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House prices and credit risk: Evidence from the United States☆

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ABSTRACT

This paper investigates the determinants of nonperforming loans (NPL), with a special focus on house price fluctuations. Using a panel of U.S. banks, the analysis is carried out across different loan categories and different types of banks. It is found that house price fluctuations significantly affect the dynamics of NPL, while the magnitude of the impact varies across loan categories and bank types.

1. Introduction

The recent subprime mortgage crisis in the United States has demonstrated the key role that the housing market plays in destabilizing the financial system. From the late 1990s, there was a sharp increase in the subprime mortgages fuelled by low interest rates and lax lending standards. However, while the quality of banks' loan portfolios was deteriorating by the constant growth of the subprime mortgages, the default rates remained artificially low due to the rapid house price appreciation. The booming house prices and low default rates encouraged banks to invest heavily in the real estate market, which eventually led to the creation of a speculative real estate bubble.

The collapse of the real estate bubble exerted enormous pressure on the banks that were highly exposed to the real estate market. In particular, many banking institutions suffered from severe liquidity shortages due to a sharp increase in their nonperforming real estate loans. In fact, falling house prices undermined the value of real estate collaterals, which motivated many subprime mortgage borrowers to default on their loan repayments. Higher default rates, in turn, led to credit contraction and tightening of the lending standards in banks. As a consequence, the housing demand substantially dropped, while the housing supply was increasing due to the rising number of real estate foreclosures. The imbalances between supply and demand further reduced house prices and exacerbated deteriorating credit market conditions, which severely affected the real economy and led to high default rates across all loan categories.

Fig. 1 demonstrates the relationship between U.S. house prices, bank lending, and nonperforming loans (NPL). It appears that there is a close relationship between house prices, aggregate loan level, and aggregate NPL in the U.S. banking system. In other words, rising house prices are associated with increased lending and low default rates, while NPL increase substantially when house prices and real estate lending drop. In addition, Fig. 1 shows that NPL dynamics vary significantly across loan categories and bank types. More specifically, it appears that the impact of house price fluctuations is much higher on real estate loans, compared to other loan categories. It also emerges that, compared to savings institutions (SI), commercial banks (CB) suffer from higher loan losses in response to deteriorating market conditions.

Against this background, it is clear that understanding how house prices affect the quality of loan portfolios is of crucial importance to

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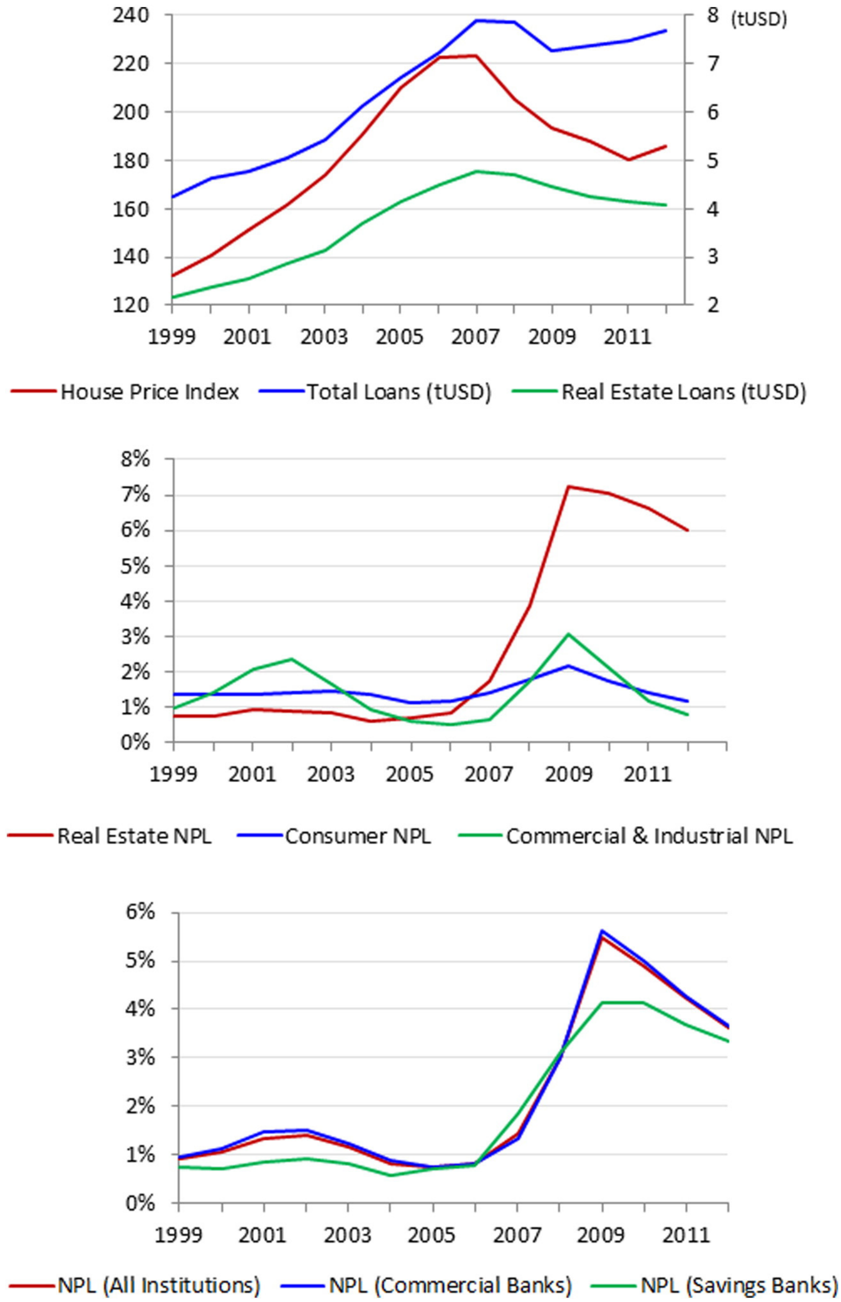

Fig. 1. House Price Index, aggregate lending behavior, and NPL dynamics across loan categories and bank types. *Sources*: FHFA and FDIC.

financial institutions and regulators interested in maintaining financial stability. Accordingly, this study uses dynamic panel data models to empirically investigate the impact of house price fluctuations on the evolution of NPL across U.S. banks. The analysis is further extended by examining if this relationship varies across different loan categories and different types of banks.

This paper complements the existing literature in several ways. First, we specifically examine the impact of house price fluctuations on the quality of loan portfolios at bank-level. Available empirical works focus primarily on the role of house prices in destabilizing the banking system as a whole (see, e.g., Reinhart and Rogoff (2008); Barrell et al. (2010)), while the impact of house prices on the quality of loan portfolios in individual banks is less investigated. Closely related to this particular aspect of our analysis, Pan and Wang (2013) study the threshold effects of income growth on the relationship between house prices and NPL. However, Pan and Wang (2013) only consider the asymmetric impact of house prices on NPL, whereas other credit risk determinants may also have asymmetric effects on default rates. In this empirical study, we account for potential asymmetric effects of all credit risk determinants on default rates by investigating NPL dynamics during different time periods.

Second, to the best of our knowledge, this is the first study that investigates how different loan categories are affected by house price movements. Using aggregate NPL to examine the relationship between house prices and the quality of loan portfolios may be challenged as the composition of loan portfolios varies widely across banking institutions (Louzis et al., 2012). In addition, it is evident in Fig. 1 that NPL dynamics vary substantially across different loan categories. Therefore, it is essential to investigate the sensitivity of different loan categories to house price fluctuations in order to develop an insight for financial regulators to provide better regulatory practices for individual banks with different loan portfolio compositions.

Third, potential differences between determinants of NPL across different types of the U.S. depository institutions have remained undetected, despite their important regulatory implications. It is argued that a bank's lending policies reflect its risk attitude, which in turn depends on its mission and institutional structure (see Salas and Saurina (2002)). Furthermore, as seen in Fig. 1, there are major differences between NPL dynamics of CB and SI over time. Therefore, this study adds to the existing credit risk literature by examining if the impact of house prices on the evolution of NPL varies across two types of depository institutions, namely CB and SI.[1]

Finally, another feature of this paper is that we assess the house price-credit risk nexus based on state-level data and during different macroeconomic conditions. It is argued that the dynamics of house prices vary widely both over time and across geographical regions (see, e.g., Mian and Sufi (2009); Holly et al., (2010)). In particular, despite the recent boom and bust cycle in U.S. national house prices, the patterns of house prices were non-uniform across states. While some states, such as California and Florida, experienced substantial changes in the house prices over both boom and bust periods, some states, such as Vermont and Montana, only underwent rapid house price appreciation, and some other states, such as Georgia and Michigan, only faced large declines over the bust period. These substantial variations in regional house prices reflect differences in the housing market supply and demand, which in turn depend on demographic and socio-cultural factors, local economic conditions, regional regulations and jurisdictions, and local financial systems. Although these factors can contribute markedly to the diversity of credit risk within the United States, the impact of time and regional variations in house prices on the evolution of credit risk has been largely neglected by the literature. Therefore, we investigate the impact of state-level house price fluctuations on the evolution of NPL during different macroeconomic conditions.

