Journal of Banking & Finance 37 (2013) 1720–1732

Contents lists available at SciVerse ScienceDirect

Journal of Banking & Finance

journal homepage: www.elsevier.com/locate/jbf

House prices, bank instability, and economic growth: Evidence from the threshold model

Huiran Pan [a,*], Chun Wang [b]

[a] Economics Department, California State University, Fullerton, CA 92834, USA
[b] Brooklyn College, City University of New York, NY 11210, USA

ARTICLE INFO

Article history:
Received 17 March 2012
Accepted 8 January 2013
Available online 30 January 2013

JEL classification:
C23
G21
O11
R30

Keywords:
House price
Bank instability
Economic growth
Threshold estimation

ABSTRACT

This paper examines the effects of house prices on bank instability when gauged at various levels of income growth. Bank stability may respond differently to house price changes or deviations from fundamental values in an economic boom environment than in a bust circumstance. A threshold estimation technique developed by Hansen (1999) is applied to a panel of 286 U.S. Metropolitan Statistical Areas (MSAs) over the period 1990Q1–2010Q4. We consider two house price indicators: the house price changes and the house price deviations from long-run equilibrium. The results suggest the existence of income growth threshold effects in the relationship between house prices and bank instability. Specifically, there are two income growth thresholds when using the house price changes and one income growth threshold when the house price deviations are applied. Robustness results using the non-MSAs sample from 1995Q1 to 2010Q4 provide further evidence of income growth threshold effects.

1. Introduction

The role of the real estate market in the U.S. economy is undoubtedly important and conditions in the housing market signal the state of the economy as a whole. The U.S. economy has been sluggish for 4 years since the subprime mortgage crisis developed in 2007 and 2008, which was triggered by the 2005 housing bubble burst. The banking system, which functions as mortgage lenders and frequently uses real estate as collateral, is a link between the housing market and the macro-economy. Recent bank failures have been associated with the housing bubble burst. For example, over four hundred U.S. banks failed in 2008–2011.[1] This paper addresses the questions of whether and how house prices affect the stability of banks under different income growth levels using the house prices and bank variables of 286 U.S. Metropolitan Statistical Areas (MSAs) from 1990Q1 to 2010Q4. What distinguishes our work from the previous studies on the relationship between house prices and bank stability is that our work (1) takes into account the various levels of income growth and (2) uses disaggregated data[2] which better reveals the heterogeneity of regional real estate markets and commercial banks in the US.[3]

We define housing markets as MSAs, which correspond to labor market areas within which workers are willing to commute. MSAs can vary considerably from the national average of house prices. Despite the sizable boom-bust pattern in house prices at the national level, regional housing markets in the U.S. experience considerable heterogeneity in the amplitudes of their cycles or in the house price dynamics. Sinai (2012) documents different magnitudes in the booms and busts across MSAs in the US: the 75th percentile MSA experienced 111% trough-to-peak growth in real

* Corresponding author. Tel.: +1 657 278 8694; fax: +1 657 278 3097.
E-mail addresses: hpan@fullerton.edu (H. Pan), cwang@brooklyn.cuny.edu (C. Wang).

[1] The number is based on the Failed Bank List from the Federal Deposit Insurance Corporation.

[2] Details on the data sources and coverage can be found in Section 2.3 and Appendix.

[3] We focus on commercial banks rather than bank-holding companies due to data availability. Specifically, a bank-holding company is a company that controls one or more banks, but does not necessarily engage in banking itself. A commercial bank is a bank that lends money and provides transactional, savings, and money market accounts, etc. It grants secured loans in which the borrower pledges some assets as collateral for the loan, e.g. a car or property. It also grants unsecured loans that are not secured against the borrower's assets, e.g. bank overdrafts, corporate bonds, credit-related securities, etc. Changes in banking laws now allow commercial banks to make home mortgage loans on a more liberal basis than ever before. Commercial banks are active in home financing and have become a major source for residential and commercial mortgage loans.

0378-4266/$ - see front matter
http://dx.doi.org/10.1016/j.jbankfin.2013.01.018

house prices in the 1990s and 2000s, whereas the 25th percentile MSA had only 32% trough-to-peak real house price growth. We thus take into account the heterogeneity of immobile real estate assets and the regional variation of house prices when measuring their dynamics and deviations from their fundamental values, using quarterly information on real estate prices in 286 U.S. MSAs. Housing markets vary across U.S. regions due to disparities in economic development and population growth, and they are likely to have different impacts on bank stability.

MSA-level data have been used to conduct various empirical studies related to the U.S. housing markets. For instance, Bhattacharya and Kim (2011) use a panel of 20 MSAs in the U.S. over the period 1990Q2–2009Q2 to study the impact of underlying economic factors on real house prices. In another study, Zabel (2012) investigates how the housing market affects the flow of workers across cities using house price indexes for 277 U.S. MSAs from 1990 to 2006.

