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Banking-industry specific and regional economic determinants of non-performing loans: Evidence from US states

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ABSTRACT

The present study examines state-level banking-industry specific as well as region economic determinants of non-performing loans for all commercial banks and savings institutions across 50 US states and the District of Columbia for 1984–2013. Using both fixed effects and dynamic-GMM estimations, I find greater capitalization, liquidity risks, poor credit quality, greater cost inefficiency and banking industry size to significantly increase NPLs, while greater bank profitability lowers NPLs. Moreover, higher state real GDP and real personal income growth rates, and changes in state housing price index reduce NPLs, while inflation, state unemployment rates, and US public debt significantly increase NPLs. The findings imply that regular stress tests on banks' loan quality that typically underpin scenarios for a rise in NPLs, should take into account the impact of 'micro' or state-level economic conditions on NPLs, in addition to banks' capital and credit quality, and effective cost management in assessing banks financial health.

1. Introduction

The recent global financial crisis (henceforth GFC) was marked by a surge in non-performing loans (henceforth NPLs) in most nations including different regions across the US. A rising share of NPLs in the loan portfolio of banks signifies greater risks affecting both the liquidity and profitability of banks. Moreover, it represents a deteriorating balance sheet of banks. Since the GFC, NPLs are especially in the spotlight for both regulators and banks as it has been linked to bank failures, and is often a harbinger to banking crises.[1] Indeed, the increase in loan defaults, mortgage foreclosures along with a simultaneous rise in NPLs across states in the US, underscores the links between regional and national macro-financial shocks, and banking sector vulnerability. This deterioration of banks asset quality is not only financially destabilizing for the banking system but may also reduce economic efficiency, impair social welfare and decline economic activity.[2] In fact, many banking analysts have alluded NPLs as "financial pollution" due to their adverse economic consequences (Barseghyan, 2010; Gonzales-Hermosillo, 1999; Zeng, 2012). Hence, minimization of NPLs is necessary to restore a sounder banking system and foster overall financial stability in the aftermath of The Great Recession.

However, any policy response by banking regulatory authorities in the resolution of NPLs problem first requires a deeper understanding of its underlying determinants. The present study examines both state-level banking-industry specific as well as region economic determinants of NPLs across all 50 US states

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[1] Of course other factors that affect bank defaults and failure have recently come to the forefront of discussions as well. These include the role of distance-to-default, captured by per cent loss of share price, as a predictor of bank failure, in the one-period contingent-claims model of bank debt and equity pricing of Milne (2014).

[2] The impact of NPLs on the slowdown of an economy has been calibrated by Barseghyan (2010) in the context of the "lost decade" of 1990s for the Japanese economy. The theoretical foundations of such analysis involve a general equilibrium framework: a two country overlapping generations model (OLG) comprising of households, firms, banking sector and the government. Under such a framework, government provides deposit insurance to the banks. However, with a delay in government bailout, NPLs cause a decline in economic activity by crowding out capital.

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1572-3089/

and the District of Columbia spanning the longest time period of 1984–2013. Therefore, this study has a practical use in the macroeconomic analysis of the dynamics of lending and asset quality in the US banking industry.

An important responsibility of the central bank or any banking supervisory authority is to ensure a stable and efficient financial system that safeguards the interest of all participating agents. A mainstay of financial stability is a sound banking system that efficiently channelizes funds between borrowers and savers. It is in regard to prudential banking supervision bank stress tests are most useful. NPL modeling is very often used by central banks within the stress test methodology (Buncic and Melecky, 2012; Marcelo et al., 2008). So from the perspective of restoring both financial stability as well as confidence in financial markets in the US, the findings of this study bear relevance for stress tests of loan quality. Moreover, insights can be gained about future levels of problem loans and probabilities of failure, which are of direct interest to both regional and federal supervisors as well as market analysts.

The role of regional economic indicators in influencing NPLs is especially motivated by the fact that many states with large declines in house prices also experienced relatively large declines in personal income, state GDP and relatively large increases in unemployment rates. Hence, it remains interesting to consider the extent to which NPLs are associated with changes in state-level economic conditions in the US. Given the importance of this topic, to the best of my knowledge, the present study is the first of its kind that exploits the determinants of NPLs in both commercial banks and savings institutions in the US, especially bringing forward the role of regional banking and economic conditions.[3] Using state as a political unit is further justified on the grounds that most banks in the US operate in either one or a few states only. Thus using state-level variables allows to better exploit the dynamics between the regional economic conditions and state-level NPLs. Such an exercise is also useful to evaluate the relative importance of state-banking industry level vis-a-vis regional economic factors in affecting NPLs.

The remainder of the paper proceeds as follows: Section 2 provides a survey of recent pertinent literature on NPLs. Section 3 introduces the relevant determinants of NPLs and their theoretical underpinnings. Section 4 provides some trends and patterns in the data as well as statistical diagnostic tests. Section 5 presents the estimation models and discusses the results. Finally, Section 6 concludes.

2. Literature survey of recent NPL literature

The recent GFC has sparked an interest in understanding the drivers of NPLs in different regions of the world. These have ranged from cross-country analysis i.e. panel data models to country-specific case studies. The empirical literature on the determinants of NPLs is based on theoretical models that deal with the business cycle with an explicit role for financial intermediation. The financial accelerator theory as discussed in Bernanke and Gertler (1989), Kiyotaki and Moore (1997), is the widely used theoretical framework to link NPLs with a nation's macroeconomic environment.

The macroeconomic determinants of NPLs can be also traced to the theoretical literature on life-cycle consumption models such as Lawrence (1995) that introduces explicitly the probability of default. Such models imply that borrowers with low incomes have higher rates of default due to increased risk of facing unemployment and being unable to settle their obligations. Additionally, banks charge higher interest rates to riskier clients. Thus, the default probability depends on current income and the unemployment rate, which is linked to the uncertainty regarding future income and the lending rates. I next survey the very recent literature here.

Much like in the US, the banking industry in several European nations was also plagued recently by surges in NPLs. This has sparked a burgeoning body of literature in studying NPLs across the Atlantic. Using bank-level data, Klein (2013) investigates NPLs in 16 Central, Eastern and South-Eastern European nations, and find both bank-specific as well as macroeconomic factors to influence NPLs. Skarica (2014) uses quarterly data from 2007 to 2012 for 7 Central and East European countries, to explore the macroeconomic determinants of NPLs, and find both unemployment and inflation rates to increase the growth of NPLs while real GDP growth has a negative effect. Jakubik and Reininger (2013) examine the determinants of NPLs in 9 Central, Eastern and Southeastern European (CESEE) countries comprising of Bulgaria, Croatia, the Czech Republic, Hungary, Poland, Romania, Russia, Slovakia and Ukraine. Using GMM estimations with quarterly data from 2004 to 2012, the authors find real GDP growth and national stock price index to reduce NPLs while a nation's exchange rate, private credit-to-GDP and past NPLs to increase present period's NPLs.

Moving toward the euro area region, Makri et al. (2014) examine the role of both macroeconomic and bank-specific factors on NPLs in 14 countries in the Eurozone and find a strong influence of both categories of variables on NPLs. Messai and Jouini (2013) examine the issue for 85 banks in Italy, Greece and Spain, respectively, for 2004–2008 and find both economic growth and bank profitability to reduce NPLs while unemployment rates, real interest rates, and poor credit quality to positively influence NPLs.