In essence, the empirical results reveal that house prices significantly affect the quality of banks' loan portfolios. More specifically, there is a strong negative relationship between changes in house prices and evolution of NPL in individual banks, which supports the view that house prices can serve as a key macroprudential indicator (see, e.g., Davis and Zhu (2009); Barrell et al. (2010)). We also find that the impact of house prices on NPL is more pronounced during adverse economic conditions. In fact, we show that most bank-specific and systematic factors have asymmetric impact on loan losses during different economic conditions. This important finding complements the credit risk literature as similar studies examine the potential asymmetric effects of only one variable on default rates (see, e.g., Marcucci and Quagliariello (2009); Pan and Wang (2013)). Furthermore, unlike prior studies in the banking literature, we show that the effects of house prices on loan losses vary significantly across different loan categories. More specifically, it is shown that falling house prices lead to higher loan losses in real estate loan portfolios, implying that banks with higher real estate lending may face greater financial constraints when house prices drop. Our empirical results also show that the impact of house prices varies among bank types. In particular, we show that CB are more sensitive to falling house prices although SI are traditionally mandated to concentrate on residential mortgages. It is also found that the impact of house prices on loan losses varies depending upon the quality of loan portfolios. In other words, lower quality loan portfolios are more sensitive to house price fluctuations. This particular finding supports the view that there is a circular relationship between house prices, bank lending behavior, and loan losses. Finally, we show that our key findings remain unchanged when we assess the robustness of our results by using different house price indicators, different econometric methodologies, and alternative model specifications.

The remainder of this paper is organized as follows. Section 2 provides some theoretical background and highlights the hypotheses to be tested. In Section 3, the empirical models and estimation procedure are introduced. Section 4 describes the data, while Section 5 discusses the empirical results associated with each hypothesis. In Section 6 we report findings from further empirical checks. Section 7 concludes.

2. Empirical hypotheses

Credit risk analysis is a major issue in the field of banking and finance, and, therefore, it is not surprising that the number of theoretical and empirical studies concerning credit risk is relatively large. A main strand of research postulates that credit risk is tightly linked to business cycles (see, e.g., Koopman and Lucas (2005); Pesaran et al. (2006); Quagliariello (2007)). According to this literature, lending standards and borrowers' default and financing policies are closely related to the state of economy in different phases of business cycles. More importantly, Marcucci and Quagliariello (2009) show that the impact of business cycle on bank credit risk is more pronounced during a macroeconomic downturn.

In addition to the business cycle, banks' risk exposure is likely to be affected by the housing cycle. On the one hand, house price fluctuations may substantially influence the risk-taking behavior of banks as (i) residential mortgage loans typically form a large portion of a bank's aggregate loan portfolio; (ii) real estate assets are widely used as collateral for other loans to secure loan repayments (Davis and Zhu, 2009; Goodhart and Hofmann, 2008). On the other hand, changes in house prices can largely affect the creditworthiness of households and mortgage borrowers as housing is a major component of household wealth (Flavin and Yamashita, 2002; Paradiso et al., 2012), and the wealth effects of housing are greater than other financial assets (Case et al., 2005).

In this context, understanding the drivers of housing cycles is of crucial importance as it can shed light on the linkage between housing prices and credit risk. In fact, just like any other asset, equilibrium house prices are determined by a wide range of factors influencing supply and demand in the housing market. Housing supply strongly depends on the real construction costs as well as physical and regulatory constraints, while the main drivers of housing demand are macroeconomic fundamentals such as local population growth, real disposable income, interest rates, and unemployment rates. Therefore, house prices and business cycle may move together (see, e.g., Davis and Heathcote (2005); Leamer (2007)).

Another factor that plays a central role in the determination of house prices is the credit supply by banks (see, e.g., Davis and Zhu (2011)). Indeed, bank lending greatly amplifies the effects of small income shocks through the real economy by altering the value of borrowers' net-worth. In an influential paper, Bernanke et al. (1996) refer to this amplification mechanism as the "financial accelerator" or "credit multiplier". The main idea behind the financial accelerator is the interplay between borrowers' net worth and their borrowing capacity that arises due to credit market imperfections and asymmetric information between lenders and borrowers in the credit market. Prospective borrowers are usually required to put up collateral to secure their loan repayments, and collateralized assets are often in the form of real estate. Therefore, aggregate borrowing capacity of firms and households is associated with house prices. In this context, rising house prices increase the value of real estate collaterals and lead to greater net-worth for borrowers, which further increase their borrowing capacity (see, e.g., Bernanke and Gertler (1989); Kiyotaki and Moore (1997); Iacoviello (2005)).

The empirical literature presents a two-way relationship between bank lending and house prices: banks largely influence house price dynamics through their lending behavior, while lending policies are greatly affected by house price movements (see, e.g., Gerlach and Peng (2005); Mora (2008); Gimeno and Martinez-Carrascal (2010)). In this context, the co-movement of bank lending and house prices may imply procyclicality in the banking system where most banks may take the same policy actions as they are systematically exposed

[1] Savings institutions include all U.S. savings banks and savings and loan associations.

to similar conditions. In particular, the procyclicality and trend-chasing behavior in bank lending may occur in both lending level (Berger and Udell, 2004; Borio et al., 2001) and lending concentration (Mei and Saunders, 1997). The procyclicality in bank lending not only increases the speed and magnitude of house price fluctuations but also stimulates procyclical default rates (see Marcucci and Quagliariello (2008)). In other words, banks that become heavily exposed to the housing market during a booming period may severely suffer from high loan losses when house prices drop. This is consistent with the idea that risk builds up during booms and materializes during periods of economic downturns (see, e.g., Borio and Lowe (2002); Pesola (2011)).

Furthermore, several studies that examine the causes of the recent subprime mortgage crisis support the idea that there is a cyclical relationship between house prices, bank lending, and default rates (see, e.g., Reinhart and Rogoff (2008); Hott (2011)). In an influential study, Mian and Sufi (2009) investigate the relationship between mortgage credit expansion and default rates using detailed ZIP code-level data. Comparing prime and subprime ZIP codes, they show that subprime ZIP codes experienced higher mortgage credit growth from 2002 to 2005, which in turn led to higher default rates in subprime ZIP codes from 2006. They reveal that unprecedented higher mortgage credit growth was accompanied by higher house prices in subprime ZIP codes. In fact, they demonstrate that increased expectations of future house price growth, improved income prospects of subprime borrowers, and supply shift in mortgage credit were the main drivers of mortgage credit expansion to subprime ZIP codes.

Against this background, and despite the abundance of theoretical works on house prices and financial stability (see, e.g., Demirgüç-Kunt and Detragiache (2005); Barrell et al. (2010)), research that follows this line of literature is rather silent on the relationship between housing market and default rates at bank-level. One exception is the study by Pan and Wang (2013), who analyze the existence of an income growth threshold effect in the relationship between house prices and loan losses in U.S. banks. They show that house price changes and house price deviations from long-run equilibrium significantly affect NPL, while their impact is asymmetric during economic booms and busts. However, the threshold model employed by Pan and Wang (2013) can only detect the existence of threshold effects for house prices, whereas other credit risk determinants may also have an asymmetric impact on loan losses. More importantly, researchers have largely neglected the impact of house price fluctuations on the evolution of NPL across different loan categories and bank types. To narrow this gap, we re-examine the relationship between house prices and default rates by testing three empirical hypotheses formulated as follows:

Hypothesis 1. House price fluctuations heavily affect the quality of banks' loan portfolios.

Broadly speaking, house price fluctuations largely affect the debt servicing capacity of households and mortgage borrowers by altering their collateral position. This in turn influences homeowners' decision processes and determines those situations where default becomes the best financial alternative available for borrowers (see, e.g., Kau et al. (1994); Daglish (2009)). Moreover, changes in house prices may induce substantial spillover effects on the performance of other loan categories as real estate is widely used as collateral to secure loan repayments. Thus, it is expected that changes in house prices lead to significant variations in a bank's aggregate nonperforming assets.

Hypothesis 2. Real estate loans are more sensitive than other types of loans to house price fluctuations.

Loan categories mainly vary in terms of the type of borrowers and the collateralized assets pledged to secure loan repayment. A fall in the market value of collaterals undermines borrowers' equity position, which can play a key role in borrowers' decisions to default when they face financial distress. Thus, compared to other loan categories, real estate loans are expected to be more sensitive to adverse fluctuations in house prices as they are primarily secured by real estate, while other loan types are either unsecured or secured with assets other than real estate.

Hypothesis 3. House price changes have a non-uniform impact on the quality of loan portfolios of different types of depository institutions.

Lending policies and risk-taking behavior of banks are highly associated with a wide range of internal factors, including a bank's mission, organizational structure, ownership structure, depositor type, regulators, and agency problems (see, e.g., Salas and Saurina (2002); Laeven and Levine (2009)). In this context, SI greatly vary from CB. In particular, SI are traditionally community-oriented organizations mandated to concentrate on residential mortgages to promote home ownership, whereas CB are allowed to make various types of loans, including commercial and industrial loans.[2] Thus, the impact of house price fluctuations on credit risk is expected to be different across these two types of banks.

3. Model specification

In this section, the empirical models and econometric methodology are presented.

