Real activity forecasts using loan portfolio information*

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Abstract

Banks are important drivers of local economies as they provide capital to local businesses and households in the form of loans. To make lending decisions and monitor the extended loans banks collect detailed and often proprietary information about the financial prospects of their customers. Therefore, the state of banks' loan portfolios contains potentially useful information about contemporaneous and future local economic conditions. We investigate the association between information embedded in banks' loan portfolios and local economic conditions. Using a sample of US commercial banks for the period 1990:Q1 to 2010:Q4, we document that information about bank loan portfolios aggregated to the state-level is associated with current and future quarterly changes in state-wide economic conditions. Further, at the state-level, provision for loan and lease losses contains information that is useful for forecasting future state-level economic activity and recessions and is not contained in other state-level economic indicators. Out-of-sample tests suggest that using information about banks' loan portfolios can improve the prediction of the quarterly changes in state-level economic conditions of US states up to four quarters ahead. Our findings also indicate that bank loan portfolio information can help improve predictions of local economic conditions at more granular levels, such as the commuting zone level. Our study contributes to literatures on forecasting of regional economic conditions and on the informativeness of accounting information for the economy.

JEL Classification: *E01, E32, G21, M41.*

Keywords: Accounting information; banking; loan economic growth; portfolio quality.

1. Introduction

Economics literature has long recognized the crucial role the banking system plays in economic development. Early studies emphasize that banks can spur economic growth through affecting capital accumulation and by identifying and funding productive investments (Bagehot 1873; Schumpeter 1912). More recent studies empirically examine whether the level of financial intermediation is predictive of capital accumulation and productivity improvements at the national (e.g., King and Levine 1993; Levine and Zervos 1998) and state economy-levels (e.g. Samolyk 1994; Driscoll 2004). In deciding which positive net present value opportunities to fund, banks collect detailed, and often proprietary, information about their loan borrowers and continue to monitor them until the loan is repaid. The information about the health and prospects of loan borrowers is summarized in banks' disclosures about loan portfolios. Further, many bank loans are made to small firms and individuals that do not disclose financial information publicly (Petersen and Rajan 1994). Thus, the condition of banks' loan portfolios can provide insights about local economic activity by aggregating otherwise nonpublic information about the financial condition of businesses and households that are their borrowers. We investigate this conjecture and document that banks' loan portfolio information is predictive of state-level economic activity. Importantly, the information embedded in banks' loan portfolio related disclosures is incremental to information contained in other state-level economic indicators used for forecasting economic growth and recessions.

Bank lending by its nature is geographically segmented in local markets as loan monitoring costs increase with distance from the borrower (Salmolyk 1989; Laderman et al. 1991; Morgan and Salmolyk 2003). Petersen and Rajan (2002) point out the local nature of soft

information necessary for credit decisions.[1] Along the same lines, Agarwal and Hauswald (2010) empirically document that in small business lending, borrower proximity facilitates the collection of soft information and that a lender's ability to collect proprietary intelligence erodes with its distance from the borrower. Thus, we predict that measures of loan portfolio quality should associate with the contemporaneous and future growth in local economies. We also predict that to the extent banks incorporate proprietary soft information about borrowers into their assessments of loan portfolio quality; measures of loan portfolio quality would be incremental to leading economic indicators - which are typically based on publicly available hard information - in predicting local economic growth.

We define local economies as US states since most banks operate in a single state. For example, Morgan and Salmoyk (2003) find that at the end of 2001 the average bank holding company was operating in 1.7 states. Similarly, in our sample the average commercial bank collects over 95 percent of its deposits only from a single state. At the same time, understanding and forecasting economic trends in US states is important because they have a bearing on a wide array of matters ranging from corporate decision about the location of manufacturing units across the US (Bartik 2012) to the outcome of political elections (Niemi et al. 1995). Moreover, because of the costs involved in collecting and processing data series, most economic indicators are not directly measured beyond the state-level.[2] Therefore, we conduct our main analysis at the state-level. Nonetheless, in additional tests we show that loan portfolio quality can help improve predictions about future changes in economic conditions at the commuting zone-level.

[1] Soft information refers to information that cannot be easily and credibly communicated. By nature, soft information is hard to quantify. An example of soft information is the information obtained by a loan officer about the character of a company's manager, such as her work ethic, prudence or commitment (Petersen and Rajan 2002).
[2] Typically, indicators that are measured at more micro-levels are estimated based on state-level indicators and other indicators. For example, see Meyer and Yeager (2001) for a discussion of issues in estimation of labor and income at the county-level.

We examine banks' loan portfolio quality from three dimensions: estimated credit losses, risk premium on outstanding loans, and growth in loan portfolios. Bank managers are able to assess credit losses on their loans ahead of their realization to some extent (Liu and Ryan 2006; Nichols et al. 2009; Beatty and Liao 2011; Balasubramanyan et al. 2013) and banks tend to realize loan losses at higher rates during cyclical downturns (Laeven and Majnoni 2003).[3] Therefore, disclosure suggesting that banks expect greater losses on its outstanding loans can be indicative of slower economic growth in the future. We use the provision for loan and lease losses and the change in nonperforming loans to measure expected credit losses on banks' loan portfolios. Banks price protect against greater credit risk by charging a higher interest rate on loans (Morgan and Ashcraft 2003; Harris et al. 2013). Therefore, the risk premium on outstanding loans can be indicative of trends in future economic activity.[4] Finally, growth in loan portfolios can also be indicative of future economic activity. Banks are more willing to extend loans during expansionary phases and they raise their lending standards during contraction periods (Gilchrist and Zakrajsek 2012a). At the same time, demand for credit is also higher during expansions and falls during contractions. Therefore, trends in the growth rate of loan portfolios 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 period 1990:Q1 through 2010:Q4. We calculate state-level values of banks' loan portfolio variables by aggregating the relevant accounting variables for all commercial banks with operations in a

[3] Prior research provides some evidence consistent with bank managers using loan quality metrics for earnings 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.

[4] Similar arguments have been made in prior literature to explain the informativeness of credit spreads on corporate bonds (e.g., Gilchrist et al. 2009; Gilchrist and Zakrajsek 2012b) and the spread between commercial paper and Treasury bill rate (e.g., Friedman and Kuttner 1992) for future economic activity.

given US state. We identify the state(s) a bank operates using the Summary of Deposits (SOD) data collected by the Federal Deposit Insurance Corporation (FDIC). If a bank operates in more than one state, we adopt the approach used in the prior literature (e.g., Daly et al. 2003; Cetorelli and Strahan 2006) and estimate the extent of its operations in different states based on the proportion of deposits it collects in each state.

We use the state 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 for each of the 50 US states and is calculated using a system of models that include the following four state-level measures as inputs: nonfarm payroll employment, average hours worked in manufacturing, unemployment rate, and wage and salary disbursements deflated by consumer price index. [5] The trend in each state's index is set to the trend of its Gross State Product (GSP), which is disclosed on annual frequency. The coincident index has been used in the literature as a timely and comprehensive proxy for economic activity in US states (e.g., Massa et al. 2013; Massa and Zhang 2013).

We first examine the association between measures of loan portfolio quality and current and future changes in the state coincident index. In particular, we regress cumulative and marginal quarterly changes in the state coincident index on the state-level measures of loan portfolio quality. We find that the association between the contemporaneous change in coincident index and all measures of bank loan information is statistically significant in predicted directions. The economic and statistical significance of the bank variables gradually decrease as we predict changes in the coincident index farther into the future. Nonetheless, measures of expected credit losses, provision for loan and lease losses and change in nonperforming loans,

[5] 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.

remain predictive of cumulative and marginal changes in the state-level coincident index at least up to four quarters ahead.

We then test whether loan portfolio quality provides incremental information beyond state-level leading economic indicators in forecasting changes in the coincident indexes. Controlling for the growth rate in state-level personal income, state-wide change in housing prices, stock returns of firms headquartered in a state, the state-wide unemployment rate, the lagged changes in the state coincident index and the Federal Reserve Bank of Philadelphia's predicted growth rate of the coincident index, we find that provision for loan and lease losses is statistically significant when forecasting changes in the coincident index. For example, when the dependent variable is the cumulative change in the four-quarter ahead coincident index, the coefficient on provision for loan and lease losses is a negative and statistically significant 0.372. The contribution of provision for loan and lease losses to the prediction of changes in the coincident index is also economically significant. For example, one standard deviation increase in provision for loan and lease losses is associated with a 0.113% decrease in each of the next four quarters in the coincident index. To compare, the average quarterly change in the state coincident index is 0.476%. The information content of the remaining measures of loan portfolio quality is subsumed by the state-level leading economic indicators mentioned above.

Forecasting economic contractions is especially important because they can be a source of much economic hardship and can lead to social and political problems (Montgomery et al. 1998). Accordingly, we investigate the predictive content of banks' loan information for state-wide economic recessions, where we define state-level recessions as two or more quarters of negative changes in the state-wide coincident index. We find that provision for loan and lease losses has incremental explanatory power in predicting state-recessions. Again, the other loan

portfolio quality measures do not provide incremental information beyond the state-level economic indicators.

We also assess whether out-of-sample forecasts of coincident indexes can be improved upon with information about provision for loan and leases losses, which provides incremental explanatory power in the in-sample tests. Using expanding windows, we compare the forecasting performance of a model which includes state-level provision for loan and lease losses along with other state-level macroeconomic indicators against benchmark regression models that omit state-level provision for loan and lease losses. Based on Campbell and Thompson (2008) out-of-sample R^2 statistic, we find that, on average, models which include state-level provision for loan and lease losses reduce mean squared error by 16% to 18% in one quarter ahead predictions and 24% to 29% in four quarter ahead predictions of changes in state coincident indexes compared to benchmark models.