Surveying some recent individual European country-specific analyses, Louizis et al. (2012) use data for 9 Greek commercial banks and examine NPLs in consumer, business and farm loan categories. The authors find NPLs to be mainly influenced by macroeconomic variables. Salas and Saurina (2002) examine Spanish commercial and savings banks, and find GDP growth to lower NPLs. Macit (2012) investigates NPLs for 15 largest commercial banks in Turkey using quarterly data from 2005 to 2010. Both bank-specific and macroeconomic variables significantly influence NPLs. Similarly, Cifter et al. (2009) find lagged industrial production to influence NPLs in the Turkish banking industry for 2001–2007.[4]

Turning to studies looking at other regions, Beck et al. (2013) examine the role of key macroeconomic indicators in 75 countries (both advanced and emerging economies) for the period 2000–2010, and find real GDP, nominal effective exchange rates, share prices and real lending rates to significantly affect NPLs. Espinoza and Prasad (2010) use a panel dataset from 1995 to 2008 for 80 banks in the Gulf Co-operation Council region and find NPLs to worsen as economic growth lowers and interest rates and risk aversion increase. Likewise, Nkusu (2011) examine the issue for 26 advanced economies for the period 1998–2009 and confirm that adverse macroeconomic determinants are associated with rising NPLs. Buncic and Melecky (2012) estimate determinants of NPLs by using GMM estimations using annual data for 54 high- and middle-income countries from 1994 to 2004. Explanatory variables include the lagged NPL ratio, real GDP growth, CPI inflation, the (ex post) real interest rate and changes in the nominal U.S. dollar exchange rate for each country, while a vector of control variables comprising

[3] In a somewhat different but related topic, other earlier studies that have examined issues of loan quality across US states include Gambera (2000), Keeton (1999), Keeton and Morris (1987).

[4] Other individual country-specific studies in Europe include Nikolaidou and Vogiazas (2014) for Bulgaria; Podpiera and Weill (2008) for banks in Czech Republic; and Quagliarello (2007) for Italy. Studies covering other regions include Misra and Dhal (2010), Dash and Kabra (2010) for India; Zeng (2012) for China; Hu et al. (2004) for Taiwan.

of the log of GDP per capita, the credit-to-GDP ratio and the share of foreign currency loans in total loans. Although not covering the GFC years, the authors find the changes in exchange rate and the control variables to be statistically insignificant. De Bock and Demyanets (2012) estimate panel regressions again using annual data for 25 emerging market economies for 1996–2010 that include the lagged dependent variable and unobserved country effects. Real GDP contraction, currency depreciation against the US dollar, weaker terms of trade and outflows of debt-creating capital (portfolio debt and bank loans) lead to a higher aggregate NPLs of the banking sector.

Clearly synthesizing these studies, a common finding is NPLs are countercyclical to overall country-specific macroeconomic conditions.

3. Determinants of NPLs in the US banking industry

I draw on the extant literature to identify variables in the context of the present analysis. Unlike the existing literature that uses national-level data the current study employs state-level data. As noted previously, this is motivated by the fact that the US banking industry, due to its unique historical institutional origins had restrictions on branching geographically. As a legacy of this, till today most banks restrict their operation within a few states only. Thus, banks in any given state may be more sensitive to regional conditions than national aggregates. I also distinguish between NPLs in commercial banks vis-à-vis savings institutions, again a distinction that has its origins in the unique evolution of the US banking industry.[5] Furthermore, most studies focus more on macroeconomic and external factors in influencing NPLs, and less on banking industry specific factors. With a study across states, I include several relevant state banking variables.

3.1. State banking-industry specific determinants of NPLs

Credit growth: Keeton (1999) using a simple model of the market for bank loans, show that faster loan growth leads to higher loan losses. When banks increase their supply of loans, they reduce their interest rates charged on loans and lower their minimum credit standard. Such a reduction in credit standards increases the chances of loan defaults by borrowers. A priori, I expect loans growth to positively affect NPL. I measure this by loans-to-assets ratio, similar to Klein (2013). This measure also reflects liquidity risk since loans are less liquid and riskier but have a greater expected return than other assets, like government securities in banks portfolio.

Bank capitalization: The effect of bank capitalization on NPLs can be ambiguous. On the one hand, managers in banks with low capital bases have a moral hazard incentive to engage in risky lending practices along with poor credit scoring and monitoring borrowers (Keeton and Morris, 1987). This 'moral hazard' hypothesis implies an inverse relationship between equity capital and NPLs. On the other hand, managers in banks that are highly capitalized may resort to a liberal credit policy under the notion of 'too big to fail' (Rajan, 1994) implying a positive relationship between capital and NPLs. I measure capitalization by total equity capital-to-total assets, muck like Klein (2013), Louizis et al. (2012), Macit (2012), Makri et al. (2014).

Loan loss provision: This variable reflects credit quality of banks and the overall attitude of the banking system to control risks. The theoretical underpinning of this is the 'moral hazard' hypothesis, first discussed by Keeton and Morris (1987). They argue that banks with poor credit quality have moral hazard incentives by increasing the riskiness of their loan portfolio, which in turn results in higher NPLs. I measure credit quality by provision for loan and lease losses-to-total loans, similar to Messai and Jouini (2013), Nikolaidou and Vogiazas (2014). A rise in this ratio is expected to positively influence NPLs.

Bank diversification: Banks income or earning streams can be decomposed into interest and non-interest incomes. The former includes traditional commercial bank activities like interest earned from different types of loans, and investment securities. The latter covers investment banking, asset management and insurance underwriting, fee-paying and commission-paying services, trading and derivatives. Recently with banking sector deregulation in the US, especially with the repeal of the Glass–Steagall Act in 1999, there has been an increase in the latter's share. With economic heterogeneity across states in the US it is imperative to control for diversification. I measure diversification by the share of non-interest income-to-total income for each state, much like Louizis et al. (2012). More diversification in the banks business model improves loan quality and reduces credit risk. So, I expect a negative impact of bank diversification on NPLs.

Bank profitability: Highly profitable banks have fewer incentives to engage in high-risk activities. So profitability is expected to negatively impact NPLs, following the 'bad management' hypothesis of Berger and DeYoung (1997). In rebuttal, higher profits could also increase NPLs. This possibility is shown in the model of Rajan (1994) where credit policy is not determined solely by the maximization of banks' earnings but also by the short-term reputation concerns of banks' management. Consequently, bank managers may attempt to manipulate current earnings resorting to a 'liberal credit policy.' In this manner, a bank may attempt to convince the market for its profitability by inflating current earnings at the expense of rising NPLs in the future. I measure profits by return on assets (ROA) of banks in each state.

Operating efficiency: the effect of cost efficiency is ambiguous. On the one hand, following the 'skimping hypothesis' of Berger and DeYoung (1997) banks which devote fewer resources to monitor lending risks will be more cost-efficient. However, will have an increasing number of NPLs in the future. This implies a negative effect of efficiency on NPLs.[6] On the contrary, higher cost inefficiency would increase NPLs again following the 'bad management' hypothesis, as bank managers with poor skills in credit scoring and monitoring borrowers increase costs and give out poor quality loans. Operating efficiency is measured by non-interest expenses divided by total assets, in a way similar to Espinoza and Prasad (2010), Louizis et al. (2012).

Size: States with large-sized banking industry, banks may increase their leverage too much and extend loans to lower quality borrowers. In larger sized markets, banks often resort to excessive risk taking since it is difficult to impose market discipline by regulators and banks expect government protection in the case of failures (see Stern and Feldman, 2004). Thus, NPLs may be positively impacted by the size. States like Florida or Georgia provide anecdotal evidence of this. I measure size by total assets divided by number of banks in each state.

[5] Historically, in the US banking industry savings institutions started with the original purpose of accepting savings deposits and lending for home mortgages. Most savings institutions were established as mutual banks, meaning they were owned by their depositors, and did not issue stocks. Over time most savings institutions issue stocks and have also expanded their businesses. They offer checking as well as savings accounts, and they make other types of loans.