3.1. Empirical models

This study considers the ratio of NPL to total gross loans as proxy for credit risk exposure of banks.[3] NPL are defined as loans past due for 90 days, or more, and still accruing interest plus loans in nonaccrual status. In this case, using a dynamic specification is essential to account for time persistence of NPL (see, e.g., Nkusu (2011); Tabak et al. (2011); Louzis et al. (2012)). Accordingly, to test Hypothesis 1, we consider the following dynamic model:

$$R_{it} = \alpha R_{it-1} + S_{it}\beta + I_{it-1}\gamma + \mu_i + \delta_t + \varepsilon_{it} \quad (1)$$

where R_{it} is the credit risk of bank i at time t. On the right hand side, α is a scalar, β and γ are vectors of parameters to be estimated, μ_i is the bank-specific unobserved heterogeneity, δ_t is a time dummy to control for cross-sectional dependence, and ε_{it} is the idiosyncratic disturbance term. The systematic factors affecting credit risk are included in the S_{it} vector. In particular, $S_{it} = [GDP_{it}, IR_{it}, U_{it}, HP_{it}]$ where GDP_{it} is the state-level real GDP growth rate, IR_{it} is the real lending interest rate, U_{it} is the state-level unemployment rate, and HP_{it} is the rate of changes in the state-level real house prices. Finally, $I_{it} = [LC_{it}, LA_{it}, INE_{it}, SIZE_{it}, CR_{it}, NIM_{it}]$ is a vector of bank-specific variables where LC_{it} is the loan concentration ratio,[4] LA_{it} is the loan to asset ratio, INE_{it} is the cost to income ratio, $SIZE_{it}$ is the log of total assets, CR_{it} is the equity to asset ratio, and NIM_{it} is the net interest margin. These variables are consistently used in the literature as the determinants of NPL and credit risk.[5] Following the procedures used in most previous works, this study uses the lagged bank-specific variables in modeling NPL (see, e.g., Berger and DeYoung (1997); Davis and Zhu (2009); Tabak et al. (2011); Pan and Wang (2013)). In fact, the inclusion of the lagged idiosyncratic variables is essential (i) to avoid simultaneity effects between NPL and bank-specific variables; (ii) to account for the potential time delay between changes

[2] For a detailed discussion about differences between commercial banks and savings institutions see Madura (2014).

[3] Salas and Saurina (2002) suggest applying a logarithmic transformation on NPL to allow it to vary in the range $(-\infty, \infty)$. However, since NPL typically take values in the range (0, 0.10), such transformation is not very useful (Quagliariello, 2007).

[4] The concentration ratio is defined as the Herfindahl–Hirschman index (HHI) of three major loan categories in a bank: real estate loans, commercial and industrial loans, and consumer loans. If PL_{jit}, $j = 1, 2, 3$ represents the portfolio shares of the jth loan category, then $HHI_{it} = \sum(PL_{jit}^2)$ is defined as the HHI of bank i at time t.

[5] See Louzis et al. (2012) for a review of the determinants of NPL.

in managerial decisions and changes in the quality of loan portfolios as reported in the balance sheet data.

The two remaining hypotheses can be tested by estimating a simple variant of the model in Eq. (1). For the purpose of testing Hypothesis 2, let L be the set of loans and $\mathrm{LC_k}$ for $k = 1,2,3$ be the subset of loans in three broad loan categories, namely real estate loans, commercial & industrial loans, and consumer loans.[6] Accordingly, NPL can be classified into three broad categories: real estate NPL (RENPL), commercial and industrial NPL (CINPL), and consumer NPL (CNPL). Thus, to investigate the impact of house prices on NPL of different loan categories, Eq. (1) is modified as follows:

$$\tilde{R}_{it} = \alpha\tilde{R}_{it-1} + S_{it}\beta + I_{it-1}\gamma + \mu_i + \delta_t + \varepsilon_{it} \tag{2}$$

where $\tilde{R}_{it} = (R_{it}|LC_k)$ represents the credit risk in each loan category. All other regressors are defined as in Eq. (1).

As for Hypothesis 3, let Θ be the set of U.S. depository institutions, $\theta_1 = \{x \in SI \subset \Theta\}$ be the subset of SI, and $\theta_2 = \{x \in CB \subset \Theta\}$ be the subset of CB so that $\theta_1 \cap \theta_2 = \varnothing$. That is, each institution is classified as either a savings institution or a commercial bank. To examine if the type of an institution is a factor influencing the determinants of NPL, Eq. (1) is modified as follows:

$$\overline{R}_{it} = \alpha\overline{R}_{it-1} + S_{it}\beta + I_{it-1}\gamma + \mu_i + \delta_t + \varepsilon_{it} \tag{3}$$

where $\overline{R}_{it} - (R_{it}|\theta_\zeta), \zeta = 1, 2$. This model allows us to investigate the sensitivity of credit risk to changes in house prices across different types of depository institutions.

3.2. Econometric methodology

To estimate the dynamic models (1)–(3), we use the system generalized method of moments (GMM) estimator proposed by Blundell and Bond (1998) with a finite sample correction for the two-step covariance matrix derived by Windmeijer (2005). Using GMM estimator is essential to deal with the endogeneity of the lagged dependent variable. More specifically, as the lagged dependent variable is a function of μ_i, and, therefore, correlated with the error term, $\mu_{it} = \mu_i + \delta_t + \varepsilon_{it}$, preliminary panel data models such as *OLS*, fixed effects, and random effects produce biased and inconsistent estimates (Blundell and Bond, 1998; Bond, 2002). To overcome this issue, Arellano and Bond (1991) propose the first-differenced GMM estimator, which takes first-differences to remove the unobserved bank-specific effects, μ_i, and to use lagged values of endogenous variables as instruments in the first-differenced equation.

The first-differenced GMM estimator, however, is likely to perform poorly when the instruments are weak (Blundell and Bond, 1998).[7] In such cases, as weak instruments become less informative, the first-differenced GMM estimators suffer from serious downward finite-sample bias, particularly when the number of time periods available is small. To address this issue, Blundell and Bond (1998) propose the system GMM estimator, which uses the forward orthogonal deviations instead of first-differences. The key idea behind the system GMM estimator is to simultaneously estimate a system of two equations: one in first-differences and the other one in levels. Accordingly, the lagged level values are used to instrument first-differenced equation, while the lagged first-differenced values are used to instrument the equation in levels. Once the instrument matrix is constructed, the two-step system GMM estimator can be calculated. The two-step GMM estimator is asymptotically more efficient than the one-step estimator, and also relaxes the assumption of homoscedasticity in the error terms (see Arellano and Bond (1991); Blundell and Bond (1998)). However, due to its dependence on the estimated residuals, the two-step GMM estimator may impose a severe downward bias on the estimated standard errors, particularly in small samples (see, Bond (2002); Windmeijer (2005)). Therefore, we apply the finite sample correction technique proposed by Windmeijer (2005) to provide corrected variance estimates.[8]

As the consistency of the system GMM estimators hinges upon the assumption that the instruments are exogenous, we consider two specification tests to investigate the reliability of this crucial assumption. The first specification test is the Hansen (1982) test of overidentifying restrictions, which evaluates the joint validity of the instruments. Under the null hypothesis of valid moment conditions, the Hansen test statistic has an asymptotic χ^2 distribution (see Arellano and Bond (1991); Arellano and Bover (1995); Blundell and Bond (1998)). The second specification test is the Arellano and Bond (1991) test of no serial correlation in the first-differenced disturbances. Rejection of the null hypothesis of no serial correlation in the first-differenced disturbances at an order greater than one suggests that the disturbances are serially correlated, which renders the consistency of the GMM estimator (see Arellano and Bond (1991); Roodman (2009)).

Finally, we examine the presence of error cross-section dependence in our regression models.[9] It is argued that when errors are correlated across panel units, GMM estimators are inconsistent (see Sarafidis and Robertson (2009); Sarafidis et al. (2009)). In order to cope with potential error cross-section dependence, we include time dummies in our regression models, which is equivalent to cross-sectional demeaning of the data. This approach can control for cross-section dependence, unless the impact of unobserved common factors differs across panel units (heterogeneous cross-section dependence). To investigate whether the cross-sectional dependence in the error term is eliminated after inclusion of time dummies we can either rely on $AR(2)$ test or use a Sargan's type difference test proposed by Sarafidis et al. (2009). Rejection of the null hypothesis of Sarafidis et al. (2009) test implies heterogeneous cross section dependence, thereby inconsistency of GMM estimators.

4. Data

Our empirical analysis is based on annual panel data of U.S. banking institutions over the period 1999–2012. The dataset comprises a combination of macroeconomic and bank-specific variables. Data on NPL and other bank-specific variables are obtained from the FDIC database, which provides balance sheet and income statement data for individual insured banks in the U.S. banking system. As far as systematic risk factors are concerned, data on state-level GDP growth rate and unemployment rate are retrieved from the Bureau of Economic Analysis (BEA) and the Bureau of Labor Statistics (BLS), respectively. Also, the interest rate and inflation rate data are obtained from the Federal Reserve Economic Data (FRED). Finally, the house price data are extracted from the Federal Housing Finance Agency (FHFA) database, which provides state-level House Price Index (HPI) data.[10] Note that house prices, GDP growth rates and interest rates are considered in real terms.[11]

[6] Following the Federal Deposit Insurance Corporation (*FDIC*) loan classification, we define (i) real estate loans as loans that are primarily secured by real estate; (ii) consumer loans as loans to individuals for personal expenditures; (iii) commercial and industrial loans as loans designed for commercial and industrial purposes.