In additional tests, we investigate the usefulness of loan portfolio quality measures in predicting economic activity at the commuting zone-level. Commuting zones were developed by the Department of Agriculture in the 1980s for the purpose of delineating local labor markets and economies.[6] Each zone is composed of several counties and each county belongs to one zone. Since there is no summary measure of economic activity at the commuting zone-level, we use changes in unemployment rates as an indicator of economic activity. We find that the two measures of expected credit losses, provision for loan and lease losses and changes in non-performing loans, continue to provide incremental predictive power for four-quarter-ahead changes in unemployment rates after controlling for lagged changes in unemployment rate. The finding that loan quality measures are useful in predicting future economic activity at the commuting zone-level is significant since it suggests that publicly available data about banks

[6] See Tolbert and Sizer (1996) for a comprehensive overview of identification of commuting zones.

may be helpful in predicting economic growth at levels where few other leading indicators are available.

Our study is related to the nascent and growing literature investigating the relation between accounting information and macroeconomic indicators. Gallo et al. (2013) find that aggregate accounting earnings are useful in predicting Federal Reserve's future monetary policies. Shivakumar (2006) and Kothari et al. (2013) find that aggregate earnings surprises contain information about future inflation. Kothari et al (2013) also show that macroeconomic forecasters do not fully utilize this information. Hann et al. (2012) document that aggregate earnings' forecasts by sell-side stock analysts do not fully incorporate information about macroeconomic news. Several other studies have examined the informativeness of aggregate earnings with respect to nominal and real GDP forecasts (e.g., Kalay et al. 2013; Konchitchki and Patatoukas 2013, 2014; Nallareddy and Ogneva 2014). Shivakumar (2007, 2010) calls for additional research to better understand of the associations 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 drawing linkages between accounting estimates and macroeconomic conditions we document the predictive content of a previously unexplored set of accounting information, information about the condition of banks' 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 local regions depending on the characteristics of the local regions (e.g., their interstate linkages, industrial composition). Disparities in local economic conditions may be obscured when aggregated at the national level. For example, consider changes in US state coincident indexes

during the three months ended in September 2005 and September 2008, presented in Figure 1. According to National Bureau of Economic Research (NBER), the national US 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. In fact, during our sample period the correlation between the coincidence of state-level and national recessions is only 54 percent.

Our study is also related to research examining the relationships between local economic conditions and bank performance. Neely and Wheelock (1997) examine how bank profitability and asset quality is associated with state economic conditions, and find that dispersions in state economic conditions can explain a large portion of the observed differences in bank profitability and asset quality. Nuxoll et al. (2003) examine whether current and past state-level economic data can improve off-site bank monitoring models. They find that current and past economic data do not improve predictions of bank failures or asset quality. Samolyk (1994) reports that in financially distressed regions, local bank credit problems can constrain economic activity.[7]

The rest of the paper is organized as follows. Section 2 provides institutional information and presents our predictions. Section 3 describes the research design and sample selection. Section 4 presents our findings and Section 5 concludes the paper.

2. Background information and empirical predictions

In the US, whether privately-held or publicly-traded, every national, state-member, and insured non-member commercial bank is required by the FFIEC to file Reports of Condition and Income as of the close of business on the last day of each calendar quarter. These filings contain

[7] Samolyk (1994) investigates the regional credit view which posits that performance of the banking sector can influence economic activity. She reports that in states where lagged nonperforming loan shares are above the national average, bank balance-sheet condition explains more of state-level income growth. Unlike our study, she does not investigate the incremental contribution of bank loan quality information beyond leading economic indicators in predicting future changes in state-level economic activity.[8] Banks are required to use the *incurred loss model* as described in Statement of Financial Accounting Standard No. 5 to estimate the losses on loans held for investment. This model requires that loss should be recognized when probable and can be reasonably estimated as of the date of the financial statements.

financial statements as well as mandatory disclosures about banks' loan portfolio quality. To examine whether these disclosures are informative about local economic conditions, we focus on three attributes of the banks' loan portfolio quality – estimated credit losses, risk premium on outstanding loans, and the growth rate of the loan portfolio.

We use two measures, the provision for loan and lease losses and changes in nonperforming loans, to capture the trend in credit losses of banks' loan portfolios. The provision for loan and lease losses is an estimate of credit losses attributable to originating and holding loans during the relevant accounting period, and the expected loss conditional on default of such loans. In every quarter, banks reevaluate their loan portfolios and record provisions for loan losses to bring the allowance for loan and lease losses to a level enough to cover losses that are projected to occur over the next four quarters (OCC Handbook 1998).[8] In other words, the provision recorded in each quarter reflects an adjustment to banks' projections of loan performance. Consistent with this conjecture, prior research has documented that provisions contain forward-looking information. (e.g., Liu and Ryan 2006; Nichols et al. 2009; Beatty and Liao 2011; Balasubramanyan et al. 2013).[9]

Nonperforming loans refer to loans that lag in scheduled payment and are equal to the sum of nonaccrual loans (i.e., loan that are more than 90 days delinquent and not accruing interest), past due loans (i.e., loans that are more than 90 days delinquent and still accruing interest) and troubled restructured loans. Relative to the allowance and provision, which are more discretionary and prone to being used to manage book value and earnings, nonperforming

[8] Banks are required to use the *incurred loss model* as described in Statement of Financial Accounting Standard No. 5 to estimate the losses on loans held for investment. This model requires that loss should be recognized when probable and can be reasonably estimated as of the date of the financial statements.

[9] The extent to which individual banks are forward-looking in accounting for their loan losses varies in the cross-section depending on several characteristics including ownership, loan composition, business cycles, profitability, regulatory capital ratios, etc. For example, Nichols et al. (2009) report that, relative to privately held banks, publicly traded banks are more timely in recognizing loan losses.

loans are less discretionary (Beaver et al. 1989; Griffin and Wallach 1991). Harris et al. (2013) document that both provisions and nonperforming loans contain information relevant for predicting future credit losses. Therefore, we use provision for loan and lease losses as well as nonperforming loans to capture trends in the credit risk profile of banks' loan portfolios.

Risk premium on loans--the difference between average yield on loans and the risk free rate--can also be informative about future economic conditions. Risk premium banks charge on loans is primarily determined by borrowers' probability of default. Theoretically, banks can price protect themselves for greater risk in lending by charging higher interest. Consistent with this notion, Harris et al. (2013) show that loan yield is positively associated with future credit losses. Using a sample of commercial and industrial loans, Morgan and Ashcraft (2003) document that loan spreads are predictive of loan performance up to four quarters ahead. Similarly, prior research reports that credit spreads on corporate bonds (e.g., Gilchrist et al. 2009; Gilchrist and Zakrajsek 2012b) and the spread between commercial paper and the T-bill rate (e.g., Friedman and Kuttner 1992) has information about future economic activity. Therefore, risk premium on loans can provide information relevant for the state of the economy as credit risk is likely to be lower (higher) during expansions and increases (decreases) as the economy contracts (expands). However, the market for bank lending may not operate like other markets where the prices do all the adjustment in response to changes in risk for the market to clear. Rather than raising interest rates on loans, banks may tighten lending standards and cut off credit to the marginal borrowers that do not meet the higher standards (Lown et al. 2000; Lown and Morgan 2006).

The final attribute of loan portfolio quality we examine is loan growth. Firms demand more credit during expansions and banks are more willing to lend during such times. On the contrary, during contractions, credit demand falls. At the same time banks raise their lending

standards during contractionary periods and are reluctant to lend (e.g., Lown et al. 2000; Lown and Morgan 2006). Gilchrist and Zakrajsek (2012a) report that bank lending is highly cyclical. Therefore, the growth rate of bank lending is likely to be informative about the contemporaneous and future states of the economy. We conjecture that loan growth is higher when the economy is expanding or expected to expand and examine whether the growth rate of banks' loan portfolios is predictive of local economic conditions.

3. Research design, data, and sample selection

3.1. Research design

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

Our study investigates whether information about loan portfolios aggregated at a local economy level is informative about the contemporaneous and future conditions of the local economy. We use US states as the unit of aggregation since measures and benchmark predictors of economic growth are available at the state-level and it is possible to identify commercial banks operating in a given state with good precision. 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 (Adams et al. 2007; Salmolyk 1989). 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 (they define a market as a Metropolitan Statistical Area or all rural counties in a single 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 percent to only about 75 percent from 1994 to 2001. In our setting, the diversification across markets is even less because we conduct our tests using commercial bank

data, not bank holding company data, and commercial banks usually operate as local subsidiaries of bank holding companies. In particular, 77 percent of commercial banks in our sample collect deposits from only one state during the entire period that they appear in our sample and the average bank collects over 95 percent of its deposits in a single state (see Appendix A).

Further, forecasting local economic conditions is important as they influence a variety of decisions and it is an area that remains relatively under-researched. For example, local economic conditions influence corporate decisions like the location of retail and manufacturing units (Bartik 2012), labor demand and participation (Tokle and Huffman 1991), and outcomes of political elections (Niemi et al. 1995). Moreover, national economic trends can materialize differently across the local economies depending on individual areas' characteristics. For example, the correlation between the coincidence of a recession at the state- and national-level in the US during our sample period is only 0.54, when a state recession is defined as two or more quarters of negative change in the coincident index. Therefore, we choose US states as the unit of analysis in our main tests. In Section 4.4, we conduct additional analyses to demonstrate that information about loan portfolios has predictive content at an even finer level, namely at the commuting zone-level.