[6] Risk-averse managers are willing to trade off reduced earnings for reduced risk, especially when their wealth depends on the performance of the bank. In order to improve loan quality, they will increase monitoring and incur higher costs, affecting the measure of operating efficiency.

3.2. Regional economic conditions

State economic activity: I use both growth rates of state real GDP and state real personal income, as well as state unemployment rates to capture state economic activity. These regional economic variables highlight the effect of state business cycles on loan quality. Following the broad literature, I expect a negative impact of both state real GDP and real personal income growths on NPLs, and a positive effect of state unemployment rates on NPLs.

Regional inflation rates: The relationship between NPLs and inflation is ambiguous. Theoretically, for unchanged nominal interest rates inflation should reduce the real value of debt and hence make debt servicing easier. This should lower NPLs. However, high inflation may pass through to nominal interest rates, reducing borrowers' loan-servicing capacity or it can negatively affect borrowers' real income when nominal wages are sticky. If the income does not increase in line with inflation, a rise in inflation increases costs (for both households and corporates) and thus lowers the amount of available funds for debt repayment (see *inter alia* Louizis et al., 2012; Nkusu, 2011; Skarica, 2014). This would cause NPLs to rise. State-level inflation data are not available. As its closest proxy, I use the percentage change of the CPI of the largest urban center either in the state or closest to that state.

State housing price index: Rising home prices boost financial wealth and can help borrowers face unexpected adverse shocks or ease their access to credit by boosting the value of the underlying homes used as collateral (Beck et al., 2013; Nkusu, 2011). In this regard, changes in house price are expected to negatively affect NPLs. Anecdotal evidence of this was found in the recent US housing market crisis where precipitous decline in real estate prices across states was typically followed by large scale delinquencies, foreclosures and rising NPLs.

State home ownership rates: is measured by the proportion of houses that are owner-occupied. Much like housing prices, a rise in home homeownership in any state, helps borrowers to use it as collateral. This will reduce NPLs. On the contrary, greater homeownership also increases chances of loan defaults, especially if the loans are not originated and scrutinized carefully. This implies a positive effect of homeownership on NPLs.

State housing starts: Greater housing starts reflect better economic health of each state. This may reduce NPLs. But at the same time, can lead to more mortgage defaults, thereby raising NPLs.

3.3. National economic determinants

Real interest rates: a rise in real lending rates (i.e. with floating interest rates) increases the real value of borrowers' debt and makes debt servicing more expensive. This will increase loan defaults and hence NPLs. I use the bank prime loan rate (the interest rate charged on loans by banks to businesses) adjusted by the aforementioned regional inflation rates to measure real lending rates. Moreover, greater interest-rate uncertainty affects banks source of funds that in turn influences loans growth and hence NPLs (Elijah et al., 2014).

Federal public finances: can positively affect NPLs. First, deterioration of public finances places a 'ceiling' on the market evaluation of credibility for the national banks and consequently banks become hard-pressed for liquidity (Reinhart and Rogoff, 2010). In this context, banks have to cut lending and thus debtors cannot refinance their debts. Moreover, a rise in public debt may lead to fiscal measures, especially cuts in social expenditure and the wage component of government consumption (Perotti, 1996). This may render unserviceable a number of outstanding loans, as households' income will experience a negative shock, while second-order effects in corporate loans may take place due to decreasing demand. I use both the percent changes in federal budget deficit or surplus and public debt both as a share of GDP to measure federal public finances, as in Louizis et al. (2012), Makri et al. (2014).

4. Data and preliminary statistical diagnostics

Banking-industry specific data are retrieved from the balance sheet and income statements of each state. These are available at the FDIC website under "Historical Statistics on Banking." State GDP and personal income are sourced from US BEA while state-level unemployment rates and regional CPI are taken from US BLS. Finally, data on state homeownership and housing starts are from the US Census Bureau; state housing price indices are taken from the US Federal Housing Finance Agency. Table 1 summarizes the variables and their corresponding sources.

Aggregate data for the entire banking system of each state (in contrast to bank level data) are considered preferable as the risk of non-representativeness of the sample is reduced (see *inter alia* Boudriga et al., 2009). At the same time, studies based on bank-by-bank, while very useful in a micro-prudential context, cannot study the impact of cross-state differences with respect to structural

Table 1
Description of variables.

	Description	Source	Expected sign	Mean	Std. dev.	*N*
Banking-industry specific variables						
Capitalization	Equity capital-to-assets	FDIC	+/−	0.092	0.024	1530
Credit growth	Loans-to-assets	FDIC	+	0.622	0.099	1530
Credit quality	Loans and lease loss provision-to-total loans	FDIC	+	0.010	0.012	1530
Diversification	Non-interest income-to-total income	FDIC	−	0.289	0.116	1530
Operating efficiency	Non-interest expenses-to-total assets	FDIC	+	0.034	0.012	1530
Return on assets	Net pre-tax income-to-total assets	FDIC	−	0.014	0.011	1530
Industry size	Log of total assets-to-number of banks	FDIC	+	13.035	1.353	1530
Regional economic conditions						
State real GDP growth	Inflation adjusted percent change in GDP	US BEA	−	2.487	3.444	1530
State real personal income growth	Inflation adjusted percent change in personal income	US BEA	−	2.488	2.463	1530
Unemployment rates	Unemployed-to-labor force	US BLS	+	5.834	1.962	1530
Inflation	Percent change in regional CPI	US BLS	+/−	2.842	1.323	1530
Housing price index	HPI	US FHFA	−	240.522	111.975	1530
State homeownership rates	Proportion of households that is owner-occupied	US Census Bureau	+/−	67.522	6.583	1520
State housing starts	Privately hold housing units authorized by building permits	US Census Bureau	+/−	1612.418	2045.025	1326
National economic conditions						
Real interest rates	Nominal lending rate adjusted for regional inflation	Federal Reserve	+	4.201	2.077	1530
Deficit-to-GDP	Budget deficit or surplus as a percent of GDP	US Census Bureau	+	−3.141	2.788	1530
Debt-to-GDP	Public debt as a percent of GDP	US Census Bureau	+	62.873	15.280	1530

Table 2
Average NPLs across states.

States	Full-sample	Average 2007–2010	Average 1987–1992	States	Full-sample	Average 2007–2010	Average 1987–1992
Alabama	1.401	3.341	1.126	Montana	2.127	2.729	2.585
Alaska	2.753	2.841	5.791	Nebraska	1.349	1.438	1.464
Arizona	2.533	4.560	4.416	Nevada	2.301	4.435	2.456
Arkansas	1.794	2.724	1.911	New Hampshire	1.923	1.634	2.602
California	2.229	2.747	3.695	New Jersey	2.127	2.597	3.994
Colorado	1.987	3.401	2.949	New Mexico	2.108	3.472	3.119
Connecticut	2.243	2.522	5.021	New York	2.691	2.139	5.808
Delaware	1.897	3.211	1.668	North Carolina	1.949	4.444	1.316
District of Columbia	2.596	4.110	5.793	North Dakota	1.428	1.258	1.865
Florida	2.126	5.069	2.281	Ohio	1.969	4.333	1.816
Georgia	1.715	4.428	1.544	Oklahoma	2.294	1.983	3.756
Hawaii	1.400	1.890	1.047	Oregon	1.659	3.425	1.930
Idaho	1.524	3.605	1.181	Pennsylvania	1.496	1.772	2.411
Illinois	2.008	3.522	2.412	Rhode Island	2.001	2.034	3.628
Indiana	1.519	2.384	1.519	South Carolina	1.649	3.737	1.544
Iowa	1.257	1.579	1.286	South Dakota	2.682	4.806	2.759
Kansas	1.649	2.905	1.770	Tennessee	1.633	3.065	1.714
Kentucky	1.649	1.843	1.665	Texas	2.187	2.144	4.706
Louisiana	2.436	3.387	4.305	Utah	1.562	2.008	2.110
Maine	1.299	1.165	2.437	Vermont	1.487	1.281	2.490
Maryland	1.689	2.817	2.499	Virginia	1.466	2.508	1.989
Massachusetts	1.532	0.863	4.085	Washington	2.163	5.588	2.129
Michigan	1.704	4.001	1.300	West Virginia	1.373	1.453	1.715
Minnesota	1.631	2.500	2.236	Wisconsin	1.540	3.214	1.348
Mississippi	1.297	1.804	1.457	Wyoming	1.999	2.114	2.787
Missouri	1.494	2.391	1.813				