[7] Weak instruments are uncorrelated with the error term but they are only weakly correlated with the endogenous variable. Weak instrument problem in the case of the first-differenced GMM estimator usually occurs when time series are persistent, $(\alpha \to 1)$, and/or the relative variance of the fixed effects increases, $(\sigma_\mu^2/\sigma_\varepsilon^2 \to \infty)$.

[8] We also report robust standard errors to account for potential problems that may arise from heteroskedasticity and clustering of observations within banks while using the Windmeijer (2005) finite sample correction in our *GMM* models.

[9] We thank the anonymous referee for this insightful suggestion.

[10] The *HPI* is derived from data provided by Fannie Mae and Freddie Mac, and is a measure of average house price changes in repeat sales or refinancings on the same single-family properties.

[11] Data on nominal *GDP* growth rate, interest rate, and house prices are adjusted for inflation by using national-level consumer price index data obtained from the International Financial Statistics (*IFS*) database.

We then refine the sample by removing banks with less than 6 consecutive observations on all variables. This is done to ensure that sufficient data is available for instrumenting endogenous variables when the GMM estimator is applied. Furthermore, to ensure that state-level macroeconomic data is available for all the sample banks, we only consider the domestic banks and the banks that are headquartered in states. The resulting sample is an unbalanced panel consisting of 8367 depository institutions with 106,276 bank-year observations.

Table 1 presents the summary statistics of the variables used in this analysis. For each variable, mean, median, standard deviation, skewness and kurtosis are reported. It appears that, on average, 1.534% of total gross loans in the sample banks are nonperforming. More interestingly, sample banks, on average, faced higher NPL in real estate loans, compared to other loan categories. Average HHI for loan concentration is 0.610, indicating that loan portfolios of the U.S. banks are concentrated on specific types of loans. In addition, loans form, on average, 63.917% of the asset portfolios in the sample banks, meaning that the U.S. banks are mainly concentrated on the lending activities. Overall, the sample banks seem to be well capitalized as indicated by 10.842% of average capital ratios. However, this indicator has a relatively large standard deviation, suggesting that the level of capitalization varies widely among the sample banks. Finally, average NIM is 4.047%, indicating that the sample consists of banks with profitable loan portfolios.

Table 1
Descriptive statistics.

	Acronym	Mean	Median	Std. dev.	Skewness	Kurtosis
Nonperforming loans	NPL_{it}	1.534	0.774	2.456	5.870	82.270
Real estate NPL	$RENPL_{it}$	1.613	0.660	2.879	5.644	71.504
Commercial & Industrial NPL	$CINPL_{it}$	1.469	0.331	3.762	10.661	203.642
Consumer NPL	$CNPL_{it}$	0.863	0.290	2.306	15.938	453.234
Loan loss allowance	LLA_{it}	1.473	1.287	0.833	3.758	36.185
Loan concentration	LC_{it}	0.610	0.573	0.173	0.625	2.422
Loan to asset ratio	LA_{it}	63.917	65.871	15.584	−0.706	3.565
Inefficiency	INE_{it}	0.715	0.667	0.414	10.525	189.419
Size	$SIZE_{it}$	11.875	11.723	1.352	1.148	6.349
Capital ratio	CR_{it}	10.842	9.768	4.916	6.197	76.090
Net interest margin	NIM_{it}	4.047	3.997	1.118	4.460	73.447
Real GDP growth	GDP_{it}	1.875	1.970	2.402	−0.377	4.856
Real interest rate	IR_{it}	3.050	3.041	1.733	0.103	1.763
Unemployment rate	U_{it}	5.647	5.233	1.940	1.034	3.826
Real house price growth	HP_{it}	0.701	1.113	4.945	0.095	5.775

5. Empirical results

In this section, we empirically test the hypotheses in Section 2. We first test Hypothesis 1 using model (1), and then we test the second and third hypotheses using models (2) and (3), respectively.

In order to investigate the potential asymmetric impact of house prices on the evolution of NPL during different economic conditions, we split the sample into two sub-sample periods, 1999–2005 and 2006–2012. Accordingly, each equation is estimated over three time periods: the full sample period and the sub-sample periods. Furthermore, investigating the impact of state-level house prices on NPL may be challenged as some banks have spread their branches across state borders after the relaxation of branching restrictions.[12] One may expect banks operating in multiple states to be less exposed to economic conditions of the state in which they are headquartered. To take this important feature of the data into account, we distinguish between banks that operate in one state, known as intrastate banks, and banks that operate in multiple states, known as interstate banks. In doing so, we refer to the Summary of Deposits (SOD) database, provided by the FDIC, and divide the sample banks into intrastate and interstate banks based on the geographical distribution of their deposit-taking branches. Therefore, each model is first estimated for all the depository institutions, and then a separate estimation is carried out for intrastate banks only.[13]

Table 2 presents the estimation results for model (1). Results are reported for three pairs of equations, corresponding to three sampling periods. Equations I and II represent the results for the full sample period, 1999–2012; equations III and IV show the estimation results for the first sub-sample period, 1999–2005, while equations V and VI correspond to the second sub-sample period, 2006–2012. In addition, within each pair of equations, the first equation represents the results for all the sample banks, while the second equation corresponds to the intrastate banks only.

From Table 2 it appears that the estimated coefficients of the house price fluctuations are negative and statistically significant in all the equations. These empirical results support Hypothesis 1 that the quality of loan portfolios is highly sensitive to house price fluctuations. In other words, rising house prices improve the debt servicing capacity of borrowers, whereas falling house prices may reduce the value of underlying collaterals and induce higher default rates. More importantly, the estimated coefficients of house price fluctuations are approximately six times higher in the second sub-sample period, compared to those in the first sub-sample period. It indicates that rising house prices slightly reduce credit risk, while falling house prices trigger a large increase in NPL. This empirical evidence is consistent with the finding of Pan and Wang (2013) that house price fluctuations have asymmetric effects on NPL. One potential explanation is that rising house prices are often associated with low default rates, excessive lending by banks, and high credit demand from risky investors with optimistic expectations about the future of house prices. Excessive risk accumulation heavily exposes banks to the housing market, and, as a result, banks suffer severely from high loan losses when house prices drop.

As far as other macroeconomic factors are concerned, from Table 2, it appears that the estimated coefficients for the unemployment rate and real interest rate are positive and statistically significant across all the periods. As expected, a rise in unemployment and borrowing costs reduces the households' disposable income and their ability to service their debts. Similarly, it appears that the impact of the real GDP growth on NPL is negative and statistically significant across all the periods, suggesting that positive income shocks translate into lower credit risk. However, the impact of all the macroeconomic variables on NPL is a few times higher during the second sub-sample period, which has been characterized by adverse macroeconomic conditions. These results support the empirical findings of Marcucci and Quagliariello (2009) that the business cycle has asymmetric effects on bank credit risk.

As for the internal factors, we obtain positive and statistically significant coefficients for the lagged NPL across all the equations in Table 2. However, the results show that, compared to the first sub-sample period, the estimated coefficients are higher during the second sub-sample period, indicating that NPL is more persistent and sticky during macroeconomic downturns. Our empirical results also reveal that the estimated coefficients of LC_{it} are significant across all the periods, but they obtain different signs in the two sub-sample periods: positive in the first period and negative in the second period. One possible explanation for this result is that a higher loan portfolio concentration typically indicates a higher ratio of real estate loans to total gross loans in most U.S. banks. Therefore, banks with higher ratio of real estate loans to total loans may experience less default rates when the house prices are rising, while they suffer dramatically from high NPL during adverse house price movements.

Consistent with the empirical results of Davis and Zhu (2009), the estimated coefficient of LA_{it} is always positive and significant. This indicates that banks with more reliance on their interest income have less

[12] The deregulation process culminated in 1994 with the passage of the Interstate Banking and Branching Efficiency Act, which allowed banks to work across state borders without any formal authorization from state authorities.

[13] Due to lack of state-level NPL data, we do not conduct a separate analysis for interstate banks.

Table 2
GMM estimation results for NPL in the U.S. depository institutions.

