0.025	0.037	0.060
		(0.41)	(0.66)	(0.76)	(0.88)	(0.41)	(0.72)	(0.78)	(1.05)
$LEADINDEX_{s,t}$		0.403 ***	0.349 ***	0.308 ***	0.273 ***	0.403 ***	0.294 ***	0.222 ***	0.161 ***
		(25.84)	(24.99)	(24.66)	(20.75)	(25.84)	(17.13)	(11.32)	(7.05)
$LEADINDEX_{s,t-1}$		0.062 ***	0.060 ***	0.055 ***	0.053 ***	0.062 ***	0.057 ***	0.045 ***	0.049 ***
		(4.24)	(3.93)	(3.79)	(3.83)	(4.24)	(3.00)	(2.64)	(2.65)
$VWRET_{s,t}$		0.000	0.000	0.001	0.001	0.000	0.001 *	0.001	0.001
		(0.60)	(1.28)	(1.35)	(1.23)	(0.60)	(1.67)	(1.63)	(0.89)
State FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE		Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared		0.90	0.88	0.86	0.85	0.90	0.80	0.75	0.72
Obs. Count		4,700	4,650	4,600	4,550	4,700	4,650	4,600	4,550

Panel B: Out-of-sample tests

	Cumulative ΔCOINDEX $_{t,t+i}$			Marginal ΔCOINDEX $_{t+i-1,t+i}$		
i	Obs. Count	R^2_{os}	Δ|Error|	Obs. Count	R^2_{os}	Δ|Error|
1	3,750	10.2%	-0.009***	3,750	10.2%	-0.009***
2	3,700	11.0%	-0.008***	3,700	11.8%	-0.014***
3	3,650	14.0%	-0.012***	3,650	16.5%	-0.024***
4	3,600	17.2%	-0.017***	3,600	20.3%	-0.036***

Table 9: Timeliness of provision for loan and lease losses

This table presents linear regression analysis of the association between changes in economic conditions and information about loan portfolios at the state level for high and low timeliness state-quarters, controlling for other known predictors of economic conditions. Timeliness of the provision is measured as the difference in adjusted R^2 of the following two regressions that are estimated for each state-quarter separately using expanding windows, where the first estimation is based on 20 observations per state:

$$PLLTL_t = \alpha + \beta_1 x\Delta NPLTL_{t-1} + \beta_2 x\Delta NPLTL_{t-2} + \beta_3 xEBP_t + \beta_4 xCR_t + \varepsilon_t,$$
$$PLLTL_t = \alpha + \beta_1 x\Delta NPLTL_{t+1} + \beta_2 x\Delta NPLTL_t + \beta_3 x\Delta NPLTL_{t-1} + \beta_4 x\Delta NPLTL_{t-2} + \beta_5 xEBP_t + \beta_6 xCR_t + \varepsilon_t.$$

For each state, quarters are classified into high (low) timeliness category if one-quarter-lagged value of additional R^2 is above (below) the state's median over the sample period. The dependent variable is the four-quarter-ahead cumulative change in state coincident index. Definitions of all other variables are available in Appendix A. All models include state and time fixed effects and standard errors are clustered by state and time. *, ** and *** denote significance at a two-sided 10%, 5%, and 1% level, respectively.