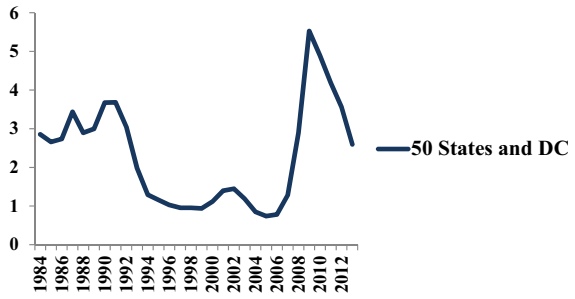

Fig. 1. Non-performing loans in US commercial banking industry 1984–2013.

characteristics on asset quality. Moreover, exploiting cross-state variation in NPL trends is likely to yield more robust results than an analysis of bank-level data or individual states since time series for NPLs are typically short, covering at most 30 years of annual data.

NPLs data are available from 1984 onwards. Thus the dataset comprises of a balanced panel of 50 states and the District of Columbia spanning 1984–2013. Using panel data allows me to capture the state-specific effects and the unobservable differences between states. I can also control for the biases generated by potential heterogeneity and omitted variable problems.

4.1. Measuring NPLs

Following the most commonly used definition, NPLs are defined as the sum of total loans and leases past due 90 days or more and non-accrual loans, divided by total (gross) loans. Fig. 1 provides an ocular view of NPLs in the US commercial banking industry for the time period of analysis. There is an increase in NPLs during the US banking crisis of the late 1980s to the early 1990s followed by a decline till the mid-2000s. More recently there is a much larger increase in NPLs till year 2010. Finally, for the second decade of the new millennium, NPLs in banks' balance sheet decline suggesting an improvement in the asset quality of US commercial banks.

Table 2 shows the average NPLs across each state over the entire sample period as well as for the crisis years of 2007–2010. For a comparative perspective column 3 shows the same for 1987–1992, a time period characterized by banking industry instability in the US. While the average NPLs in the US commercial banking system was 2.29% for the full-sample, during 2007–2010 it stood at 3.65% that is slightly higher than the average value of 3.29% during 1987–1992. Pointedly, Table 2 also reveals that 30 states had a greater share of NPLs during 2007–2010 compared to the crisis of 1987–1992, while the opposite holds for 21 states.[7]

Fig. 2(a)–(d) shows the scatter plot between NPLs with four regional economic variables, respectively. Both real state GDP and personal income growths as well as increases in state HPI are negatively correlated with NPLs while there is a positive correlation between state unemployment rates and NPLs. Fig. 3(a)–(d) next shows the same for NPLs with some of the state-level banking industry variables. NPLs exhibit a positive correlation with credit quality and overhead costs-to-assets, but are negatively correlated with banks' capital-to-assets and ROA.

Following convention in the credit risk literature, the dependent variable Y_{it} is expressed as log(NPLs/(1 − NPLs)) where NPLs is the NPLs ratio, similar to Espinoza and Prasad (2010), Klein (2013), Wenzel et al. (2014). This logit transformation ensures that the dependent variable spans over the interval $[-\infty; +\infty]$ as opposed to between 0 and 1, and is distributed symmetrically. It also allows avoiding non-normality in the error term and accounts for nonlinearities in the sense that larger shocks to the explanatory variables may cause a large, nonlinear response in the transformed dependent variable (see Wenzel et al., 2014).

4.2. Panel unit root tests

All other variables are also expressed in their logarithmic forms. I perform the Levin et al. (2002) panel unit root test that assumes a common unit root process, as well as the Im et al. (2003); Fisher-ADF tests that assume individual unit root processes. Table 3

[7] The states with the highest average NPLs during the recent banking crisis were Arizona, Florida, Georgia, North Carolina and Washington. The ones with the highest NPLs during the 1987–1992 banking crisis were Alaska, Connecticut, District of Columbia, New York and Texas.

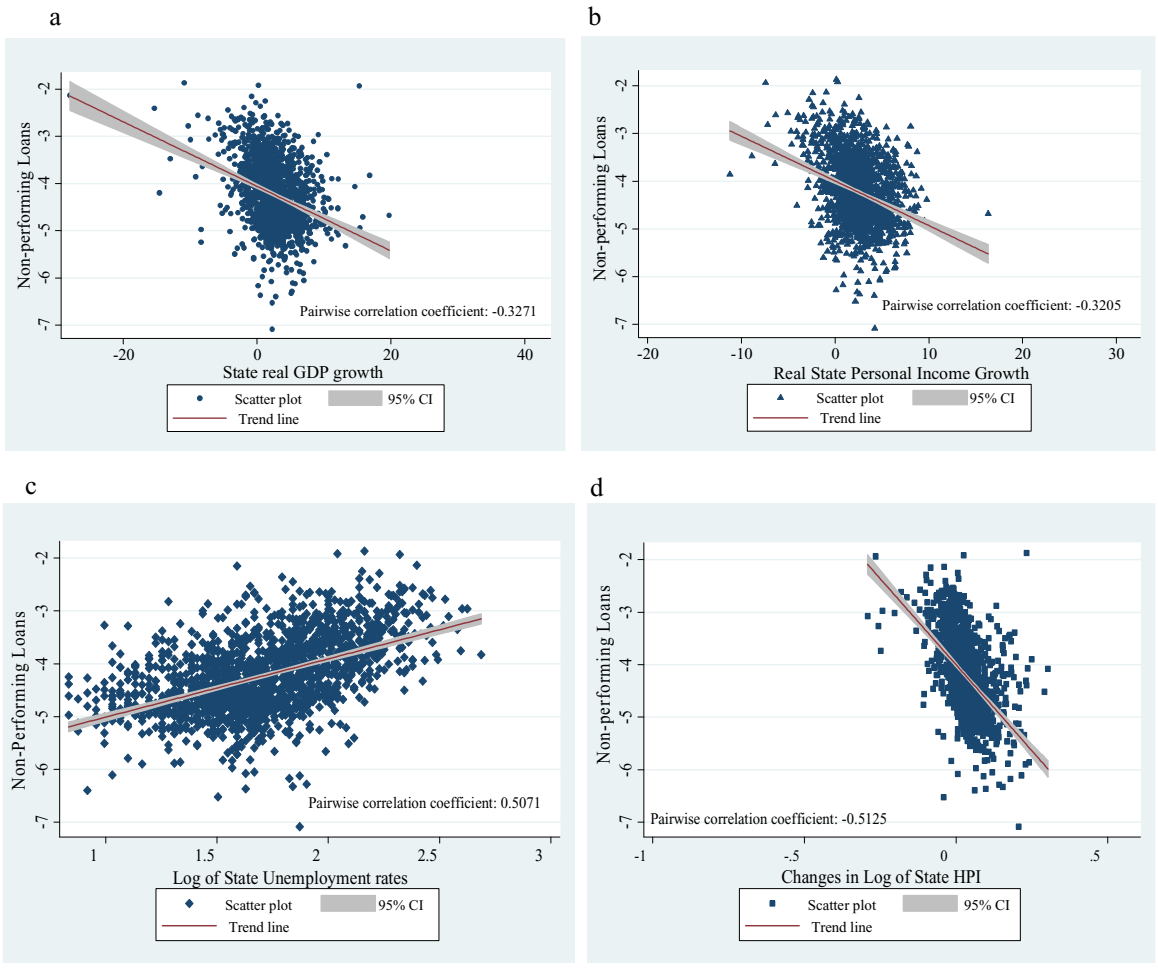

Fig. 2. (a) NPL and state real GDP growth. (b) NPL and state real personal income growth. (c) NPL and state unemployment rates. (d) NPL and changes in state HPI.