	I	II	III	IV	V	VI
	1999–2012		1999–2005		2006–2012	
Regressors	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
NPL_{it-1}	0.689*** (0.020)	0.692*** (0.021)	0.608*** (0.069)	0.610*** (0.070)	0.704*** (0.023)	0.712*** (0.022)
GDP_{it}	−0.041*** (0.003)	−0.039*** (0.003)	−0.019*** (0.003)	−0.019*** (0.003)	−0.042*** (0.005)	−0.038*** (0.005)
IR_{it}	0.035*** (0.004)	0.035*** (0.005)	0.027*** (0.006)	0.029*** (0.006)	0.066*** (0.008)	0.065*** (0.008)
U_{it}	0.102*** (0.008)	0.099*** (0.008)	0.033*** (0.008)	0.038*** (0.008)	0.081*** (0.009)	0.078*** (0.009)
HP_{it}	−0.051*** (0.002)	−0.051*** (0.002)	−0.010*** (0.002)	−0.011*** (0.002)	−0.068*** (0.005)	−0.069*** (0.005)
LC_{it-1}	0.425*** (0.053)	0.405*** (0.056)	−0.115** (0.049)	−0.099** (0.048)	0.632*** (0.105)	0.629*** (0.113)
LA_{it-1}	0.008*** (0.001)	0.008*** (0.001)	0.003*** (0.001)	0.003*** (0.001)	0.009*** (0.001)	0.009*** (0.001)
INE_{it-1}	0.041 (0.041)	0.006 (0.031)	−0.090*** (0.032)	−0.112*** (0.037)	0.031 (0.149)	−0.103 (0.115)
$SIZE_{it-1}$	0.035*** (0.007)	0.034*** (0.008)	−0.046*** (0.010)	−0.053*** (0.012)	0.054*** (0.014)	0.034** (0.014)
CR_{it-1}	−0.005** (0.002)	−0.004 (0.003)	0.004*** (0.001)	0.003* (0.002)	−0.001 (0.006)	0.002 (0.006)
NIM_{it-1}	0.040*** (0.010)	0.038*** (0.010)	0.037*** (0.009)	0.041*** (0.009)	0.040** (0.020)	0.032* (0.018)
Constant	−1.289*** (0.113)	−1.235*** (0.114)	0.487*** (0.201)	0.554*** (0.213)	−1.820*** (0.282)	−1.473*** (0.247)
# observation	97,898	91,497	50,557	48,164	36,283	33,143
# banks	8367	7821	7337	6986	6081	5554
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.779	0.913	0.582	0.552	0.844	0.924
Hansen p-value	0.194	0.197	0.154	0.147	0.115	0.264

Notes: The dependent variable is the ratio of nonperforming loans to total gross loans. All the U.S. banks are considered in equations I, III, and V, while equations II, IV, and VI present estimation results for intrastate banks. All equations are estimated using a dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. All equations include time dummies. Huber–White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

liquidity and face higher default rates than their counterparts with more diversified sources of income. The sign of the net interest margin is positive and significant in all the periods, suggesting that higher NIM_{it} is associated with riskier portfolios (see also Quagliariello (2007)). Finally, the impact of bank size on NPL varies across different periods under consideration. Smaller banks suffer from higher NPL levels during the first sub-sample period, implying that smaller banks have less market power, less economies of scale, and less diversification among their customers and products (see Salas and Saurina (2002)). Nonetheless, larger banks suffer from higher NPL during the second sub-sample period, which may be attributed to higher agency costs and more difficulties in monitoring the quality of loan portfolios in large institutions.

Looking at the estimated parameters in Table 2, it appears that the empirical results for all the sample banks are very similar to those of the intrastate banks. In other words, the exclusion of the interstate banks from the sample banks does not have a marked impact on the estimation results. This is mainly because the number of intrastate banks in the sample is relatively large, and, therefore, the full sample results are mainly driven by the intrastate banks.

In Table 2, we also report the results for the Hansen test of overidentifying restrictions and Arellano and Bond (1991) test for the first and second order autocorrelation in the first-difference residuals. Results show that the instruments are valid, and that the null hypothesis of no serial correlation cannot be rejected. Furthermore, using the Sargan's type difference test proposed by Sarafidis et al. (2009), we did not find any strong evidence of cross-sectional dependence in the error term. In summary, the empirical results strongly support Hypothesis 1 that there is a strong relationship between credit risk and house price fluctuations. Our empirical results also reveal that the impact of house prices on the evolution of NPL is stronger during economic downturns.

We now test Hypothesis 2, which postulates that different loan categories respond differently to house price fluctuations. Table 3 presents the system GMM estimation results of model (2) for RENPL. It emerges that the estimated coefficients of the house price fluctuations are negative and significant across all the equations, suggesting that house prices remarkably affect the evolution of real estate NPL in different economic conditions. More importantly, the impact of house prices on the quality of real estate loans is much stronger during the second period, indicating an asymmetric relationship between house prices and RENPL. The results also reveal that the real estate NPL are highly sensitive to other systematic factors, while the impact of macroeconomic factors on the RENPL is more pronounced during the second period. As regards the bank-specific factors, it appears that the quality of real estate loans is highly affected by LA_{it} $SIZE_{it}$ and NIM_{it}.

Our estimation results of model (2) for CINPL are reported in Table 4. It appears that the estimated coefficients of house price changes are insignificant during the first period. However, house prices significantly contribute to the CINPL in the second sub-period, perhaps due to spillover effects of the falling house prices and the deterioration of the aggregate liquidity position in the financial system. In addition, the commercial and industrial NPL are highly affected by other systematic factors in the first sub-sample period, while the impact of these factors weakens during the second period. It is also revealed that $SIZE_{it}$ is the only institutional factor that significantly contributes to the CINPL. Bank size obtains negative coefficients across all the equations, which reflects economies of scale, better diversification of customers and products, and better risk management in larger banks (see also Salas and Saurina (2002)).

As for the consumer NPL, the estimation results in Table 5 show that the CNPL determinants are rather different from those of other loan categories. Notably, none of the systematic factors remarkably affect the quality of consumer loans during the first sub-sample period, while GDP_{it}, IR_{it}, and HP_{it} contribute to the CNPL in the second period. This implies that unexpected shocks arising from falling house prices and adverse economic growth largely affect the borrowers' wealth in the second period. Consequently, borrowers can no longer use their wealth as a buffer to service their debts (see, e.g., Rinaldi and Sanchis-Arellano (2006); Nkusu (2011)). Among bank-specific variables, LC_{it}, and $SIZE_{it}$

Table 3
GMM estimation results for RENPL.

	I	II	III	IV	V	VI
	1999–2012		1999–2005		2006–2012	
Regressors	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$RENPL_{it-1}$	0.714*** (0.028)	0.721*** (0.030)	0.660*** (0.069)	0.671*** (0.069)	0.672*** (0.027)	0.685*** (0.028)
GDP_{it}	−0.051*** (0.004)	−0.049*** (0.005)	−0.026*** (0.005)	−0.027*** (0.005)	−0.048*** (0.006)	−0.045*** (0.007)
IR_{it}	0.036*** (0.006)	0.036*** (0.006)	0.034*** (0.008)	0.034*** (0.008)	0.079*** (0.011)	0.080*** (0.011)
U_{it}	0.097*** (0.011)	0.092*** (0.012)	0.039*** (0.010)	0.042*** (0.011)	0.099*** (0.012)	0.093*** (0.013)
HP_{it}	−0.062*** (0.003)	−0.062*** (0.003)	−0.009*** (0.003)	−0.009*** (0.002)	−0.094*** (0.007)	−0.096*** (0.007)
LC_{it-1}	0.448*** (0.067)	0.441*** (0.072)	−0.066 (0.065)	−0.023 (0.060)	0.526*** (0.141)	0.574*** (0.154)
LA_{it-1}	0.006*** (0.001)	0.007*** (0.001)	0.002** (0.001)	0.002** (0.001)	0.007*** (0.002)	0.006*** (0.002)
INE_{it-1}	0.054 (0.060)	−0.004 (0.047)	−0.120** (0.047)	−0.165*** (0.057)	0.052 (0.151)	−0.090 (0.121)
$SIZE_{it-1}$	0.055*** (0.009)	0.046*** (0.011)	−0.059*** (0.014)	−0.075*** (0.019)	0.084*** (0.018)	0.047** (0.019)
CR_{it-1}	−0.004 (0.004)	−0.003 (0.005)	0.005* (0.003)	0.005* (0.003)	−0.005 (0.009)	−0.001 (0.010)
NIM_{it-1}	0.095*** (0.015)	0.095*** (0.015)	0.052*** (0.012)	0.053*** (0.013)	0.144*** (0.033)	0.144*** (0.033)
Constant	−1.630*** (0.163)	−1.490*** (0.169)	0.583** (0.284)	0.748** (0.326)	−2.361*** (0.373)	−1.860*** (0.358)
# observation	84,478	78,315	39,763	37,531	31,334	28,264
# banks	6937	6415	5758	5431	5249	4734
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.649	0.699	0.198	0.189	0.489	0.476
Hansen p-value	0.288	0.258	0.441	0.449	0.267	0.291

Notes: The dependent variable is the ratio of real estate nonperforming loans to total gross real estate loans. All the U.S. banks are considered in eq uations I, III, and V, while equations II, IV, and VI present estimation results for intrastate banks. All equations are estimated using a dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. All equations include time dummies. Huber–White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

are the only institutional factors that significantly contribute to the CNPL in all the periods. The estimated coefficients of bank size are negative and significant, implying better diversification and more scale efficiency in larger banks. Also, positive coefficients of LC_{it} suggest that banks with more concentrated loan portfolios may suffer from higher CNPL.

Summarizing, we find clear support for Hypothesis 2, which postulates that, compared to other loan categories, real estate loans are

Table 4
GMM estimation results for CINPL.