We use the state coincident index published by the Federal Reserve Bank of Philadelphia as a measure of economic activity at the state-level. This index is calculated monthly for 50 states and serves as a comprehensive and timely measure of economic activity at the state-level (e.g., Massa, Yasuda and Zhang 2013; Massa and Zhang 2013).

To examine the association between information about loan portfolios and changes in state coincident index we estimate the following least squares regression model:[10]

[10] In untabulated analysis, use a panel vector autoregression with two lags to analyze the concurrent association between changes in coincident index and each of the variables in this model individually without the fixed effects.

$$\Delta COINDEX_{s,t+i} = \alpha + \beta_1 xPLLTL_{s,t} + \beta_2 x\Delta NPLTL_{s,t} + \beta_3 xEXYIELD_{s,t} + \beta_4 xLGROWTH_{s,t} + \beta_5 xALLTL_{s,t-1} + \sum_{m=1}^{m=49} \beta_{5+m} xFE_s + \varepsilon_{s,t} \quad , \tag{1}$$

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 sampling period is quarterly, but the forecasting horizon *i* varies from one to four quarter 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. $EXYIELD_{s,t}$ is the difference between the ratio of state-level interest and fee income on loans to average state-level total loans and three-month treasury-bill rate. $LGROWTH_{s,t}$ is the quarterly percentage growth in state-level loans. $ALLTL_{s,t-1}$ is one quarter lagged value of state-level allowance for loan and lease losses scaled by end of quarter state-level total loans. 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 in a given quarter. For banks that operate in more than one state, we weigh accounting variables by the percentage of 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. Daly et al. 2003; Cetorelli and Strahan 2006).[11]

Our results remain qualitatively similar with the exception of excess yield, which is not associated with the coincident index.

[11] If the percentage of deposits a bank has in a given state is not a good indicator of the bank's lending operations in that state as banks may collect deposits in a state different from where they lend, using the data on deposits to compute bank lending in a given state can result in noisy estimates of banks' operations in the different US states. To address this concern, we investigate the robustness of our findings by restricting the sample to banks that operate

In this model we predict β_1, β_2, and β_3 to be negative since higher provisions, nonperforming loans and risk premiums should imply weaker economic conditions. We predict β_4 to be positive as growth in financing should be positively associated with economic growth. Beatty et al. (1995) and Wahlen (1994) explain that over (under) reserving in prior periods would lead to lower (higher) current period provisions, accordingly we include lagged allowance for loan and lease losses to control for any such effect. Following these studies we include $ALLTL_{s,t-1}$ as a control variable. 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. Finally, we include state-fixed effects (FE_s) in our regressions to control for omitted time invariant state-specific characteristics that may influence the informativeness of accounting information with respect to the local economy. To account for serial correlation, we cluster standard errors by quarter.[12]

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

To assess the usefulness of information about loan portfolios in predicting future 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 state-level indicators that are useful in predicting economic conditions?

We use two measures as benchmark predictors of state-level macroeconomic conditions: state leading index ($LEADINDEX_{s,t}$) and value-weighted stock return of publicly traded firms ($VWRET_{s,t}$) headquartered in a given state. State leading index is published by the Federal Reserve Bank of Philadelphia specifically as a predictor of the six-month *growth rate* of the

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branches in only one state and focusing on state-years for which such banks account for at least 75 percent of total state-wide deposits. The results using the restricted sample are qualitatively similar to those reported in the paper.

[12] Our results are not sensitive to leaving out state fixed effects and double-clustering in firm and time dimensions simultaneously.

state's coincident index. The state leading indexes are constructed using vector autoregressions utilizing current and prior values of the state coincident indexes, state-level housing permits, state initial unemployment insurance claims, delivery times from the Institute for Supply Management manufacturing survey and the interest rate spread between the 10-year Treasury bond and 3-month Treasury bill. We use value-weighted stock return of publicly-traded firms as an additional control since Korniotis and Kumar (2013) show that stock returns of local firms also vary with state-business cycles. We calculate this measure using data from *CRSP*.

In particular, to examine the usefulness of banks' loan information we estimate the following linear model:

$$\begin{aligned}\Delta COINDEX_{s,t+i} = \alpha + \beta_1 xPLLTL_{s,t} + \beta_2 x\Delta NPLTL_{s,t} + \beta_3 xEXYIELD_{s,t} + \beta_4 xLGROWTH_{s,t} \\ + \beta_5 xALLTL_{s,t-1} + \beta_6 xLEADINDEX_{s,t} + \beta_7 xVWRET_{s,t} + \sum_{m=1}^{m=49} \beta_{7+m} xFE_s + \varepsilon_{s,t} \quad .\end{aligned} \tag{2}$$

To the extent information about loan portfolios reflects factors other than those that are captured by the leading index and stock returns, we expect to observe statistically significant coefficients on β_1- β_4.

As an alternative specification, we also report results where we replace $LEADINDEX_{s,t}$ with other economic indicators that are available at the state-level and to some extent are incorporated into the calculation of leading index. In particular, we include the concurrent and lagged changes in state coincident index, percentage change in a state's purchase-only housing price index obtained from the Federal Housing Finance Agency ($\Delta HOUSING_{s,t,}$), and quarterly growth rate in total personal income ($PIGROWTH_{s,t}$) and change in state-level unemployment rate ($\Delta UNRATE_{s,t}$) both of which are obtained from the Bureau of Economic Analysis. The alternative specification is:

$$\begin{aligned}\Delta COINDEX_{s,t+i} = \gamma &+ \delta_1 xPLLTL_{s,t} + \delta_2 x\Delta NPLTL_{s,t} + \delta_3 xEXYIELD_{s,t} + \delta_4 xLGROWTH_{s,t} \\ &+ \delta_5 xALLTL_{s,t-1} + \sum_{r=0}^{r=3} \delta_{6+r} x\Delta COINDEX_{s,t-r} + \delta_{10} xHOUSING_{s,t} + \delta_{11} xPIGROWTH_{s,t} \\ &+ \delta_{12} x\Delta UNRATE_{s,t} + \delta_{13} xVWRET_{s,t} + \sum_{m=1}^{m=49} \delta_{13+m} xFE_s + \varepsilon_{s,t} \quad .\end{aligned} \tag{3}$$

3.2. Sample selection and descriptive statistics

Our sample is comprised of US commercial banks that file the Reports of Condition and Income (also known as "call reports") with the FFIEC. We begin our sample selection with 832,224 quarterly bank observations which span 84 quarters from 1990:Q1 to 2010: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.[13] Our sample period ends with the last quarter of 2010 since consistency of data items in call reports changed in 2011.

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 (*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 non-negative and less than end of quarter total loans, (iii) absolute value of provision for loan and lease losses (*RIAD4230*) is less than the average balance of total loans, and (iv) interest income (*RIAD4010*) is non-negative and is smaller than the average balance of total loans.[14] These filters eliminate 63,570 observations with missing/invalid data. Even after these filters, some observations exhibit extreme loan growth in our sample. To ensure our results are not driven by

[13] For example, Tax Reform Act of 1986 eliminated the opportunity to subtract, as a pre-tax expense, any provision for loan losses beyond actual charge-offs. Additionally, Kim and Kross (1998) shows that 1989 change in bank capital standards largely eliminated banks' incentives to use loan loss provisions and charge-offs for capital management purposes.

[14] In the call reports, income statement items are reported on a year-to-date basis. We calculate quarterly values by first-differencing the values for all quarters except the first quarter of each year.

these outliers –which could be data errors– we eliminate 7,686 observations that are in the top and bottom half-percentile based on loan growth rate. Our results 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.[15] 2,117 bank-quarters have missing/invalid data on state-level deposits and hence are excluded from the analysis. Our final sample contains 758,851 bank-quarters from 15,949 unique banks.

(Insert Table 1 about here)

Table 1 reports descriptive statistics at the bank-level for the final sample. The average bank has $746 million in total assets and $439 million in total loans. A comparison of these values with the 75th percentile values, which are $184 million and $117 million for total assets and total loans, respectively, suggests that most of the banks in our sample are relatively small and a few of them are very large. Median loan growth is about 1.72% per quarter and the median quarterly provision for loan and lease losses is 0.05% of average total loans. The median allowance for loan losses is about 1.35% of end of quarter total loans which is larger than 0.76%, the median of nonperforming loans. On average, the annualized yield on loans is about 8.76%.

[15] In support of this argument, 99% of the banks in 1994 SOD file operate in only one state. As a robustness check we also used 1994 values as a proxy for each bank's operations in a given state for years before 1994 and find that the results are qualitatively similar to those reported.

Appendix A provides the distribution of bank-quarter observations in our sample across the states. 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 Appendix A is greater than that reported in Table 1. In our sample, the state of Texas (Alaska) has the most (fewest) number of bank-quarterly observations. The average percentage of operations of banks in a given state based on the SOD data is also provided in Appendix A. Over our sample period, the average bank has over 95% of its operations in a single state. In fact, 77% of the banks in our sample collect deposits from a single US state during the entire period that they appear in our sample. This suggests bank-level variables aggregated to the state-level are likely to provide information about the local economy in a representative manner.

Table 2 presents the descriptive statistics for the variables used in the state-level analyses. The table provides statistics for 50 states and 83 quarters. The District of Columbia is not included in our tests since The Federal Reserve Bank of Philadelphia does not estimate the coincident index and leading index for the District of Columbia. The first quarter of the sample period is used for calculation of changes therefore it is also not included in our tests.