Table 3
Panel unit root test results.

	Levin, Lin and Chu *t*	Prob	Im, Pesaran and Shin *W*-stat	Prob	ADF-Fisher chi-square	Prob
NPL	−5.681	0.000	−4.633	0.000	161.748	0.000
Log of ROA	−4.336	0.000	−1.529	0.063	274.602	0.000
Log of capital-to-asset	−6.192	0.000	−3.524	0.000	145.213	0.003
Log of loans-to-assets	−2.616	0.005	−4.200	0.000	170.086	0.000
Log of credit quality	−0.795	0.213	−5.760	0.000	196.688	0.000
Log of diversification	2.771	0.997	1.327	0.908	87.762	0.841
Log of loans-to-deposits	−0.053	0.479	−1.874	0.031	146.360	0.003
Log of OCA	−1.527	0.063	0.926	0.823	94.287	0.694
Log of unemployment rates	−8.532	0.000	−8.114	0.000	237.057	0.000
Log of homeownership	2.118	0.983	1.642	0.950	79.476	0.952
Log of housing starts	−4.375	0.000	−2.171	0.015	116.715	0.151
Log of inflation	−23.488	0.000	−16.659	0.000	452.843	0.000
Log of real loan rate	3.025	0.999	−0.772	0.220	85.950	0.873
State real GDP growth	−21.841	0.000	−19.747	0.000	550.028	0.000
Real personal income growth	−25.285	0.000	−20.921	0.000	591.012	0.000
Log of state GDP per capita	−1.811	0.035	152.218	0.001	−3.868	0.000

presents the panel unit root results where the null hypothesis is of non-stationarity. Variables that exhibit unit roots in their levels form were first-differenced to induce stationarity.[8]

5. Estimation methodology and results discussion

5.1. Static estimation

The static framework uses a fixed effects estimation model that controls for the effect of time-invariant unobserved heterogeneity across states, captured by state-specific dummies. Because the regression analysis is limited to a specific set of states and all the variables are time varying, I find it reasonable to use this estimation technique as one of the methods. The fixed-effects model

[8] Maddala and Wu (1999) argue that the individual unit root tests for panel data performs best when compared with tests that assume common unit roots, as it does not require a balanced panel data set. Hence, for purposes of robustness checks I perform both common and individual panel unit root tests on the variables.

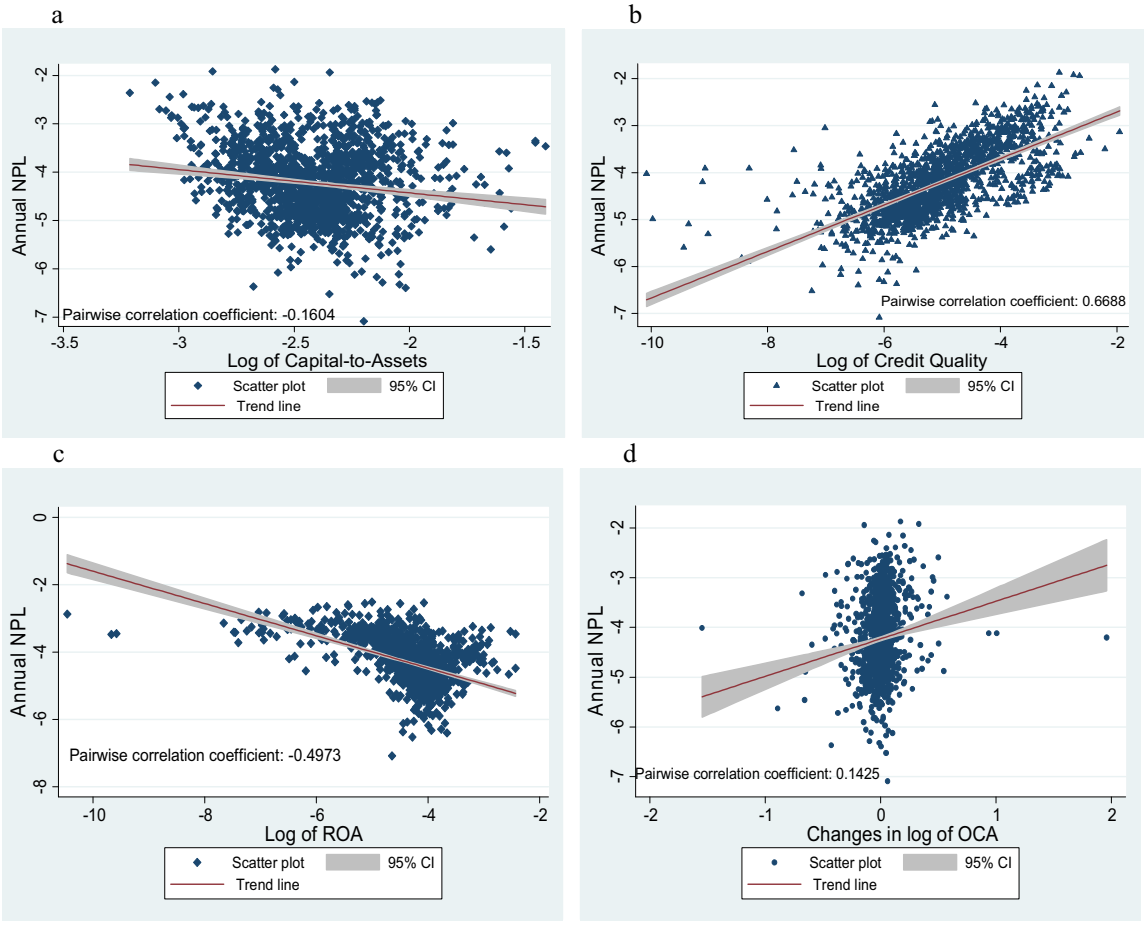

Fig. 3. (a) NPL and capital-to-assets. (b) NPL and credit quality. (c) NPL and return on assets. (d) NPL and overhead costs to assets.

also allows controlling for state-invariant but time variant unobserved factors (like institutional and regulatory changes in the US banking industry) by using time dummies.[9] Moreover, the use of state-specific effects addresses the omitted-variables bias problem.

$$Y_{it} = a_{0_{it}} + a_{j_{it}}(X_{it}^{j}) + a_{k_{it}}(X_{it}^{k}) + \mu_i + \lambda_t + \varepsilon_{it} \quad (1)$$

where Y_{it} denotes the logit transformation of NPLs for state i in period t; (X_{it}^{j}) denotes a vector of state banking-industry specific variables; (X_{it}^{k}) represents the vector of state economic variables. i represents each state and t each year; μ refers to state fixed effects, λ is time fixed effects and ε_{it} is an independently and identically distributed error term. Results are shown in Table 4.

Gleaning first at the banking-industry specific variables, a 1% increase in loans-to-assets increase NPLs by 0.17–0.34%, this implies greater loan growth (and liquidity risks) positively and significantly influences NPLs, following the 'lax credit standards' hypothesis of Keeton (1999).[10] Likewise, a 1% rise in loan-loss provision, capturing inferior credit quality, increases NPLs by 0.26–0.3% in accordance with the 'moral hazard hypothesis.' Somewhat surprisingly, greater diversification positively influences NPLs, suggesting a higher share of non-interest income increases more risks for banks. A 1% percent rise in ROA lowers NPLs by 0.14–0.23%, again consistent with the 'moral hazard hypothesis.' This implies in a more profitable banking industry, banks are engaged in more prudent lending and carefully originate their loans, causing a reduction in NPLs. The extent of capitalization, operating efficiency and banking-industry size are statistically insignificant.