	Low Timeliness				High Timeliness			
$PLLTL_{s,t}$	-0.414	-0.622 **	-0.079	-0.113	-1.008 **	-0.903 **	-0.256 *	-0.465 **
	(-1.53)	(-2.28)	(-0.54)	(-0.68)	(-2.21)	(-2.15)	(-1.71)	(-2.50)
$\Delta NPLTL_{s,t}$		-0.197 **	0.001	-0.086		-0.163 ***	-0.118	-0.157 **
		(-2.35)	(0.02)	(-1.46)		(-2.72)	(-1.60)	(-2.43)
$\Delta EXYIELD_{s,t}$		0.005	0.001	-0.007		0.004	0.003	0.001
		(0.38)	(0.11)	(-0.85)		(0.24)	(0.32)	(0.09)
$LGROWTH_{s,t}$		0.003	0.001	0.001		0.001	0.000	0.000
		(1.14)	(0.68)	(0.36)		(0.29)	(0.39)	(0.13)
$ALLTL_{s,t-1}$		0.267	0.123	0.172 *		-0.020	-0.030	0.018
		(1.57)	(1.45)	(1.83)		(-0.16)	(-0.50)	(0.27)
$LEADINDEX_{s,t}$			0.280 ***				0.256 ***	
			(15.55)				(11.51)	
$LEADINDEX_{s,t-1}$			0.053 ***				0.033	
			(3.08)				(1.28)	
$VWRET_{s,t}$			0.000 *	0.000			0.000	0.001
			(0.36)	(0.82)			(0.47)	(1.24)
$\Delta COINDEX_{s,t}$				0.586 ***				0.546 ***
				(8.21)				(10.24)
$\Delta COINDEX_{s,t-1}$				-0.190 ***				-0.184 ***
				(-3.66)				(-3.67)
$\Delta COINDEX_{s,t-2}$				0.102 ***				0.067
				(2.95)				(1.52)
$\Delta COINDEX_{s,t-3}$				-0.029				0.010
				(-0.62)				(0.32)
$\Delta HOUSING_{s,t}$				0.062 ***				0.031
				(2.78)				(1.51)
$PIGROWTH_{s,t}$				0.028				0.033 ***
				(1.34)				(3.31)
$\Delta UNRATE_{s,t}$				0.224 **				0.331 ***
				(2.24)				(4.38)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.74	0.75	0.86	0.83	0.79	0.79	0.87	0.85
Obs. Count	1,750	1,750	1,750	1,750	1,750	1,750	1,750	1,750

Table 10: Predicting commuting zone-level unemployment using loan portfolio information

This table presents summary statistics (Panel A) and estimates from linear regression analysis of the association between changes in unemployment rates and loan portfolio information (Panel B) at the commuting zone level for the 1994:Q1-2013:Q4 period. Commuting zones (CZ) are defined based on the Department of Agriculture's definition in 2000. CZ-level aggregates of accounting items are calculated as the sum of values for all banks operating in a given CZ in a quarter. For banks that operate in more than one CZ, each item is weighted by the percentage of the bank's operations in the given CZ, where percentage of operations is measured using summary of deposits data. Definitions of all variables are available in Appendix A. All models include CZ and time fixed effects and standard errors are clustered by CZ and time. *, **, and *** denote significance at a two-sided 10%, 5% and 1% level, respectively.

Panel A: Summary statistics

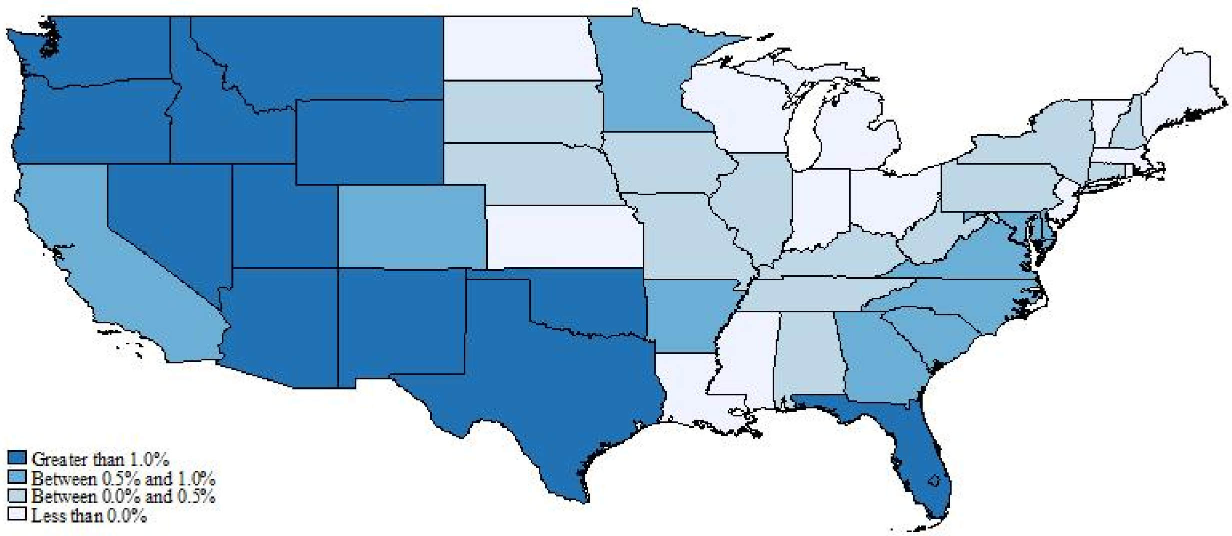
	Obs. Count	Mean	St. Dev	25%	50%	75%
$PLLTL_{cz,t}$	52,912	0.168	0.215	0.060	0.102	0.189
$\Delta NPLTL_{cz,t}$	52,912	0.026	0.342	-0.098	-0.002	0.108
$\Delta EXYIELD_{cz,t}$	52,912	-0.067	1.010	-0.463	-0.011	0.485
$LGROWTH_{cz,t}$	52,912	1.478	5.633	-0.295	1.632	3.466
$ALLTL_{cz,t-1}$	52,912	1.643	0.609	1.301	1.499	1.823
$\Delta UNRATE_{cz,t,t+4}$	52,912	0.015	0.316	-0.149	-0.023	0.128