(Insert Table 2 about here)

Table 2 Panel A reports summary statistics for the sample at the state-level and Panel B reports pairwise Pearson and Spearman correlation coefficients between variables. Δ*HOUSING* is not available for the first four quarters of sample period since Federal Housing Finance Agency started disclosing the housing index in 1991. At the state-level, median quarterly loan growth (*LGROWTH*) is around 2.0%. This is slightly higher than the median national loan growth rate of 1.64% for the same period according to data from the Federal Reserve Economic Data. The mean and median values for *PLLTL* are 0.26% and 0.14%, respectively, suggesting

that around a quarter percent of average loan balance is recorded as expected losses in a given quarter. In contrast, the median *ΔNPLTL* is close to zero. The Pearson correlation coefficient between these two variables is only 0.34 suggesting that there are significant differences in the attributes of credit risk captured by each of the variables. The Pearson correlation between *EXYIELD*, which is equal to the difference between the annualized ratio of interest and fee income on loans to average balance of loans and three-month treasury bill rate, and *PLLTL* is 0.63, suggesting that provisions are higher when credit risk is elevated.

The correlations between state-level loan portfolio variables and changes in coincident index are in the expected directions and statistically significant. Pearson correlation coefficients between concurrent values of *ΔCOINDEX* and *LGROWTH*, *PLLTL*, *ΔNPLTL*, and *EXYIELD* are 0.18,-0.35, -0.53, and -0.15, respectively. Moreover, these loan portfolio variables also have significant univariate associations with *LEADINDEX* which measures predicted future economic conditions. Overall, these correlations suggest that loan portfolio information is associated with current and future economic conditions, raising the prospect that they may be useful for predicting economic activity. In the next section, we use multivariate tests to analyze the relations between loan portfolio information and current and future economic conditions. In these tests we also examine whether loan portfolio variables provide incremental explanatory power beyond other state-level economic indicators in predicting economic activity.

4. Results

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

We begin our analysis by examining whether loan portfolio data aggregated at the state-level are associated with current and future economic activity within a state. We measure future

economic activity using cumulative and marginal changes in coincident index, where cumulative changes are calculated as

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

and marginal changes are calculated as:

$$\Delta COINDEX_{s,t+i-1,\, t+i} = 100 * ((COINDEX_{s,t+i} - COINDEX_{s,t+i-1})/ COINDEX_{s,t+i-1}). \quad (5)$$

Cumulative change is the average change in 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 3 we present estimates from equation (1) using least squares regression, where we cluster standard errors by quarter. Consistent with our predictions, a decline (improvement) in aggregate loan portfolio quality is generally associated with a concurrent and future deterioration (improvement) in state economic conditions. The concurrent association between coincident index and aggregate loan portfolio quality is statistically significant for all measures of aggregate loan portfolio quality. The association between one quarter ahead coincident index and aggregate loan portfolio quality is also significant for all variables except excess yield (*EXYIELD*).

(Insert Table 3 about here)

The economic and statistical significance of variables gradually decrease as we predict farther in the future. Nonetheless, provision for loan and lease losses (*PLLTL*) and changes in nonperforming loans (*ΔNPLTL*) continue to predict future changes in the coincident index in the longer horizon up to four quarters ahead. The estimated coefficient on *PLLTL* ranges between -1.218 (-1.021) and -1.368 (-1.364) when the dependent variables is the cumulative (marginal) change in the coincident index ranging from one-quarter ahead to up to four-quarters ahead.

With respect to *ΔNPLTL* , the magnitude of the coefficient ranges between -0.885 (-0.632) and -1.122 (-1.122) when the dependent variable varies between one-quarter ahead to four-quarter ahead cumulative (marginal) change in the coincident index. Moreover, their contribution to the prediction of coincident index is economically significant. For example, all else equal, if the provision for loan and lease losses as a percentage of total loans increases by one standard deviation (i.e., 0.304) then the last column in cumulative change analysis shows that coincident index from current quarter t to quarter t+4 decreases by 1.481% ((0.304 x -1.218) x 4). Similarly, one standard deviation increase in the change in nonperforming loans as a percentage of total loans (i.e., 0.243) is associated with 0.860% ((0.243 x -0.885) x 4) decline in coincident index during the same cumulative period. As the coefficients indicate, the predictive power of provisions is greater than that of the nonperforming loans in the long-term. This is consistent with provisions containing more forward-looking information than nonperforming loans. Lagged allowance for loan and lease losses (*ALLTL*), which is included as a control for under-or over-reserving in prior periods has a positive and statistically significant coefficient in all models.

In untabulated tests, we test and find that the significant coefficient on PLLTL is not driven by the recent financial crisis years (i.e., 2007-2010) but the coefficient on ALLTL becomes insignificant or marginally significant in most models when these years are excluded. This suggests that the positive coefficient on *ALLTL* is likely driven by the fact that it is a stock variable that adjusts slowly relative to the dependent variable which measures changes in a given period.[16]

The coefficient of determination, R^2, provides a measure of in-sample forecasting accuracy. This measure indicates that the models can explain between 22% and 37% of the

[16] For example the economy exhibited positive growth rates since bottoming in the second quarter of 2009, while the allowances for loans and leases losses, which increased drastically in 2008, remained high until the end of our sample period.

variation in future changes in coincident index. Accordingly, these results suggest that information about loan portfolios is strongly associated with current and future changes in state-level economic activity. In the next section we test whether loan portfolio information contains information that is not reflected in known predictors of future changes in state-level economic activity.

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

In this section, we examine whether information about loan portfolios provides information incremental to that contained in other state-level 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 and cluster standard errors by quarter. Table 4 presents results from this analysis.

In Table 4 Panel A, the known state-level economic indicators include state-leading index (*LEADINDEX*) and value-weighted stock returns from firms headquartered in the state (*VWRET*). Controlling for these two variables, provision for loan and lease losses and excess yield are statistically significant in expected directions when predicting one-quarter-ahead changes in coincident index. The remaining loan portfolio variables, including changes in nonperforming loans, are statistically not significant in all models suggesting that these variables are not incrementally informative in predicting economic activity. The predictive power of excess yield also diminishes beyond one quarter. Among the loan portfolio variables that are predicted to be associated with changes in state coincident index, only provision for loan and lease losses remains statistically significant in all models using both cumulative and marginal changes in the coincident index as the dependent variable. The estimated coefficient on provision for loan and lease losses ranges between -0.218 (-0.218) to -0.372 (-0.455) when the dependent

variable from one-quarter ahead cumulative (marginal) change in coincident index to the four-quarter ahead change. The ability of provisions in predicting relatively long term changes in economic activity is consistent with the fact that provisions incorporate information about loan losses that are projected to occur at least over the next four quarters for most loan pools (OCC Handbook 1998).

The contribution of provision of loan and lease losses in predicting changes in coincident index is economically significant as well. For example, all else equal, if provision for loan and lease losses increases by one standard deviation, the four-quarters ahead column in the cumulative changes regression implies that the state coincident index would decline by 0.113% (=0.304 x -0.372) on average each quarter over the next four quarters or about 0.452% ((=0.304 x -0.372) x 4) in total. In comparison, in the same analysis one standard deviation increase in leading index predicts that the state coincident index would increase by 0.602% (=1.609 x 0.374) on average each quarter over the next four quarters. The average quarterly change in state coincident index is 0.476%. The association between value-weighted quarterly stock returns of firms headquartered in a given state (*VWRET*) and changes in coincident index are also positive and statistically significant, suggesting that it is incrementally useful in the prediction of state-level economic activity as well.

(Insert Table 4 about here)

In Table 4 Panel B, we replace the state-leading index with four other macroeconomic measures including the concurrent and three lags of the change in coincident index, percentage change in a state's purchase-only housing price index obtained from the Federal Housing Finance Agency (Δ*HOUSING*), quarterly growth rate in total personal income (*PIGROWTH*) and change in state-level unemployment rate (Δ*UNRATE*). The results in Panel B with respect to loan

portfolio based variables remain similar to those in Panel A with the exception that excess yield becomes statistically insignificant in all models. However, provision for loan and lease losses remains statistically significant and negative in all models. Relative to Panel A, the magnitude of the coefficient on provision for loan and lease losses is slightly larger. The estimated coefficient ranges between -0.298 (-0.298) and -0.528 (-0.656) when the dependent variable from one-quarter ahead cumulative (marginal) change in the coincident index to the four-quarter ahead change.

In Panel B, the slope coefficient on the current quarter's and the lagged changes in state-wide coincident index are statistically significant in predicting one quarter ahead changes in coincident index. The current quarter change in the state-wide housing price index is positively associated with future changes in the coincident index. However, the current quarter growth in total personal income is negatively and the current quarter change in unemployment rate is positively associated with future changes in the coincident index. These counterintuitive results with respect to personal income and unemployment rate are due to the inclusion of concurrent and lagged changes in coincident index in the model along with concurrent growth in personal income and change in unemployment rate. The coincident index explicitly incorporates changes in state-level unemployment rate and wage and salary disbursements, a major component of personal income.[17]

To summarize, the evidence presented in Table 4 suggests that aggregate state-level 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 in the state it is also incrementally predictive about changes in the economic conditions after

[17] In untabulated tests we confirm that personal income growth is positively and change in unemployment rate is negatively associated with future changes in coincident index when the concurrent and lagged values of coincident index are excluded from the model.

controlling for other contemporaneous predictors of state-level economic conditions. Whereas, the information content of the other loan portfolio measures is subsumed by known predictors of future state-level economic activity.