Turning to the regional economic determinants, both state real GDP and real personal income growth rates as well as increases in state housing price indices lower NPLs. On the other hand, a 1% rise in unemployment rate increases NPLs by 0.32–0.46%. Housing starts are also positively significant indicative of its deleterious effect on loan default, while interest rates are insignificant. In general, these results indicate a strong dependence of both individuals and businesses ability to repay loans during the upward phase of each state's business cycle.

5.2. Dynamic estimation

NPLs are typically persistent, which would suggest that the response of credit losses to the macroeconomic cycle could take time to materialize, although it would also imply that NPLs would then cumulate to high levels (Klein, 2013). As a consequence, I specify a dynamic model by including a lagged value of NPLs to capture the issue of persistence of NPLs and the effect of omitted explanatory variables. Moreover, the state banking-industry specific variables are most likely to be endogenous with NPLs. Rising NPLs reflect a deterioration of banks' balance sheets and asset quality, which in turn may lower banks leverage and/or reduce profits.

[9] The fixed effects estimation allows the unobserved state specifics to be arbitrarily correlated with the determinants of asset quality. Under the assumption of strict exogeneity it also takes into account the state-specific differences.

[10] As a sensitivity analysis loans-to assets ratio was replaced with logarithmic values of total loans-to-state nominal GDP as in Esa et al. (2015), Jakubik and Reininger (2013); and total loan growth, muck like in Espinoza and Prasad (2010), Messai and Jouini (2013), as alternate measures. The coefficients of these two variables were positively significant and similar to loans-to-assets.

Table 4
Fixed effects results.
Terms in brackets denote *t*-stat based on robust standard errors.
The coefficients in bold denote statistically significant values.
The fixed effects results include both state and time dummies.

	[1]	[2]	[3]	[4]	[5]
Constant	**−3.386*****	**−3.735*****	**−3.726*****	**−4.909*****	**−3.91*****
	(−16.035)	(−14.977)	(−14.94)1	(−12.374)	(−16.034)
Capital-to-asset	0.102	0.004	−0.005	0.034	0.009
	(1.363)	(0.055)	(−0.067)	(0.442)	(0.118)
Loans-to-asset	**0.169*****	**0.341*****	**0.343*****	**0.282*****	**0.335*****
	(2.645)	(5.548)	(5.581)	(4.096)	(5.431)
Loan loss provision	**0.306*****	**0.272*****	**0.273*****	**0.255*****	**0.272*****
	(19.362)	(18.00)	(18.082)	(15.966)	(17.906)
Diversification	**0.179*****	**0.123****	**0.121****	**0.11***	**0.124****
	(2.775)	(2.041)	(2.012)	(1.782)	(2.05)
Overhead costs to-total assets	−0.131	−0.064	−0.057	−0.028	−0.061
	(−1.483)	(−0.775)	(−0.698)	(−0.337)	(−0.74)
ROA	**−0.227*****	**−0.151*****	**−0.151*****	**−0.139*****	**−0.153*****
	(−12.136)	(−7.844)	(−7.807)	(−6.469)	(−7.932)
Industry size	−0.058	−0.010	−0.011	−0.006	−0.008
	(−1.491)	(−0.28)	(−0.302)	(−0.165)	(−0.227)
Real GDP growth		**−0.849****		**−0.656***	**−0.852****
		(−2.408)		(−1.764)	(−2.398)
Real personal income growth			**−1.47*****		
			(−2.626)		
Unemployment rates		**0.322*****	**0.318*****	**0.455*****	**0.36*****
		(4.873)	(4.807)	(5.979)	(5.526)
Inflation		**−4.123*****	**−4.123*****	**−2.706*****	
		(−3.061)	(−3.062)	(−1.876)	
HPI		**−1.723*****	**−1.67*****	**−1.785*****	**−1.88*****
		(−6.634)	(−6.358)	(−6.057)	(−7.338)
Homeownership		−0.586	−0.601	−0.711	**−0.529*****
		(−1.273)	(−1.306)	(−1.412)	(−1.145)
Housing starts				**0.133*****	
				(3.508)	
Real interest rates					0.321
					(0.255)
Adj R^2	0.740	0.776	0.776	0.771	0.774
F-stat.	47.986	53.339	53.397	48.036	52.848
AIC	0.696	0.541	0.540	0.561	0.548
Cross-sections/*N*	51/1418	51/1360	51/1360	51/1228	51/1360

* Indicates significance at 10% level.
** Indicates significance at 5% level.
*** Indicates significance at 1% level.

In the presence of a lagged dependent variable, using a fixed effect model is erroneous as the error term is correlated with the lagged NPLs term thus leading to inconsistent estimates. To deal with this and the aforementioned endogeneity concern, I use the systems-GMM estimation developed by Arellano and Bover (1995), Blundell and Bond (1998).[11]

$$Y_{it} = a + \delta Y_{i,t-1} + \sum_{j=1}^{J} (a_j X_{it}^j) + \sum_{j=1}^{K} (a_k X_{it}^k) + \varepsilon_{it} \quad (2)$$

A value of δ between 0 and 1 implies persistence of NPLs. The state-level economic determinants of NPLs are considered as predetermined (and hence instrumented IV style), while the state banking-industry specific variables are modeled as endogenous (and instrumented GMM-style in the same way as the lagged dependent variable). I also include time dummies.

Results in Table 5 confirm some findings using the fixed effects model. Both greater loans-to-asset (specifications 4 and 5) and loan loss provision positively influences NPLs while greater bank profitability lower NPLs. Moreover, the systems-GMM estimation provides certain findings that are an improvement than the fixed effects results. Pointedly, the capital-to-assets ratio exhibits a positive and significant coefficient. This is supportive of the 'too big to fail' hypothesis that banks with more capital resort to lax credit checking and liberal lending policies that in turn eventually culminate in rising NPLs. Greater operating inefficiency is now positive and significant, supporting the 'bad management' hypothesis. Likewise, greater size of the state banking industry increases NPLs, as expected a priori. Finally, greater diversification by banks is now statistically insignificant. Moreover, I find a high degree of persistence of NPLs, with the previous year's NPLs affecting the present year's by 52–53%. This implies a shock to NPLs will have prolonged effect on each state's banking sector and it would take time to reduce NPLs.

The regional economic variables exhibit the same sign and significance as in the fixed effects results, again confirming the countercyclical nature of NPLs. Interestingly; inflation now changes sign and is positively significant. This implies, a rise in inflation is not matched by a commensurate rise in nominal incomes, causing real income to fall. This adversely affects the ability to make loan payments, hence leading to a rise in NPLs. Much like the fixed

[11] The Arellano and Bond (1991) difference-GMM estimator has been criticized when applied to large panels with small *T*, the argument being under such conditions this estimator is inefficient. This could be an issue here with a time period from 1984 to 2013. To avoid such problems, I use system-GMM estimation developed by Arellano and Bover (1995), Blundell and Bond (1998). The methodology essentially regresses levels and changes in NPLs on the lags of the same variable as well as other explanatory variables using lagged levels as instruments. This reduces potential biases in finite samples and any asymptotic imprecision associated with the difference estimator.

Table 5
Systems-GMM estimation results.
Terms in brackets denote *t*-stat based on robust standard errors clustered in states.
The coefficients in bold denote statistically significant values.