	I	II	III	IV	V	VI
	1999–2012		1999–2005		2006–2012	
Regressors	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$CINPL_{it-1}$	0.317** (0.135)	0.332** (0.148)	0.350*** (0.034)	0.352*** (0.035)	0.472*** (0.114)	0.452*** (0.120)
GDP_{it}	−0.017*** (0.006)	−0.017*** (0.006)	−0.016** (0.008)	−0.016** (0.008)	−0.013 (0.011)	−0.008 (0.012)
IR_{it}	0.027*** (0.010)	0.027*** (0.010)	0.072*** (0.015)	0.075*** (0.016)	0.039** (0.017)	0.045** (0.018)
U_{it}	0.130*** (0.020)	0.126*** (0.022)	0.125*** (0.022)	0.137*** (0.023)	0.130*** (0.022)	0.133*** (0.023)
HP_{it}	−0.024*** (0.003)	−0.023*** (0.003)	0.001 (0.005)	0.003 (0.006)	−0.031*** (0.009)	−0.034*** (0.010)
LC_{it-1}	0.688* (0.398)	0.619 (0.413)	0.775*** (0.268)	0.897*** (0.300)	0.781 (0.534)	0.938 (0.651)
LA_{it-1}	0.005** (0.002)	0.005** (0.002)	0.002 (0.002)	0.002 (0.002)	0.008** (0.003)	0.007** (0.003)
INE_{it-1}	0.185** (0.090)	0.164* (0.092)	0.153 (0.217)	0.132 (0.227)	0.568* (0.341)	0.496 (0.372)
$SIZE_{it-1}$	−0.108*** (0.033)	−0.122*** (0.045)	−0.202*** (0.025)	−0.252*** (0.033)	−0.153*** (0.041)	−0.214*** (0.062)
CR_{it-1}	−0.017** (0.007)	−0.016** (0.008)	0.010 (0.009)	0.009 (0.009)	0.003 (0.011)	−0.002 (0.011)
NIM_{it-1}	0.033 (0.024)	0.035 (0.021)	0.017 (0.022)	0.017 (0.022)	−0.010 (0.029)	−0.004 (0.030)
Constant	0.893** (0.427)	1.035* (0.551)	1.899*** (0.430)	2.328*** (0.505)	0.699 (0.504)	1.483** (0.670)
# observations	73,204	67,621	29,803	27,956	19,261	16,862
# banks	6096	5628	4312	4402	3223	2821
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.297	0.320	0.924	0.914	0.192	0.423
Hansen p-value	0.162	0.165	0.336	0.328	0.382	0.282

Notes: The dependent variable is the ratio of commercial & industrial nonperforming loans to total commercial & industrial loans. All the U.S. banks are considered in eq uations I, III, and V, while equations II, IV, and VI present estimation results for intrastate banks. All equations are estimated using a dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. All equations include time dummies. Huber–White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

Table 5
GMM estimation results for CNPL.

	I	II	III	IV	V	VI
	1999–2012		1999–2005		2006–2012	
Regressors	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
$CNPL_{it-1}$	0.316*** (0.086)	0.346*** (0.095)	0.232** (0.107)	0.219** (0.108)	0.380*** (0.121)	0.352*** (0.132)
GDP_{it}	−0.013*** (0.004)	−0.014*** (0.004)	−0.001 (0.004)	−0.001 (0.004)	−0.017*** (0.006)	−0.019*** (0.006)
IR_{it}	0.010** (0.005)	0.010** (0.005)	0.010 (0.009)	0.008 (0.010)	0.018** (0.009)	0.019* (0.010)
U_{it}	0.019*** (0.006)	0.019*** (0.006)	0.021 (0.014)	0.029* (0.015)	0.014 (0.010)	0.014 (0.011)
HP_{it}	−0.001 (0.002)	−0.001 (0.002)	−0.001 (0.004)	0.002 (0.005)	−0.012* (0.007)	−0.014* (0.008)
LC_{it-1}	0.217** (0.090)	0.216** (0.100)	0.667*** (0.213)	0.792*** (0.232)	0.747*** (0.241)	0.934*** (0.276)
LA_{it-1}	0.003*** (0.001)	0.003*** (0.001)	0.001 (0.001)	0.001 (0.001)	−0.002 (0.002)	−0.002 (0.002)
INE_{it-1}	−0.070 (0.065)	−0.099 (0.067)	−0.140 (0.173)	−0.240 (0.184)	0.073 (0.133)	−0.003 (0.151)
$SIZE_{it-1}$	−0.051*** (0.011)	−0.063*** (0.015)	−0.162*** (0.028)	−0.207*** (0.036)	−0.080*** (0.026)	−0.132*** (0.039)
CR_{it-1}	−0.001 (0.004)	−0.002 (0.004)	0.010** (0.004)	0.010** (0.005)	0.009 (0.008)	0.003 (0.006)
NIM_{it-1}	0.001 (0.010)	−0.004 (0.011)	0.010 (0.016)	0.008 (0.017)	0.025 (0.024)	0.019 (0.025)
Constant	0.696*** (0.167)	0.847*** (0.209)	2.215*** (0.494)	2.683*** (0.578)	1.005*** (0.330)	1.682*** (0.431)
# observations	77,095	71,631	36,809	34,807	20,347	18,184
# banks	6434	5973	5330	5036	3404	3042
AR(1) p-value	0.000	0.000	0.001	0.002	0.000	0.001
AR(2) p-value	0.225	0.235	0.127	0.143	0.992	0.929
Hansen p-value	0.297	0.265	0.159	0.239	0.214	0.266

Notes: The dependent variable is the ratio of consumer nonperforming loans to total gross consumer loans. All the U.S. banks are considered in eq uations I, III, and V, while equations II, IV, and VI present estimation results for intrastate banks. All equations are estimated using a dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. All equations include time dummies. Huber–White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

more sensitive to house price fluctuations. We also provide empirical evidence that all loan categories are highly sensitive to house price changes during economic downturns. Comparing different loan categories, we find that real estate loans are the most sensitive category to GDP_{it}, which is typically considered as the main proxy for business cycle fluctuations. The RENPL are also the most persistent category of NPL. Finally, the sensitivity of the NPL to various institutional factors varies among different loan categories.

We now extend our analysis to different types of depository institutions. In order to do so, we follow the FDIC charter type classification and split the depository institutions in our sample into commercial and SI. The two types of institutions are functionally similar as they both accept deposits and issue loans. However, SI are traditionally community oriented organizations that specialize in mortgage lending, whereas CB make various types of loans including commercial and industrial loans.[14]

The GMM estimation results for the commercial and SI are presented in Tables 6 and 7, respectively. From Table 6 it emerges that the quality of loan portfolios of the CB is highly sensitive to the house price movements. Notably, the estimated coefficients of HP_{it} are negative and statistically significant across all the periods. In addition, all other macroeconomic factors as well as some bank-specific factors, such as LC_{it}, LA_{it}, and $SIZE_{it}$, significantly contribute to the NPL in CB.

From Table 7, however, it appears that the NPL dynamics are rather in the SI. Unlike CB, SI are less sensitive to the institutional factors. More specifically, none of the bank-specific variables has a remarkable impact on NPL in the SI. However, the estimated coefficients of the lagged dependent variables are slightly higher in the SI, suggesting that NPL are more persistent in SI. As regards the systematic factors, it is found that the quality of loan portfolios of the SI is significantly affected by the macroeconomic variables. In particular, the NPL dynamics in the SI are highly sensitive to the business cycle (see also Salas and Saurina (2002)). The results also show that the impact of the macroeconomic factors on NPL is stronger in the second period, which is consistent with the findings of Marcucci and Quagliariello (2009).

As in the case of CB, the estimated coefficients of HP_{it} are negative and statistically significant in all the equations when SI are considered. However, compared to the CB, the impact of HP_{it} on the NPL in the SI is higher during the first period and lower in the second period. This indicates that CB are more sensitive to house price developments in downturns. One possible explanation is that, like SI, CB become heavily exposed to the housing markets during a booming period. However, CB do not specialize in mortgage lending and may invest in riskier real estate loans. Accordingly, CB may suffer from higher loan losses when house prices drop. The results in Table 7 also show that the impact of house prices on the NPL is stronger during the second period for both types of banks, which lends support to the findings of Pan and Wang (2013), who show that the impact of house price fluctuations on credit risk is stronger when the growth of personal income falls below a certain threshold level.

In light of these results, we conclude that house price fluctuations significantly affect the quality of loan portfolios across the two types of institutions, while the magnitude of the impact varies across commercial and SI during different macroeconomic conditions. These results represent evidence in favor of Hypothesis 3.

6. Further empirical checks

6.1. Quality loan portfolios, house prices, and loan losses

Several studies, including Mian and Sufi (2009) and Hott (2011), argue that rising house prices increase lenders expectations of future house price growth, which in turn may encourage them to direct credit towards subprime borrowers. As a consequence, banks suffer from high default rates in the subsequent years due to a significant worsening of the quality of loan portfolios.[15] To examine if the quality of loan

[14] Federally chartered savings institutions are currently allowed to extend their nonmortgage lending up to 30% of their assets.

[15] We thank the anonymous referee for this valuable comment.