As an extension of the analysis in Table 4, we also examine whether loan portfolio information can help predict more drastic changes in economic activity. Put differently, given that measures such as provisions aim to measure potential losses, they may also be a good predictor of recessions. In order 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 economic variables used in Table 4.

$$\begin{aligned}\Pr(STREC_{s,t+4}) = \Lambda(&\alpha + \beta_1 xPLLTL_{s,t} + \beta_2 x\Delta NPLTL_{s,t} + \beta_3 xEXYIELD_{s,t} + \beta_4 xLGROWTH_{s,t} \\ &+ \beta_5 xALLTL_{s,t-1} + \beta_6 xLEADINDEX_{s,t} + \beta_7 xVWRET_{s,t} + \sum_{m=1}^{m=49} \beta_{7+m} xFE_s + \varepsilon_{s,t}) \quad ,\end{aligned} \tag{6}$$

$$\begin{aligned}\Pr(STREC_{s,t+4}) = \Lambda(&\gamma + \delta_1 xPLLTL_{s,t} + \delta_2 x\Delta NPLTL_{s,t} + \delta_3 xEXYIELD_{s,t} + \delta_4 xLGROWTH_{s,t} \\ &+ \delta_5 xALLTL_{s,t-1} + \sum_{r=0}^{r=3} \delta_{6+r} x\Delta COINDEX_{s,t-r} + \delta_{10} xHOUSING_{s,t} + \delta_{11} xPIGROWTH_{s,t} \\ &+ \delta_{12} x\Delta UNRATE_{s,t} + \delta_{13} xVWRET_{s,t} + \sum_{m=1}^{m=49} \delta_{13+m} xFE_s + \varepsilon_{s,t}) \quad .\end{aligned} \tag{7}$$

where the dependent variable, *STREC*, is equal to one if quarter t+4 is a recession quarter for state s, and zero otherwise. 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 negative changes in the coincident index. This definition is also analogous to the conventional way of determining national recessions as two consecutive quarters of decline in GDP (e.g., Estrella and Hardouvelis 1991; Fair 1993). Based on this definition, there are 150 unique state-recessions (886 state-quarters) and the average length of state-recessions is 5.9 quarters. During the sample period, Hawaii is the most recession prone state whereas North Dakota and Wyoming have spent the least amount of time in recessions. The

correlation between indicators for state recessions and an indicator for national recessions as defined by the NBER is 54 percent, which suggests that state-recessions fairly often do not coincide with national recessions.

(Insert Table 5 about here)

We present estimates from the logistic models defined in equations (6) and (7) in Table 5. The results from the model indicate that provision for loan and lease losses have incremental explanatory power in predicting state-recessions. The coefficient on *PLLTL* is statistically significant and it is also economically large. For example, the average marginal effect of the *PLLTL* is 0.201 in the model with *LEADINDEX* and in comparison the average marginal effect of *LEADINDEX* is about -0.07 (not reported in the table). Similar to Table 4, remaining loan portfolio measures become insignificant when we control for other economic factors. These results once again indicate that provision for loan and lease losses is useful in predicting future state-level economic activity.

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

In this section, we assess the out-of-sample performance of provision for loan and lease losses in forecasting future changes in state-wide economic activity. Estrella and Mishkin (1998) show that parsimonious models work best for out of sample predictions. Based on in-sample analyses, we find that provision for loan and leases losses is the only robust banks' loan related predictor of economic activity that provides incremental explanatory power beyond other known state-level economic indicators. Accordingly, in out of sample tests we limit our analyses of the usefulness of loan portfolio information to provision for loan and lease losses. In particular, we test whether future changes in coincident index can be improved upon by using real-time

information about provision for loan and lease losses. For this analysis we estimate the following model by each state separately:

$$\Delta COINDEX_{t+i} = \alpha + \beta_1 xPLLTL_t + \beta_2 xALLTL_{t-1} + \beta_3 xLEADINDEX_t + \beta_4 xVWRET_t + \varepsilon_t \quad , \tag{8}$$

and, compare its forecasting power with the following benchmark model that excludes loan portfolio related variables:

$$\Delta COINDEX_{t+i} = \alpha + \beta_1 xLEADINDEX_t + \beta_2 xVWRET_t + \varepsilon_t \quad . \tag{9}$$

As an alternative, we also run these models by replacing $LEADINDEX_{s,t}$ with concurrent value and three lags of $\Delta COINDEX_{s,t}$, as well as $\Delta HOUSING_{s,t}$, $PIGROWTH_{s,t}$ and $\Delta UNRATE_{s,t}$. Similar to our main analysis, we run these regressions using both 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.[18] The out-of-sample forecast power of the full model defined in (8) is then compared against the benchmark models based on the out-of-sample R^2 statistic as described in Campbell and Thompson (2008). The out-of-sample R^2 statistic is estimated as follows:

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

where i ranges from zero to four, $\Delta COINDEX$ is the actual quarterly change in the state-wide coincident index, $\Delta COINDEX^{FULL}$ is the fitted value from the full predictive regressions specified in equations (8) estimated through quarter t-1, and $\Delta COINDEX^{BENCHMARK}$ is the fitted value from the benchmark predictive regressions specified in equations (9) estimated through quarter t-1. The numerator and the denominator of the ratio in (10) are the mean-squared errors

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

from full and benchmark regressions, respectively. If the out-of-sample R^2 is positive, it implies that the full predictive model has a lower mean-squared prediction error than the benchmark models. That is, provision for loan and lease losses contributes to the out-of-sample prediction of quarterly changes in the state-wide 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 6 about here)

The results of the out-of-sample forecasting power tests are reported in Table 6. In both Panel A and Panel B, the evidence suggests that provision for loan and lease losses improves the out-of-sample prediction of quarterly changes in state-wide coincident index up to four quarters ahead. The out-of-sample R^2 statistic is positive in all specifications and ranges from 16.1% to 26.3% in Panel A, and from 18.0% to 29.4% in Panel B. The comparison of mean absolute errors also indicates that mean absolute error is statistically significantly smaller in the model that includes provision for loan and lease losses compared to the benchmark model. Consistent with the in-sample findings, the contribution of provision for loan and lease losses beyond the benchmark models increases as the horizon for the prediction of the change in the coincident index becomes longer. These findings hold whether the dependent variable in estimation is cumulative or marginal changes in the coincident index.

4.4. Is loan portfolio information useful in predicting economic activity at a finer-level?

Our main findings indicate that information about loan portfolios is not only associated with the current economic conditions within a state, but also is informative about future economic conditions. In this section, we extend our tests to examine the informativeness of the information about loan portfolios at a finer delineation of the local economy, where we define

local economies using commuting zones. From an economic point of view, state boundaries are largely arbitrary and 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. 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 US 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. Because of the seasonal patterns in unemployment, we use seasonally differenced unemployment rates in these tests. In other words, the dependent variable for this analysis is equal to the difference between the unemployment rate for quarter t+4 and quarter t at the CZ-level. Similar to the main analysis, we calculate our independent variables by aggregating bank-level accounting information over all banks operating in a given commuting zone each quarter. When a bank operates in more than one commuting zone, we allocate weights to the accounting variables based on the bank's percentage of deposits originating in a given commuting zone. Since data on other control variables used in the state-level tests (*PIGROWTH*, *ΔHOUSING* and

VWRET) are not available at the CZ-level, these variables are not included in the analysis. We cluster standard errors in both time and commuting zone dimensions.

(Insert Table 7 about here)

Table 7 provides results from this analysis. Consistent with our findings at the state-level, we find that provisions 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, excess yield and loan growth are insignificantly associated with the unemployment rate at the CZ-level. Overall, based on the findings in Table 7 we conclude that loan portfolio information is also informative about local economic conditions at a finer, commuting zone-level.

5. Conclusion

We investigate whether information about loan portfolios is associated with the current and future economic activity at the state-level. We find that at the state-level, information about expected credit losses, risk premium on outstanding loans, and loan growth rate is associated with the contemporaneous and future quarterly changes of the state-wide economic activity measured using the coincident index. More importantly, we find that provision for loan and lease losses, an estimate of credit losses attributable to originating and holding loans during a period, can help predict future quarterly cumulative and marginal changes in the state-wide coincident index. The provision for loan and lease losses is also useful in forecasting state-wide recessions. The out-of-sample analysis suggests that prediction models that include aggregate state-level provisions outperform benchmark models that exclude such information. Taken together, our results have practical implications as they suggest that state-wide economic forecasts of the

coincident index can be improved upon by using real-time accounting information about banks' loan portfolios. In additional tests, we show that loan portfolio information is also useful in predicting economic conditions at a finer-level, namely the commuting zone level.

Our paper contributes to the literature studying the links between the informativeness of aggregate accounting information for the economy. We document the usefulness of the information about banks' loan portfolios for predicting local economic trends. Our findings are also relevant to research that studies the forecasting of economic trends. Importantly, we contribute to the literature that examines the prediction of economic conditions at the state-level, a topic that remains relatively under-researched due to lack of available data.