	[1]	[2]	[3]	[4]	[5]
c	**−1.534*****	**−1.55*****	**−1.222*****	**−1.502*****	**−1.156*****
	(−6.36)	(−6.33)	(−4.69)	(−5.88)	(−4.78)
Capital-to-asset	**0.103***	**0.129****	**0.17*****	0.074	0.093
	(1.76)	(2.22)	(2.99)	(1.31)	(1.55)
Loans-to-asset	0.091	0.068	0.060	**0.103***	**0.114****
	(1.54)	(1.22)	(1.02)	(1.62)	(2.01)
Loan loss provision	**0.198*****	**0.202*****	**0.194*****	**0.198*****	**0.18*****
	(12.68)	(12.92)	(12.31)	(11.88)	(11.74)
Diversification	0.025	0.025	0.020	0.011	0.018
	(0.61)	(0.58)	(0.47)	(0.83)	(0.53)
Overhead costs to-total assets	**0.218*****	**0.231*****	**0.229*****	**0.228*****	**0.191****
	(2.55)	(2.75)	(2.63)	(2.72)	(2.33)
ROA	**−0.153*****	**−0.162*****	**−0.145*****	**−0.154*****	**−0.112*****
	(−5.62)	(−6.02)	(−4.62)	(−5.55)	(−4.26)
Size	**0.099***	**0.096***	**0.105***	**0.099***	**0.095***
	(1.86)	(1.79)	(1.91)	(1.94)	(1.82)
Real GDP or personal income growth	**−1.424*****	**−0.903****	**−1.547*****	**−1.51*****	**−1.243*****
	(−4.92)	(−2.32)	(−4.83)	(−4.79)	(−4.25)
Unemployment rates	**0.097****	**0.095***	0.046	0.069	−0.069
	(2.2)	(1.99)	(1.01)	(1.59)	(−1.39)
Inflation	**1.558****	**1.96*****	**1.725****		**1.977*****
	(2.36)	(2.80)	(2.21)		(2.84)
HPI	**−1.97*****	**−2.136*****	**−2.29*****	**−1.932*****	**−2.156*****
	(−6.09)	(−6.33)	(−5.47)	(−6.00)	(−6.64)
Homeownership	−0.311	−0.322	−0.307	−0.453	−0.135
	(−0.87)	(−0.83)	(−0.87)	(−1.34)	(−0.38)
Housing starts			−0.002		
			(−0.19)		
Real interest rates				−0.101	
				(−1.34)	
Changes in budget deficit					0.002
					(0.31)
Changes in public debt					**1.523*****
					(6.15)
$NPL_{(t-1)}$	**0.521*****	**0.512*****	**0.532*****	**0.523*****	**0.539*****
	(18.82)	(18.19)	(19.57)	(18.17)	(19.43)
Time dummies	Yes	Yes	Yes	Yes	Yes
Chi sq.	5469.090	5889.510	4838.710	5471.52	5176.600
AR(1) (*p-val*)	−5.027***	−4.839***	−4.902***	5.087***	−5.011***
AR(2) (*p-val*)	−0.915	−1.004	−0.857	−0.915	−0.941
N	1360	1360	1228	1360	1360

* Indicates significance at 10% level.
** Indicates significance at 5% level.
*** Indicates significance at 1% level.

effects results, both homeownership and real interest rates are again insignificant.[12]

AR(1) and AR(2) are the Arellano–Bond tests for first and second order autocorrelation of the residuals. One should reject the null hypothesis of no first order serial correlation and not reject the null hypothesis of no second order serial correlation of the residuals. In all specifications, the requirements are met as suggested by the *p*-values of the AR(1) and AR(2) tests. These imply that the GMM results are consistent.[13]

Additionally, the changes in regional conditions may not affect NPLs immediately but after a lag of one to two years. I take such effects into consideration by using up to two-period lagged values of the regional economic variables. In general, two-period lagged value of the unemployment rates were consistently significant with the coefficients ranging from 0.17 to 0.36 in the different specifications. Likewise, one-year lagged value of the changes in state HPI was consistently negatively significant with the elasticities ranging between −0.70 and −1.09. Both one and two year lagged values of homeownership rates were negatively significant. The lagged values of real interest rates were now positively significant, following theoretical priors.

5.3. Results for savings institutions

The analysis thus far has focused on examining NPLs of commercial banks only. To provide a comparative perspective, I also present the results for savings institutions using both the fixed effects and GMM estimations in Table 6. Data on NPLs of savings institutions are available from 1990 onwards. Similar to the findings for commercial banks, greater capitalization and loan loss provision significantly increase NPLs while greater profitability lowers NPLs. However, unlike in the case of commercial banks, for savings institutions operating inefficiency, credit growth, share of non-interest income or state industry size are insignificant. This implies NPLs of savings institutions are less affected by industry-specific factors. Turning to the regional economic determinants of NPLs, rise in housing prices consistently reduce NPLs. Both real GDP and personal income growth rates, unemployment rates hold their usual

[12] As an alternate specification to the logit transformation of NPLs, I also used logarithmic value of NPLs. The results for both static and dynamic estimations were very similar and are available on request.
[13] The Hansen test of over identifying restrictions further suggests that the instruments used in all the specifications are appropriate.

Table 6
Results for savings institutions.
Terms in brackets denote *t*-stat based on robust standard errors clustered in states.
The coefficients in bold denote statistically significant values.
The fixed effects results in the left panel also include state dummies.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]
c	**−3.053*****	**−3.099*****	**−3.277*****	**−3.165*****	**−1.297***	**−1.405****	**−1.751*****	**−1.315***
	(−6.319)	(−6.408)	(−3.719)	(−6.805)	(−1.88)	(−2.01)	(−3.12)	(−1.92)
Capital-to-asset	**0.182*****	**0.178*****	**0.145*****	**0.18*****	**0.099****	**0.097****	**0.075****	**0.096****
	(4.371)	(4.278)	(3.666)	(4.319)	(2.29)	(2.35)	(2.01)	(2.17)
Loans-to-asset	−0.344	−0.364	−0.318	−0.327	0.296	0.313	0.349	0.263
	(−1.357)	(−1.439)	(−1.332)	(−1.293)	(0.96)	(1.04)	(1.15)	(0.85)
Loan loss provision	**0.269*****	**0.27*****	**0.19*****	**0.27*****	**0.18*****	**0.171*****	**0.189*****	**0.183*****
	(9.598)	(9.637)	(6.717)	(9.612)	(4.25)	(4.08)	(4.21)	(3.92)
Diversification	0.027	0.023	0.030	0.026	0.074	0.088	0.115	0.053
	(0.347)	(0.296)	(0.411)	(0.329)	(0.98)	(1.22)	(1.57)	(0.70)
Overhead costs to-total assets	0.040	0.042	0.118	0.045	−0.089	−0.085	−0.122	−0.073
	(0.403)	(0.426)	(1.245)	(0.456)	(−0.74)	(−0.75)	(−0.96)	(−0.61)
ROA	**−0.091*****	**−0.089*****	**−0.106*****	**−0.093*****	**−0.067****	**−0.082****	**−0.087*****	**−0.085*****
	(−2.774)	(−2.703)	(−3.418)	(−2.841)	(−2.05)	(−2.60)	(−3.07)	(−2.66)
Size	−0.019	−0.025	−0.012	−0.011	−0.012	−0.006	−0.017	0.002
	(−0.253)	(−0.34)	(−0.167)	(−0.149)	(−0.16)	(−0.09)	(−0.22)	(0.02)
Real GDP or personal income growth	**0.014***	**0.029****	0.012	0.014	**−0.012***	−0.012	−0.010	−0.011
	(1.625)	(2.057)	(1.472)	(1.565)	(−1.62)	(−1.38)	(−1.48)	(−1.55)
Unemployment rates	0.206	0.222	**0.341***	0.233	0.021	0.025	0.141	−0.017
	(1.225)	(1.319)	(1.964)	(1.409)	(0.17)	(0.19)	(1.38)	(−0.13)
Inflation	−2.801	−2.882	−2.531		2.902	3.089	2.872	
	(−0.812)	(−0.836)	(−0.772)		(1.46)	(1.59)	(1.51)	
HPI	**−2.470*****	**−2.634*****	**−3.292*****	**−2.611*****	**−2.849*****	**−2.949*****	**−2.599*****	**−2.796*****
	(−3.638)	(−3.817	(−4.944	(−3.913)	(−5.61)	(−5.83)	(−5.04)	(−5.67)
Homeownership	−1.680	−1.642	−1.254	−1.626	**−2.479****	**−2.47****	**−2.126****	**−2.852****
	(−1.421	(−1.39)	(−1.111)	(−1.377)	(−2.26)	(−2.24)	(−2.18)	(−2.60)
Housing starts			−0.042				−0.024	
			(−0.443)				(−0.840)	
Real interest rates				−1.915				0.055
				(−0.624)				(0.05)
$NPL_{(t-1)}$					**0.545*****	**0.544*****	**0.486*****	**0.54*****
					(7.43)	(7.37)	(7.34)	(7.25)
Time dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R^2	0.554	0.554	0.547	0.553	1816.410	2010.550	1656.030	1923.570
AIC	2.105	2.103	1.981	2.105				
F-stat	15.840	15.884	15.251	15.833				
AR(1) (*p-val*)	1066	1066	1039	1066	−3.072***	−3.075***	3.164***	−3.072***
AR(2) (*p-val*)					0.667	0.644	0.346	0.671
N	1066	1066	1039	1066	1031	1031	1018	1031