Panel B: Linear regression analysis

		$\Delta UNRATE_{cz,t,t+4}$	
	Pred.	(1)	(2)
$PLLTL_{cz,t}$	+	0.039 *	0.053 **
		(1.72)	(2.51)
$\Delta NPLTL_{cz,t}$	+	0.028 ***	0.033 ***
		(3.59)	(3.98)
$\Delta EXYIELD_{cz,t}$	+	0.001	0.001
		(0.40)	(0.39)
$LGROWTH_{cz,t}$	-	0.000	0.000
		(-0.86)	(-1.18)
$ALLTL_{cz,t-1}$		-0.031 ***	-0.031 ***
		(-3.93)	(-3.89)
$\Delta UNRATE_{cz,t-4,t}$			-0.125 ***
			(-4.07)
Time FE		Yes	Yes
CZ FE		Yes	Yes
R-squared		0.50	0.51
Obs. Count		52,912	52,912

Figure 1: Disparities in state economic conditions

Panel A: Changes in the state coincident indexes between June and September 2005



Panel B: Changes in the state coincident indexes between June and September 2008

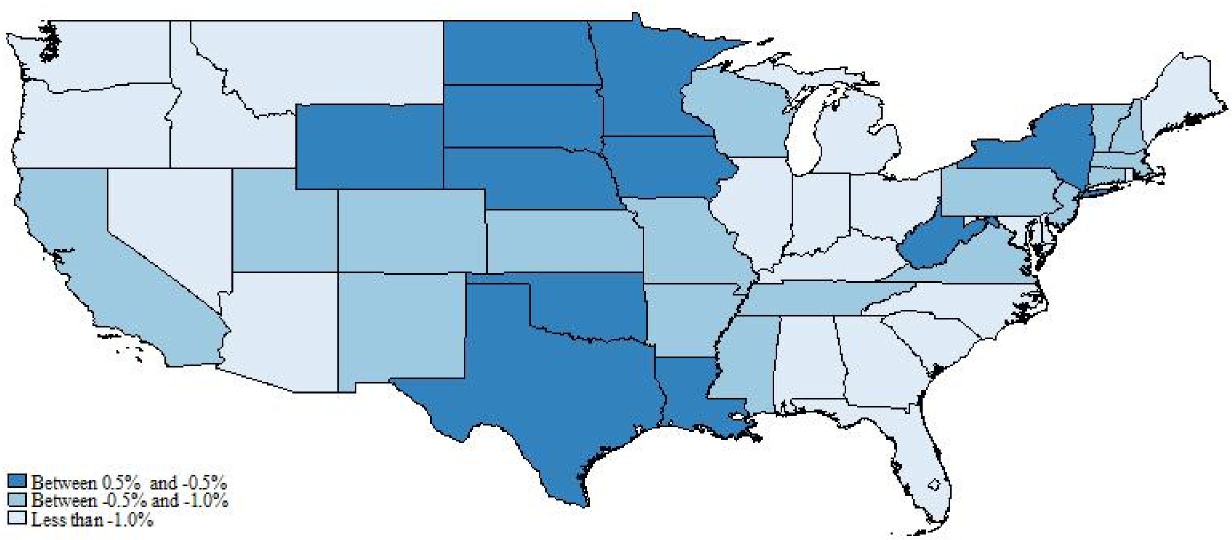


Figure 2: Data availability for prediction of the 2015:Q2 coincident index