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Appendix A: Number of banks by state

	Total Number of Bank-Quarters	Average Quarterly Number of Banks	Average Bank's % of Operations in the State
AK	680	8.2	86.7%
AL	14,633	176.3	95.0%
AR	16,319	196.6	97.5%
AZ	3,940	47.5	80.5%
CA	27,610	332.7	96.6%
CO	18,634	224.5	94.4%
CT	6,124	73.8	91.1%
DE	2,735	33.0	86.1%
FL	25,650	309.0	93.4%
GA	28,665	345.4	97.1%
HI	971	11.7	91.1%
IA	37,027	446.1	98.0%
ID	2,138	25.8	66.9%
IL	67,051	807.8	97.8%
IN	16,359	197.1	92.0%
KS	33,852	407.9	97.3%
KY	21,195	255.4	95.4%
LA	13,917	167.7	97.9%
MA	17,692	213.2	97.2%
MD	7,736	93.2	82.9%
ME	2,707	32.6	94.6%
MI	14,961	180.3	95.2%
MN	41,466	499.6	98.1%
MO	33,896	408.4	96.2%
MS	8,890	107.1	94.8%
MT	7,888	95.0	98.0%
NC	8,572	103.3	89.0%
ND	9,755	117.5	96.4%
NE	24,669	297.2	98.4%
NH	3,183	38.3	87.8%
NJ	9,629	116.0	88.2%
NM	5,193	62.6	93.7%
NV	2,525	30.4	81.2%
NY	15,813	190.5	92.2%
OH	19,941	240.3	95.1%
OK	25,730	310.0	98.5%
OR	3,997	48.2	81.0%
PA	21,209	255.5	94.5%
RI	1,035	12.5	76.1%
SC	6,675	80.4	92.5%
SD	8,386	101.0	96.9%
TN	18,227	219.6	94.0%
TX	67,184	809.4	98.0%
UT	4,375	52.7	89.4%
VA	12,777	153.9	88.5%
VT	1,865	22.5	87.1%
WA	8,533	102.8	88.5%
WI	29,064	350.2	98.1%
WV	8,761	105.6	90.0%
WY	4,251	51.2	94.4%
Total	794,085	9,567.3	95.5%

Table 1: Bank-level descriptive statistics

This table provides descriptive statistics for variables at the bank-level. Panel A reports summary statistics and Panel B reports correlation coefficients, where p-values are reported in parentheses. Data is obtained from 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 2010. *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 provision for loan and lease losses scaled by the average 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 balance of total loans.

Panel A: Summary statistics

	Obs. Count	Mean	St. Dev	25%	50%	75%
Total assets	758,851	746	15,105	38	80	184
Total loans	758,851	439	7,569	21	47	117
Loan growth	758,851	2.75	8.00	-0.92	1.72	4.75
Provision for loan losses	758,851	0.14	0.44	0.00	0.05	0.13
Allowance for loan losses	758,851	1.61	1.19	1.06	1.35	1.81
Nonperforming loans	758,851	1.42	2.17	0.24	0.76	1.75
Yield	758,851	8.76	1.98	7.45	8.76	9.84

Panel B: Correlations (Pearson below diagonal, Spearman above diagonal)

		(1)	(2)	(3)	(4)	(5)
(1)	Loan growth	-	0.02	-0.19	-0.23	0.05
			(0.00)	(0.00)	(0.00)	(0.00)
(2)	Provision for loan losses	-0.00	-	0.07	0.23	0.05
		(0.15)		(0.00)	(0.00)	(0.00)
(3)	Allowance for loan losses	-0.12	0.23	-	0.31	0.15
		(0.00)	(0.00)		(0.00)	(0.00)
(4)	Nonperforming loans	-0.17	0.28	0.42	-	0.08
		(0.00)	(0.00)	(0.00)		(0.00)
(5)	Yield	0.07	0.08	0.16	0.00	-
		(0.00)	(0.00)	(0.00)	(0.19)	

Table 2: 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, 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-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 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 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; *EXYIELD* is equal to the difference between annualized ratio of aggregate net interest income to the average balance of aggregate total loans and 3-month constant maturity treasury bill rate; *ΔCOINDEX* and *LEADINDEX* are disclosed by the Federal Reserve Bank of Philadelphia and are equal to the quarterly growth rate in state coincident index and the predictor of six-month growth rate in state coincident index (i.e., the leading index), respectively; *ΔHOUSING* is the percentage change in purchase-only housing price index of 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 quarterly stock return of firms headquartered in the given state. All variables are reported in percentages.

Panel A: Summary statistics

	Obs. Count	Mean	St. Dev	25%	50%	75%
$LGROWTH_{s,t}$	4,150	2.076	5.035	0.096	1.938	3.680
$PLLTL_{s,t}$	4,150	0.256	0.304	0.079	0.142	0.321
$ALLTL_{s,t-1}$	4,150	1.865	0.823	1.386	1.638	2.090
$\Delta NPLTL_{s,t}$	4,150	0.030	0.243	-0.075	-0.002	0.081
$EXYIELD_{s,t}$	4,150	4.486	1.581	3.372	4.511	5.358
$\Delta COINDEX_{s,t}$	4,150	0.476	0.920	0.078	0.637	1.047
$LEADINDEX_{s,t}$	4,150	0.994	1.609	0.231	1.239	1.975
$\Delta HOUSING_{s,t}$	3,950	0.859	1.719	0.146	0.951	1.720
$PIGROWTH_{s,t}$	4,150	1.241	1.198	0.655	1.272	1.866
$\Delta UNRATE_{s,t}$	4,150	0.040	0.370	-0.200	0.000	0.200
$VWRET_{s,t}$	4,150	2.669	11.800	-3.262	3.094	9.017

Panel B: Correlations (Pearson below diagonal, Spearman above diagonal)

		(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	$LGROWTH_{s,t}$	-	-0.20	-0.17	-0.13	-0.07	0.25	0.21	0.17	0.14	-0.17	0.00
			(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.77)
(2)	$PLLTL_{s,t}$	-0.04	-	0.51	0.24	0.62	-0.35	-0.28	-0.27	-0.19	0.32	-0.02
		(0.01)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.22)
(3)	$ALLTL_{s,t-1}$	-0.02	0.65	-	-0.23	0.52	0.05	0.13	-0.10	-0.03	-0.03	0.10
		(0.20)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.03)	(0.07)	(0.00)
(4)	$\Delta NPLTL_{s,t}$	-0.10	0.34	-0.11	-	-0.02	-0.39	-0.41	-0.20	-0.24	0.36	-0.09
		(0.00)	(0.00)	(0.00)		(0.24)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(5)	$EXYIELD_{s,t}$	0.11	0.63	0.60	0.04	-	-0.19	-0.07	-0.08	-0.15	0.17	0.00
		(0.00)	(0.00)	(0.00)	(0.02)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.90)
(6)	$\Delta COINDEX_{s,t}$	0.18	-0.35	-0.01	-0.53	-0.15	-	0.88	0.30	0.49	-0.63	0.09
		(0.00)	(0.00)	(0.61)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)
(7)	$LEADINDEX_{s,t}$	0.16	-0.29	0.06	-0.51	-0.06	0.90	-	0.27	0.39	-0.58	0.14
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.00)	(0.00)
(8)	$\Delta HOUSING_{s,t}$	0.11	-0.24	-0.09	-0.29	-0.07	0.39	0.39	-	0.21	-0.14	0.00
		(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)	(0.00)	(0.96)
(9)	$PIGROWTH_{s,t}$	0.07	-0.17	-0.03	-0.30	-0.12	0.49	0.40	0.24		-0.28	0.04
		(0.00)	(0.00)	(0.05)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	-	(0.00)	(0.01)
(10)	$\Delta UNRATE_{s,t}$	-0.12	0.29	-0.01	0.44	0.15	-0.71	-0.66	-0.25	-0.31	-	-0.09
		(0.00)	(0.00)	(0.69)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)	(0.00)		(0.00)
(11)	$VWRET_{s,t}$	0.03	-0.02	0.07	-0.10	-0.03	0.13	0.21	0.04	0.10	-0.15	-
		(0.07)	(0.11)	(0.00)	(0.00)	(0.11)	(0.00)	(0.00)	(0.01)	(0.00)	(0.00)	

Table 3: Predicting state-level economic conditions using loan portfolio information

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

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

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

Definitions of all other variables are available in Table 2. All models include state fixed effects and standard errors are clustered by quarter. *, **, 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
$PLLTL_{s,t}$	-	-1.216 ***	-1.364 ***	-1.368 ***	-1.297 ***	-1.218 ***	-1.364 ***	-1.360 ***	-1.168 ***	-1.021 ***
		(-4.56)	(-4.62)	(-4.72)	(-4.69)	(-4.72)	(-4.62)	(-4.56)	(-4.50)	(-4.35)
$\Delta NPLTL_{s,t}$	-	-1.331 ***	-1.122 ***	-0.998 ***	-0.934 ***	-0.885 ***	-1.122 ***	-0.882 ***	-0.768 ***	-0.632 ***
		(-4.48)	(-4.05)	(-3.88)	(-4.04)	(-4.20)	(-4.05)	(-3.50)	(-3.61)	(-3.20)
$EXYIELD_{s,t}$	-	-0.089 **	-0.057	-0.038	-0.026	-0.011	-0.057	-0.018	0.003	0.034
		(-2.43)	(-1.43)	(-0.96)	(-0.64)	(-0.27)	(-1.43)	(-0.42)	(0.07)	(0.62)
$LGROWTH_{s,t}$	+	0.022 ***	0.017 ***	0.014 ***	0.010 **	0.009 *	0.017 ***	0.010 **	0.005	0.004
		(3.92)	(3.73)	(3.14)	(2.30)	(1.80)	(3.73)	(2.23)	(0.81)	(0.47)
$ALLTL_{s,t-1}$		0.207 ***	0.325 ***	0.376 ***	0.420 ***	0.440 ***	0.325 ***	0.408 ***	0.467 ***	0.506 ***
		(3.43)	(3.63)	(3.88)	(4.15)	(4.27)	(3.63)	(3.77)	(3.84)	(3.85)
Fixed effects		State	State	State	State	State	State	State	State	State
Clusters		Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
R-squared		0.416	0.370	0.355	0.345	0.340	0.370	0.299	0.251	0.224
Obs. Count		4,150	4,100	4,050	4,000	3,950	4,100	4,050	4,000	3,950