* Indicates significance at 10% level.
** Indicates significance at 5% level.
*** Indicates significance at 1% level.

signs although their statistical significance is less consistent here. Rise in homeownership significantly reduce NPLs when using the GMM estimations. This implies homeowners can use their property as collateral that help in lowering NPLs. Housing starts or real interest rates are again insignificant. Overall, the sensitivity of NPLs of commercial banks to both regional banking and economic conditions is more than those of savings institutions.

Comparing my results with those of earlier studies, the positively significant effect of bank capitalization on NPLs across the panel of states in the US, contrasts the negative effect of this variable on NPLs found by Klein (2013) and Makri et al. (2014) in their panel of European nations. However, my findings match that of Macit (2012) for the Turkish banking industry. The positive effect of loans growth is in line with the panel studies of Espinoza and Prasad (2010), Jakubik and Reininger (2013), Klein (2013). Turning to loan loss provision, a variable that has been less used in the literature, the positive coefficient parallels the findings of Messai and Jouini (2013) for the three euro zone nations. The lack of significance of bank diversification in the US banking industry matches that of Louizis et al. (2012) for the Greek banking industry. The evidence of 'bad management' of banks cost efficiency on NPLs is consistent with that of Espinoza and Prasad (2010) for the GCC nations, Louizis et al. (2012) and Podpiera and Weill (2008) for Czech banks. Likewise, the negative impact of bank profits in each state on NPLs is in keeping with the findings of Messai and Jouini (2013), Klein (2013) and Louizis et al. (2012). Finally, the positive effect of industry size on NPLs match those of Louizis et al. (2012) but contrast those of Espinoza and Prasad (2010), where of course the authors use a different measure (logarithmic value of equity). The persistence of lagged NPLs found across states in the US matches the broad literature on both individual as well as cross-country studies.

Next, comparing the findings for the regional and national economic variables, the results for state real GDP growth match the overwhelming body of existing literature. The positively significant coefficient of state unemployment rates match those in the panel studies of Makri et al. (2014), Messai and Jouini (2013), Skarica (2014) for different European nations as well as the findings of Nkusu (2011) for advanced economies and the country-specific analysis of Louizis et al. (2012). The positive impact of inflation on NPLs found for commercial banks in the US are consistent with those of Klein (2013), Skarica (2014). On the other hand, the insignificant real interest rate found contrasts the panel studies of Beck et al. (2013), Espinoza and Prasad (2010), Messai and Jouini (2013); and that of Louizis et al. (2012) on Greece. This clearly

calls for better proxies for measuring state-level real interest rates. Finally, the evidence of 'debt hypothesis' found here match those of Louizis et al. (2012), Makri et al. (2014) for the euro zone nations.

Pointedly, unlike most other studies, this paper examines the health of the regional real estate on NPLs. The negatively significant effect of state housing price index deserves special notice. The results imply, as borrowers fail to repay their obligations toward the banks, banks in each state may be forced to liquidate their loans through the sale of collateral (mostly real estate). However, the recovered amount would fall short of the original loan, resulting in significant losses for banks. Thus for both borrowers and banks perspectives, an increase in state housing prices are extremely desirable. Notably, I also find higher NPL-elasticities for state real personal income growth compared to state real GDP growth. This suggests improvements in micro measures of economic activity like net earnings by place of residence, property income, and personal current transfer receipts that comprise personal income will be more beneficial to reduce NPLs than a corresponding rise in a more aggregate measure, like state GDP.

6. Conclusions

The assessment of overall asset quality in the US banking industry is an important element of macro-prudential surveillance. A thorough understanding of its drivers facilitates the identification of key vulnerabilities of the banking sector.

Results here provide evidence of 'too big to fail' hypothesis behavior on the part of banks. Thus, from a capital management point of view this presents a conundrum for banks. While greater capitalization may be beneficial to ensure more profits, but it enhances NPLs. This calls for an optimal extent of capital in banks' balance sheets as well as maintaining high credit standards to reduce NPLs while sustaining profits and maintaining a safety net. Likewise from an asset quality management, ensuring better quality credit and reducing excessive share of illiquid loans in banks asset portfolio will reduce NPLs in the US banking industry. Similarly, efficient cost management is a prerequisite to reduce NPLs and improve the quality of banks' balance sheet. Equally important are bank profits to reduce NPLs. High profits will lead to more prudent lending and promote financial stability of banks across states in the US.

Furthermore, state real GDP and personal income growth, unemployment rates, housing price indices and homeownership rates significantly affect NPLs, underscoring its countercyclical nature. Thus improving the economic health of each state is imperative to reduce NPLs. Finally, a reduction in the US federal government's public debt will help lower NPLs.

Regular stress tests of banks' loan quality are increasingly based on macroeconomic assumptions in order to provide common scenarios for all financial institutions participating in such an exercise. NPL determinants are a crucial part of such bank stress tests for credit risk assessment (see Wenzel et al., 2014). Stress tests for this type of risks begin by examining banks loan portfolios. Thus the significant NPL-elasticities with respect to credit quality imply a balance between the extent of portfolio diversification between risky loans (say, mortgage loans) and other types, like consumer credit or investment securities is desirable. The positively significant coefficient for loans-to assets bodes relevance for stress tests of liquidity risk.

The findings of this study bear further implications on macro-prudential policy. Bank stress tests of a general nature on the banking system in the US (macro-tests) typically undertake a scenario analysis where shocks or impact of specific variables on bank's financial conditions are assessed. The statistically significant coefficients of state-level economic variables indicate that these underlying regional or "micro" economic determinants should be included when calibrating the impact of shocks to these variables on banks financial health.

Future avenues of research can benefit by examining NPLs in the US banking industry across loan-types. To my knowledge such data are presently not available. To conclude, while NPLs remain a permanent feature of banks' balance sheets, policies and reforms should be geared to avoiding sharp increases that set into motion the adverse feedback loop between poor bank loans and the regional economy. I plan to investigate this feedback loop in future studies.

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