Table 6
GMM estimation results for NPL in the U.S. commercial banks.

	I	II	III	IV	V	VI
	1999–2012		1999–2005		2006–2012	
Regressors	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
NPL_{it-1}	0.683^{***}	0.666^{***}	0.663^{***}	0.661^{***}	0.696^{***}	0.696^{***}
	(0.023)	(0.023)	(0.079)	(0.080)	(0.025)	(0.024)
GDP_{it}	-0.039^{***}	0.666^{***}	-0.020^{***}	-0.021^{***}	-0.043^{***}	-0.039^{***}
	(0.003)	(0.023)	(0.004)	(0.004)	(0.005)	(0.005)
IR_{it}	0.036^{***}	0.035^{***}	0.034^{***}	0.034^{***}	0.068^{***}	0.065^{***}
	(0.005)	(0.005)	(0.006)	(0.006)	(0.008)	(0.009)
U_{it}	0.096^{***}	0.099^{***}	0.034^{***}	0.036^{***}	0.071^{***}	0.071^{***}
	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)
HP_{it}	-0.052^{***}	-0.053^{***}	-0.008^{***}	-0.008^{***}	-0.069^{***}	-0.069^{***}
	(0.002)	(0.002)	(0.002)	(0.002)	(0.006)	(0.006)
LC_{it-1}	0.727^{***}	0.690^{***}	-0.228^{***}	-0.209^{***}	1.139^{***}	1.092^{***}
	(0.071)	(0.076)	(0.054)	(0.060)	(0.142)	(0.156)
LA_{it-1}	0.009^{***}	0.008^{***}	0.004^{***}	0.004^{***}	0.010^{***}	0.010^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
INE_{it-1}	0.012	0.009	-0.172^{***}	-0.180^{***}	−0.017	−0.006
	(0.024)	(0.025)	(0.044)	(0.044)	(0.081)	(0.089)
$SIZE_{it-1}$	0.031^{***}	0.030^{***}	-0.040^{***}	-0.048^{***}	0.040^{***}	0.026^{*}
	(0.007)	(0.008)	(0.012)	(0.015)	(0.013)	(0.015)
CR_{it-1}	−0.001	−0.001	0.004^{**}	0.004^{**}	0.004	0.006
	(0.002)	(0.003)	(0.002)	(0.002)	(0.007)	(0.007)
NIM_{it-1}	0.008	0.009	0.037^{***}	0.037^{***}	−0.018	−0.011
	(0.008)	(0.009)	(0.009)	(0.009)	(0.016)	(0.016)
Constant	-1.294^{***}	-1.276^{***}	0.422^{***}	0.492^{***}	-1.688^{***}	-1.547^{***}
	(0.099)	(0.106)	(0.205)	(0.235)	(0.214)	(0.229)
# observations	82,427	77,666	42,534	40,800	30,447	28,040
# banks	7056	6652	6173	5919	5101	4698
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.239	0.430	0.171	0.175	0.997	0.948
Hansen p-value	0.179	0.201	0.165	0.169	0.159	0.288

Notes: The dependent variable is the ratio of nonperforming loans to total gross loans. All the U.S. commercial banks are considered in eq uations I, III, and V, while equations II, IV, and VI present estimation results for intrastate commercial banks. All equations are estimated using a dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. All equations include time dummies. Huber–White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

portfolios influences the relationship between house prices and default rates, we use loan loss allowance (LLA) as a proxy for the amount of subprime loans (or loans that are expected to default) in a bank's loan portfolio. In fact, LLA is the amount of reserves that a bank must maintain to cover its estimated credit losses on loans due to defaults and non-payment. Accordingly, our empirical models are augmented by including an interaction term between loan loss allowance and house prices. Besides, since the interaction term may be highly

Table 7
GMM estimation results for NPL in the U.S. savings institutions.

	I	II	III	IV	V	VI
	1999–2012		1999–2005		2006–2012	
Regressors	All banks	Intrastate	All banks	Intrastate	All banks	Intrastate
NPL_{it-1}	0.695^{***}	0.712^{***}	0.718^{***}	0.708^{***}	0.767^{***}	0.763^{***}
	(0.044)	(0.045)	(0.100)	(0.099)	(0.039)	(0.060)
GDP_{it}	-0.038^{***}	-0.044^{***}	-0.016^{**}	-0.014^{*}	-0.047^{***}	-0.042^{***}
	(0.009)	(0.011)	(0.007)	(0.008)	(0.011)	(0.012)
IR_{it}	0.043^{***}	0.038^{***}	0.028^{*}	0.028	0.067^{***}	0.067^{**}
	(0.011)	(0.012)	(0.016)	(0.017)	(0.019)	(0.021)
U_{it}	0.136^{***}	0.112^{***}	0.037^{**}	0.044^{**}	0.085^{***}	0.087^{***}
	(0.021)	(0.021)	(0.017)	(0.019)	(0.019)	(0.028)
HP_{it}	-0.049^{***}	-0.048^{***}	-0.015^{***}	-0.015^{***}	-0.059^{***}	-0.061^{***}
	(0.004)	(0.004)	(0.003)	(0.003)	(0.012)	(0.013)
LC_{it-1}	0.313^{*}	0.494^{**}	0.170^{*}	0.191^{*}	0.412	0.664^{*}
	(0.172)	(0.201)	(0.087)	(0.099)	(0.265)	(0.341)
LA_{it-1}	0.003^{*}	0.002^{**}	0.001	0.001	0.004	0.003
	(0.002)	(0.001)	(0.001)	(0.001)	(0.003)	(0.003)
INE_{it-1}	0.129	−0.038	0.017	0.027	0.262	−0.478
	(0.162)	(0.134)	(0.030)	(0.039)	(0.514)	(0.405)
$SIZE_{it-1}$	0.045^{**}	0.031	-0.021^{*}	-0.026^{*}	0.092^{*}	0.024
	(0.022)	(0.025)	(0.012)	(0.015)	(0.048)	(0.043)
CR_{it-1}	-0.014^{*}	-0.017^{*}	−0.003	−0.004	−0.004	−0.008
	(0.008)	(0.009)	(0.003)	(0.003)	(0.011)	(0.014)
NIM_{it-1}	0.158^{**}	0.172^{**}	0.066^{*}	0.080^{*}	0.284^{***}	0.207^{*}
	(0.064)	(0.069)	(0.038)	(0.043)	(0.108)	(0.108)
Constant	-1.618^{***}	-1.437^{***}	−0.107	−0.111	-3.021^{**}	−1.444
	(0.481)	(0.486)	(0.262)	(0.299)	(1.288)	(1.098)
# observations	15,471	13,831	8023	7364	5836	5103
# banks	1311	1169	1164	1067	980	856
AR(1) p-value	0.000	0.000	0.000	0.000	0.000	0.000
AR(2) p-value	0.578	0.551	0.187	0.124	0.492	0.345
Hansen p-value	0.231	0.255	0.134	0.171	0.249	0.195

Notes: The dependent variable is the ratio of nonperforming loans to total gross loans. All the U.S. savings institutions are considered in equations I, III, and V, while equations II, IV, and VI present estimation results for intrastate savings institutions. All equations are estimated using a dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. All equations include time dummies. Huber–White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively.

correlated with house prices, we run separate regressions by including the interaction term but without house price fluctuations. Using the interaction term allows us to investigate if the impact of house prices on default rates varies at different levels of loan loss allowance. In other words, we can examine if banks with deteriorating loan portfolios are more sensitive to house price fluctuations. Estimation results are presented in Table 8. In order to save space, we only present the estimates of house price fluctuations and the interaction term.[16] From Table 8 it appears that the interaction between house price fluctuations and loan loss allowance significantly affects aggregate NPL in all institutions, CB, and SI, while the impact is insignificant when separate loan categories are considered. This indicates that banks with higher subprime loans suffer from higher default rates when house prices drop. Furthermore, these results broadly support our previous findings regarding the impact of house prices on NPL. In particular, it is found that house price fluctuations significantly affect NPL, while real estate loans (among loan categories) and CB (among bank types) are more sensitive to falling house prices.

Table 8
Impact of interaction between loan loss allowance and house prices on loan losses.

	Dependent Variable	Explanatory Variables	With HP	Without HP
All institutions	NPL_{it}	HP_{it}	-0.040^{***} (0.003)	
	NPL_{it}	$HP_{it} \times LLA_{it-1}$	-0.013^{***} (0.002)	-0.014^{***} (0.002)
Commercial banks	NPL_{it}	HP_{it}	-0.040^{***} (0.003)	
	NPL_{it}	$HP_{it} \times LLA_{it-1}$	-0.013^{***} (0.002)	-0.014^{***} (0.002)
Savings institutions	NPL_{it}	HP_{it}	-0.038^{***} (0.007)	
	NPL_{it}	$HP_{it} \times LLA_{it}$	-0.010^{*} (0.006)	-0.032^{***} (0.006)
Real estate loans	$RENPL_{it}$	HP_{it}	-0.075^{***} (0.003)	
	$RENPL_{it-1}$	$HP_{it} \times LLA_{it-1}$	-0.001 (0.001)	-0.002 (0.002)
Commercial loans	$CINPL_{it}$	HP_{it}	-0.020^{***} (0.003)	
	$CINPL_{it}$	$HP_{it} \times LLA_{it-1}$	-0.001 (0.001)	-0.001 (0.001)
Consumer loans	$CNPL_{it}$	HP_{it}	-0.004 (0.003)	
	$CNPL_{it}$	$HP_{it} \times LLA_{it-1}$	-0.002 (0.002)	-0.003^{*} (0.002)

Notes: All equations are estimated over the period 1999–2012 and by using a dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. Huber–White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively. The detailed results with other explanatory variables are available from the authors upon request.