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

This table presents linear regressions 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 changes. The dependent variables are the concurrent changes and cumulative and marginal future changes in state coincident index (*ΔCOINDEX*), calculated as:

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

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

Definitions of all other variables are available in Table 2. All models include state fixed effects and standard errors are clustered by quarter. *, **, 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
$PLLTL_{s,t}$	-	-0.218 ***	-0.323 ***	-0.359 ***	-0.372 ***	-0.218 ***	-0.424 ***	-0.436 **	-0.455 **
		(-3.50)	(-3.26)	(-2.94)	(-2.89)	(-3.50)	(-2.86)	(-2.30)	(-2.60)
$\Delta NPLTL_{s,t}$	-	-0.022	0.006	-0.005	-0.006	-0.022	0.021	-0.032	-0.034
		(-0.39)	(0.07)	(-0.05)	(-0.06)	(-0.39)	(0.17)	(-0.22)	(-0.20)
$EXYIELD_{s,t}$	-	-0.033 ***	-0.013	0.001	0.014	-0.033 ***	0.007	0.026	0.053
		(-2.79)	(-0.70)	(0.03)	(0.52)	(-2.79)	(0.25)	(0.73)	(1.15)
$LGROWTH_{s,t}$	+	0.002	-0.000	-0.002	-0.003	0.002	-0.002	-0.005	-0.005
		(1.15)	(-0.07)	(-0.69)	(-0.81)	(1.15)	(-0.69)	(-1.04)	(-0.71)
$ALLTL_{s,t-1}$		0.066 ***	0.120 ***	0.171 ***	0.224 ***	0.066 ***	0.174 ***	0.265 ***	0.354 ***
		(3.65)	(3.47)	(3.54)	(3.75)	(3.65)	(3.21)	(3.20)	(3.27)
$LEADINDEX_{s,t}$		0.505 ***	0.456 ***	0.412 ***	0.374 ***	0.505 ***	0.407 ***	0.321 ***	0.250 ***
		(38.87)	(21.89)	(17.04)	(14.78)	(38.87)	(13.01)	(8.69)	(6.92)
$VWRET_{s,t}$		0.003 ***	0.005 ***	0.006 ***	0.006 ***	0.003 ***	0.007 ***	0.008 ***	0.008 **
		(2.89)	(3.71)	(3.60)	(3.29)	(2.89)	(3.69)	(2.80)	(2.11)
Fixed effects		State	State	State	State	State	State	State	State
Clusters		Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
R-squared		0.872	0.803	0.744	0.694	0.872	0.648	0.485	0.373
Obs. Count		4,100	4,050	4,000	3,950	4,100	4,050	4,000	3,950

Panel B: Controlling for state-level economic indicators

		Cumulative $\Delta COINDEX_{t,t+i}$				Marginal $\Delta COINDEX_{t+i-1,t+i}$			
	Pred.	i=1	i=2	i=3	i=4	i=1	i=2	i=3	i=4
$PLLTL_{s,t}$	-	-0.298 **	-0.439 ***	-0.489 ***	-0.528 ***	-0.298 ***	-0.569 ***	-0.612 ***	-0.656 ***
		(-3.64)	(-4.13)	(-3.82)	(-3.83)	(-3.64)	(-3.81)	(-3.05)	(-3.37)
$\Delta NPLTL_{s,t}$	-	-0.051	-0.030	-0.063	-0.088	-0.051	-0.027	-0.095	-0.123
		(-0.57)	(-0.27)	(-0.57)	(-0.72)	(-0.57)	(-0.19)	(-0.66)	(-0.67)
$EXYIELD_{s,t}$	-	-0.015	-0.011	-0.006	0.004	-0.015	-0.009	0.006	0.035
		(-0.80)	(-0.49)	(-0.24)	(0.12)	(-0.80)	(-0.30)	(0.14)	(0.64)
$LGROWTH_{s,t}$	+	0.001	0.000	-0.001	-0.002	0.001	-0.001	-0.004	-0.003
		(0.47)	(0.11)	(-0.41)	(-0.41)	(0.47)	(-0.16)	(-0.72)	(-0.36)
$ALLTL_{s,t-1}$		0.128 ***	0.200 ***	0.265 ***	0.311 ***	0.128 ***	0.268 ***	0.364 ***	0.434 ***
		(4.13)	(4.60)	(5.13)	(5.07)	(4.13)	(4.59)	(4.55)	(4.09)
$\Delta COINDEX_{s,t}$		1.181 ***	1.050 ***	0.961 ***	0.880 ***	1.181 ***	0.916 ***	0.763 ***	0.600 ***
		(24.26)	(15.52)	(10.94)	(8.93)	(24.26)	(9.14)	(5.23)	(4.04)
$\Delta COINDEX_{s,t-1}$		-0.418 ***	-0.308 ***	-0.283 ***	-0.277 **	-0.418 ***	-0.195 *	-0.227	-0.236
		(-5.55)	(-3.51)	(-2.80)	(-2.40)	(-5.55)	(-1.77)	(-1.49)	(-1.32)
$\Delta COINDEX_{s,t-2}$		0.201 ***	0.103	0.062	0.080	0.201 ***	0.004	-0.022	0.104
		(2.91)	(1.23)	(0.67)	(0.85)	(2.91)	(0.03)	(-0.16)	(0.87)
$\Delta COINDEX_{s,t-3}$		-0.130 ***	-0.105 **	-0.086	-0.107 *	-0.130 ***	-0.084	-0.037	-0.130
		(-3.14)	(-2.00)	(-1.55)	(-1.75)	(-3.14)	(-1.16)	(-0.47)	(-1.44)
$\Delta HOUSING_{s,t}$		0.042 ***	0.066 ***	0.076 ***	0.081 ***	0.042 ***	0.088 ***	0.101 ***	0.103 ***
		(3.19)	(3.51)	(3.46)	(3.36)	(3.19)	(3.42)	(3.14)	(2.82)
$PIGROWTH_{s,t}$		-0.037 **	-0.044 **	-0.053 **	-0.061 **	-0.037 **	-0.051 *	-0.074 *	-0.078 *
		(-2.54)	(-2.10)	(-2.07)	(-2.13)	(-2.54)	(-1.75)	(-1.95)	(-1.77)
$\Delta UNRATE_{s,t}$		0.272 **	0.361 ***	0.358 ***	0.359 **	0.272 **	0.440 ***	0.348 **	0.344 **
		(2.32)	(2.78)	(2.64)	(2.53)	(2.32)	(3.03)	(2.34)	(1.97)
$VWRET_{s,t}$		0.006 ***	0.008 ***	0.008 ***	0.009 ***	0.006 ***	0.009 ***	0.010 ***	0.010 ***
		(3.72)	(4.32)	(4.27)	(4.09)	(3.72)	(4.33)	(3.58)	(2.84)
Fixed effects		State	State	State	State	State	State	State	State
Clusters		Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter	Quarter
R-squared		0.819	0.744	0.690	0.640	0.819	0.600	0.466	0.368
Obs. Count		3,900	3,850	3,800	3,750	3,900	3,850	3,800	3,750

Table 5: 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 changes. The dependent variable is equal to one if quarter t+4 is a recession quarter for a given state, and zero otherwise. Recessions are defined as two or more consecutive quarters of negative changes in state coincident index. Definitions of all other variables are available in Table 2. All models include state fixed effects and standard errors are clustered by quarter. *, **, and *** denote significance at a two-sided 10%, 5%, and 1% level, respectively.

	Pred.	(1)	(2)	(3)
$PLLTL_{s,t}$	+	3.361 ***	1.804 **	2.989 ***
		(4.92)	(2.57)	(3.98)
$\Delta NPLTL_{s,t}$	+	1.405 **	-1.440	-0.195
		(2.49)	(-0.20)	(-0.33)
$EXYIELD_{s,t}$	+	-0.015	-0.161	0.004
		(-0.09)	(-0.94)	(0.02)
$LGROWTH_{s,t}$	-	-0.020	0.005	-0.010
		(-0.81)	(0.22)	(-0.41)
$ALLTL_{s,t-1}$		-2.539 ***	-1.814 ***	-2.443 ***
		(-4.28)	(-3.65)	(-4.23)
$LEADINDEX_{s,t}$			-0.658 ***	
			(-5.24)	
$\Delta COINDEX_{s,t}$				-1.531 ***
				(-3.81)
$\Delta COINDEX_{s,t-1}$				0.674
				(1.60)
$\Delta COINDEX_{s,t-2}$				-0.392
				(-1.20)
$\Delta COINDEX_{s,t-3}$				0.729 **
				(2.35)
$\Delta HOUSING_{s,t}$				-0.278 ***
				(-2.88)
$PIGROWTH_{s,t}$				0.227 *
				(1.88)
$\Delta UNRATE_{s,t}$				-0.718
				(-1.48)
$VWRET_{s,t}$			-0.021 *	-0.028 ***
			(-1.85)	(-2.65)
Fixed Effects		State	State	State
Clusters		Quarter	Quarter	Quarter
Pseudo R-squared		0.20	0.28	0.30
Log Pseudolikelihood		-1,588	-1,417	-1,303
Obs. Count		3,950	3,950	3,750

Table 6: Out-of-sample predictive power of provision for loan and lease losses

This table presents tests of out-of-sample predictive power of provision for loan and lease losses on 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 $LEADINDEX_{s,t}$ is replaced with $\Delta COINDEX_{s,t}$, $\Delta HOUSING_{s,t}$, $PIGROWTH_{s,t}$ and $\Delta UNRATE_{s,t}$. The dependent variables are the concurrent changes and cumulative and marginal future changes in state coincident index ($\Delta COINDEX$), calculated as:

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

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

Definitions of all other variables are available in Table 2. 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 the out-of-sample R^2 from Campbell and Thomson (2008), calculated as 1 – (MSE_{Full} / $MSE_{Benchmark}$), where MSE stands for mean squared error from estimations. |ΔError| column shows the difference in the mean absolute errors from the full and the benchmark models. t-statistics for |ΔError| are reported in parentheses. *, **, and *** denote significance at a two-sided 10%, 5%, and 1% level, respectively.