6.2. Alternative house price indicators

We now assess the robustness of our empirical results set out above by employing three alternative measures of house price fluctuations. One possible alternative to state-level house price fluctuations are changes in house prices at metropolitan statistical area (MSA) level. In fact, previous studies regarding the impact of house prices on the performance of U.S. banks have used both state-level house prices (see Berger and Bouwman (2015)) and MSA-level house prices (see Pan and Wang (2013); Favara and Imbs (2015)). Our main analysis, however, is based on state-level house prices for two important reasons: (i) to use MSA-level data, the sample should be reduced to MSA banks (banks that are headquartered in metropolitan statistical areas), meaning that a large number of non-MSA banks are dropped from the sample, (ii) many U.S. banks, particularly MSA banks, operate in more than one MSA, which may imply that they are less affected by house prices in the MSA where their headquarters are located. The FHFA provides data for two types of house price indices: a purchase only index that is calculated based on purchases and an all transaction index that is calculated based on both purchases and appraisals. So far, we have used the purchase only index as lending policies are mainly affected by purchases rather than appraisals (see Berger and Bouwman (2015)). Nonetheless, we can use all transaction House Price Index as an alternative to purchase-only house prices in order to assess the robustness of our main results. The last potential concern relates to the possibility that default rates are affected by longer-term house price fluctuations. In fact, borrowers' decisions to default may be influenced by house price movements over a longer period. Therefore, we consider the percentage change in the house prices from year $t - 2$ to year t as the third alternative to our main house price indicator.

Using these three alternative house price indicators, we re-estimate models (1)–(3) and report the results in Table 9. In order to save space, we only report the estimates of house price indicators.[17] From Table 9 it appears that most estimated coefficients are consistent in terms of sign and statistical significance with those obtained using state-level purchase-only house price fluctuations. In particular, regardless of which indicator is employed, the results reveal that changes in house prices have a negative and significant impact on default rates, while the impact is more pronounced during economic downturn. Similar results are obtained when comparing loan portfolios. More specifically, the effects of house prices on NPL vary across loan categories, with real estate loans being the most responsive category. Furthermore, in line with our previous finding, the results show that CB are more sensitive to falling house prices, compared to SI. Overall, the empirical results presented in Table 9 strongly support the robustness of our key findings regarding the effects of house prices on loan losses.

6.3. Alternative methodologies and specifications

Our findings are also robust when different econometric methodologies and model specifications are used. In particular, we tried (i) using first-difference GMM model to estimate models (1)–(3), (ii) using different model specifications by adding interaction dummies or dropping some of the explanatory variables from the main models, (iii) using alternative indicators for our credit risk determinants, (iv) using loan loss provisions instead of NPL as a proxy for credit risk. However, our key findings remained unchanged when these alternative approaches were used. The results are not reported here for the sake of brevity, but are available from the authors upon request.

7. Concluding remarks

The recent financial crisis in the United States highlights the key role that house prices play in destabilizing the financial system. In particular, falling house prices triggered a sharp increase in loan losses across U.S. banks, which in turn led to a severe macroeconomic downturn. Using a large panel of U.S. depository institutions over the period 1999–2012, we use dynamic panel data models to test three hypotheses regarding the relationship between house price fluctuations and NPL.

With respect to Hypothesis 1, we detect a strong negative relationship between house price fluctuations and NPL, i.e., falling house prices are tightly linked to higher default rates. Furthermore, the relationship between house prices and credit risk is asymmetric, meaning that the impact of house price fluctuations on the evolution of NPL is stronger during adverse macroeconomic conditions. With respect to Hypothesis 2, we find that the impact of changes in house prices varies widely across different loan categories, with real estate loans being the most responsive loan category to the housing market conditions. The test of Hypothesis 3 reveals that different types of depository

[16] Note that for other explanatory variables, the estimated coefficients are broadly similar to those presented in Section 5. The detailed results are available from the authors upon request.

[17] Note that for other explanatory variables, the estimated coefficients are broadly similar to those presented in Section 5. The detailed results are available from the authors upon request.

Table 9
Impact of alternative measures of house price fluctuations on loan losses.

	Dependent variable	Time period	'MSA-level' HP	'All-transaction' HP	'Longer-term' HP
All institutions	NPL_{it}	1999–2012	−0.0571*** (0.003)	−0.053*** (0.003)	−0.049*** (0.003)
	NPL_{it}	1999–2005	−0.002** (0.001)	−0.009*** (0.002)	−0.014* (0.008)
	NPL_{it}	2006–2012	−0.073*** (0.007)	−0.067*** (0.007)	−0.016*** (0.005)
Commercial banks	NPL_{it}	1999–2012	−0.055*** (0.004)	−0.050*** (0.003)	−0.042*** (0.004)
	NPL_{it}	1999–2005	0.001 (0.004)	−0.007** (0.003)	−0.006 (0.004)
	NPL_{it}	2006–2012	−0.073*** (0.007)	−0.063*** (0.007)	−0.019*** (0.005)
Savings institutions	NPL_{it}	1999–2012	−0.040*** (0.004)	−0.046*** (0.004)	−0.038*** (0.005)
	NPL_{it}	1999–2005	−0.007* (0.004)	−0.013*** (0.004)	−0.008** (0.004)
	NPL_{it}	2006–2012	−0.062*** (0.014)	−0.055*** (0.010)	−0.014** (0.007)
Real estate loans	$RENPL_{it}$	1999–2012	−0.081*** (0.005)	−0.059*** (0.004)	−0.051*** (0.006)
	$RENPL_{it}$	1999–2005	−0.014*** (0.002)	−0.008*** (0.003)	−0.011*** (0.003)
	$RENPL_{it}$	2006–2012	−0.105*** (0.008)	−0.089*** (0.009)	−0.034*** (0.006)
Commercial loans	$CINPL_{it}$	1999–2012	−0.022*** (0.004)	−0.020*** (0.005)	−0.026*** (0.004)
	$CINPL_{it}$	1999–2005	−0.011* (0.006)	0.002 (0.006)	−0.001 (0.006)
	$CINPL_{it}$	2006–2012	−0.029*** (0.010)	−0.032*** (0.010)	−0.036*** (0.008)
Consumer loans	$CNPL_{it}$	1999–2012	−0.008** (0.004)	−0.001 (0.001)	−0.011*** (0.002)
	$CNPL_{it}$	1999–2005	−0.014* (0.009)	−0.001 (0.002)	−0.022*** (0.005)
	$CNPL_{it}$	2006–2012	−0.002 (0.006)	−0.013** (0.006)	−0.011* (0.006)

Notes: All equations are estimated using a dynamic two-step system GMM estimator proposed by Blundell and Bond (1998) with Windmeijer's (2005) finite sample correction. Huber–White robust standard errors are reported in the parenthesis. ***, **, and * coefficients are statistically significant at 1%, 5%, and 10%, respectively. The detailed results with other explanatory variables are available from the authors upon request.

institutions react differently to the housing prices. In particular, our results show that CB are more sensitive to the house price movements during downturns.

These findings have several important implications. First, regulators should consider house prices as a key macroprudential indicator in order to promote banking stability. In this context, it is of crucial importance to provide a framework to control the circular relationship between house prices, bank lending, and loan losses. On the one hand, it is essential to control the aggregate lending level in local housing markets to ensure smooth house price movements and to avoid the creation of housing bubbles. Our empirical results reveal that severe adverse house price movements can lead to a sharp increase in default rates. On the other hand, regulators should consistently monitor the exposure of depository institutions to the housing markets. In particular, any rapid shift in the combination of loan portfolios, especially towards real estate loans, can serve as a signal for a potential rise in subprime loans, which may eventually lead to high loan losses.

Second, regulators should provide separate frameworks to examine the soundness of different loan categories. According to our empirical results, loan categories respond differently to both systematic and idiosyncratic factors. In particular, real estate loans are highly sensitive to house price fluctuations. Therefore, it is important to consistently control the quality of loan portfolios that contain a high portion of real estate loans, especially when there is a sharp rise in house prices. In fact, regulators can impose counter-cyclical capital buffers on the basis of the housing cycles to avoid severe liquidity shortages in the banking system when house prices drop.

Finally, regulators should carefully monitor different factors that may induce a shift in bank lending behavior. In particular, careful attention should be paid to any new behavior that may lead to a sharp increase in real estate lending of CB. Compared to SI, CB are expected to have less expertise in mortgage lending as they are not mandated to concentrate on residential mortgages. Besides, CB may have better access to external funding as they are able to offer a wider range of financial products. Therefore, rising house prices and lending competition may encourage them to direct credits towards subprime borrowers, which may eventually lead to higher default rates.

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