Panel A: Benchmark based on leading index

	Cumulative $\Delta COINDEX_{t,t+i}$			Marginal $\Delta COINDEX_{t+i-1,t+i}$		
i=	Obs. count	R^2_{os}	|ΔError|	Obs. count	R^2_{os}	|ΔError|
1	3,150	0.161	-0.015*** (-6.91)	3,150	0.161	-0.015*** (-6.91)
2	3,100	0.171	-0.018*** (-6.04)	3,100	0.157	-0.019*** (-5.40)
3	3,050	0.182	-0.020*** (-6.45)	3,050	0.201	-0.035*** (-7.63)
4	3,000	0.237	-0.031*** (-9.31)	3,000	0.263	-0.058*** (-11.30)

Panel B: Benchmark based on state-level economic indicators

	Cumulative $\Delta COINDEX_{t,t+i}$			Marginal $\Delta COINDEX_{t+i-1,t+i}$		
i=	Obs. count	R^2_{os}	|ΔError|	Obs. count	R^2_{os}	|ΔError|
1	2,950	0.180	0.018*** (9.32)	2,950	0.180	0.018*** (9.32)
2	2,900	0.211	0.026*** (10.35)	2,900	0.221	0.035*** (10.77)
3	2,850	0.253	0.037*** (12.71)	2,850	0.258	0.056*** (14.16)
4	2,800	0.292	0.048*** (15.17)	2,800	0.294	0.072*** (15.29)

Table 7: Predicting commuting zone-level unemployment using loan portfolio information

Panel A of this table presents summary statistics at the commuting zone-level and Panel B presents estimates from linear regression analysis of the association between changes in unemployment rates and loan portfolio information at the commuting zone-level for 1994Q1-2010Q 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 over all banks operating in a given CZ-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. *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 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; *EXYIELD* is equal to the difference between annualized ratio of aggregate net interest income to the average balance of aggregate total loans and 3-month constant maturity treasury bill rate; *ΔUNRATE* is equal to the difference between unemployment rate for quarter t+4 and quarter t at the commuting zone-level. In all models standard errors are double clustered in CZ and time dimensions. *, **, and *** denote significance at a two-sided 10%, 5% and 1% level, respectively.

Panel A: Summary statistics

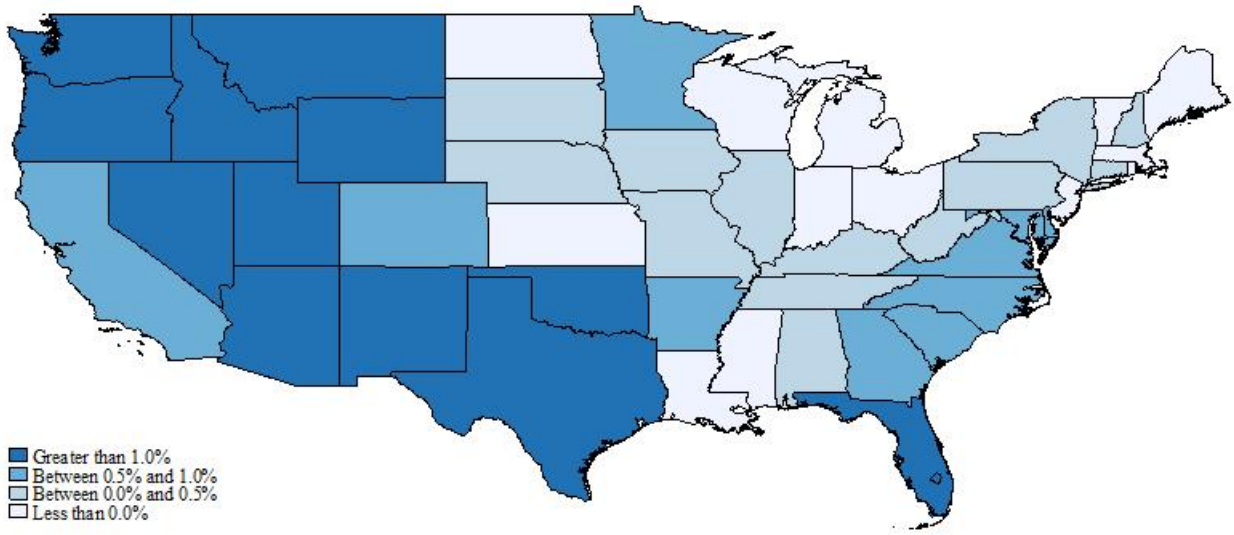
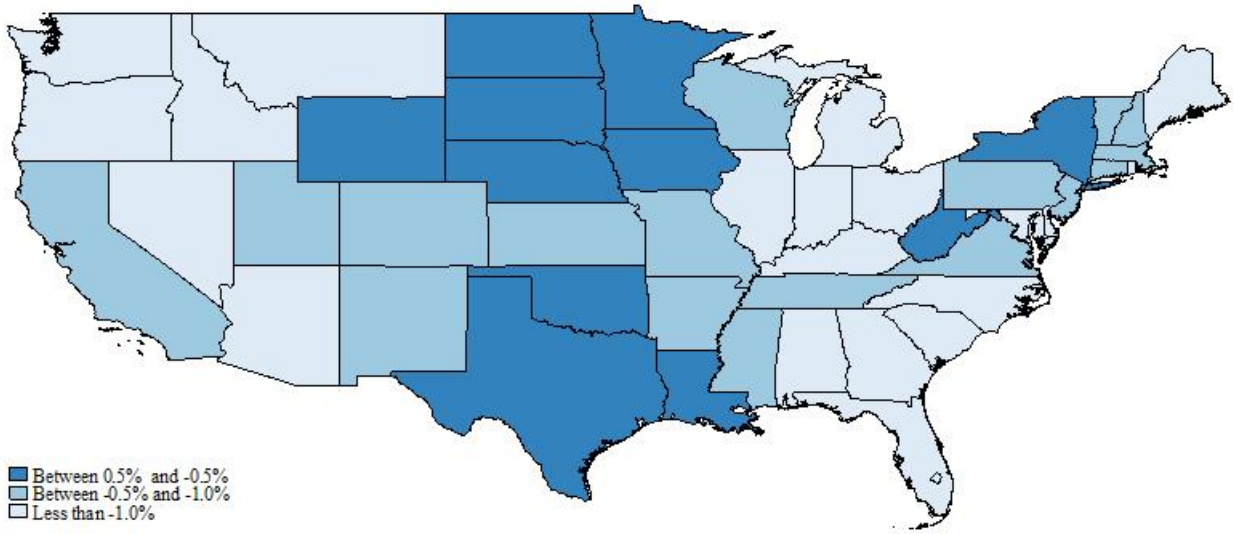
	Obs. Count	Mean	St. Dev	25%	50%	75%
$PLLTL_{cz,t}$	47,276	0.168	0.222	0.057	0.097	0.181
$\Delta NPLTL_{cz,t}$	47,276	0.044	0.343	-0.079	0.007	0.118
$LGROWTH_{cz,t}$	47,276	1.703	5.935	-0.208	1.803	3.698
$EXYIELD_{cz,t}$	47,276	4.384	1.416	3.379	4.353	5.349
$ALLTL_{cz,t-1}$	47,276	1.587	0.591	1.282	1.459	1.722
$\Delta UNRATE_{cz,t}$	47,276	0.036	0.322	-0.131	-0.006	0.148

Panel B: Linear regression analysis

		$\Delta UNRATE_{cz,t,t+4}$	
	Pred.	(1)	(2)
$PLLTL_{cz,t}$	+	0.221 **	0.247 ***
		(2.13)	(2.64)
$\Delta NPLTL_{cz,t}$	+	0.106 ***	0.116 ***
		(3.29)	(3.81)
$EXYIELD_{cz,t}$	+	0.203	0.023 *
		(1.55)	(1.79)
$LGROWTH_{cz,t}$	-	-0.007	-0.001
		(-0.40)	(-0.59)
$ALLTL_{cz,t-1}$		-0.120 ***	-0.124 ***
		(-2.91)	(-3.01)
$UNRATE_{cz,t-4,t}$			-6.000
			(-1.33)
Clusters		CZ and Quarter	CZ and Quarter
R-squared		0.07	0.07
Obs. Count		47,272	47,272

Figure 1: Disparities in state economic conditions

Panel A: Three month changes in the state coincident indexes between June and September 2005



Panel B: Three month changes in the state coincident indexes between June and September 2008