In this study, we focus on residential property (one-to-four family residential property) markets in the US, which on average account for over 76% of mortgage debt outstanding for all holders (including major financial institutions, federal and related agencies, mortgage pools or trusts, individuals, and others). Commercial property (nonfarm, non residential) markets on average account for 17% of mortgage debt outstanding for all holders; multifamily residential property markets account for 6%; and farm land accounts for 1%.[4] Thus, residential property was and remains a key element in fueling the turmoil in financial markets in terms of their share as collateral in asset-backed securitization, as opposed to other real estate segments.[5]

Following the previous empirical work, we consider two measures of the house price indicator when assessing the impact of house prices on bank instability: percentage changes in house price index and house price deviations from fundamental values. The first of these is commonly used in the literature. However, researchers have recently argued that house price deviations from the long-run equilibrium should also be considered to study the relationship between house prices and bank stability (Koetter and Poghosyan, 2010). We apply the pooled mean-group (PMG) and mean-group (MG) estimators to estimate house price dynamics and deviations from fundamental values in 286 U.S. MSAs. Our results confirm a common long-run positive relationship among house prices, personal income, and labor force growth in the MSAs, and provide evidence of a house price adjustment to the long-run equilibrium.

To assess the impact of house prices on bank instability, we need to determine the state of the banking system. Non-performing loans[6] (NPLs) have been a popular indicator used in the literature (Nkusu, 2011; Kauko, 2012, among others). However, empirical studies using disaggregated bank-specific data for MSAs in the US remain scarce. In this paper, we use NPLs to gauge bank instability at the MSA level[7]: larger amounts of NPLs relative to total loans in banks indicate increasing bank instability. Other measures for bank instability in previous studies include bank failure rates (Cebula et al., 2011) and the probability of distress events (Koetter and Poghosyan, 2010). To our knowledge, NPLs are the best available measure of bank instability for commercial banks in U.S. MSAs.

In the literature, there are two competing theories about the effects of house prices on bank stability: the collateral value hypothesis (Daglish, 2009; Niinimaki, 2009) and the deviation hypothesis (Von Peter, 2009; Gerlach and Peng, 2005). The collateral value hypothesis argues that rising house prices promote bank stability by increasing the value of the houses owned by the bank and the value of the collateral pledged by borrowers; thus, it suggests a negative relationship between nominal house price changes and the bank's NPLs. In contrast, the deviation hypothesis contends that persistently rising house prices enhance larger exposure and the accumulation of risky assets in banks due to (1) a bank's excessive lending to risky borrowers at cheap rates and (2) risky borrowers' higher credit demand from banks who bet on further rises in house prices; consequently, it predicts a positive relationship between house price deviations from the fundamental values and the bank's NPLs. Koetter and Poghosyan (2010) find evidence using data on housing markets and banks in Germany during 1995–2004 to support the deviation hypothesis where bank instability is attributed to house price deviations instead of to changes in nominal house prices.

We conjecture that the responses of NPLs to house price changes or deviations could be different when gauged at various levels of income growth, and then apply the threshold model proposed by Hansen (1999) to test the above two hypotheses under different income growth levels. Banks' asymmetric responses to house price changes or deviations during booms and busts might be attributed to the bounded rationality of investors as described in Gennaioli and Shleifer (2010), Gennaioli et al. (2012), and Dieci and Westerhoff (2012). Ample empirical evidence shows that human agents generally act in a boundedly rational manner, and are subject to limited ability and the use of simple heuristics to predict prices or returns (Kahneman et al., 1986; Smith, 1991). Not all contingencies are represented in the investors' thought processes, and only the most likely events are retrieved (Gennaioli and Shleifer, 2010). This local thinking, or neglect of low probability risks, results in over-issuance of new securities and financial fragility (Gennaioli et al., 2012). A sharp decline in prices due to fire sales after a substantial surprise to the market can have especially adverse welfare consequences (Shleifer and Vishny, 2010; Stein, 2012). On the other hand, appreciation in prices would have a less severe impact. Other influential models include Day and Huang (1990), Chiarella (1992), De Grauwe et al. (1993), Chiarella et al. (2002), and De Grauwe and Grimaldi (2006), and Dieci and Westerhoff (2012).

To test our conjecture, we use the threshold model to examine the impact of house prices on bank instability under different income growth levels and estimate the income growth threshold endogenously, instead of imposing an exogenous criterion for splitting the sample by income growth levels. Personal income growth rate is the threshold variable which interacts with one of the house price indicators in the threshold model. We consider two model specifications depending on which house price indicator interacts with the threshold variable (personal income growth rate). Empirical results suggest the existence of income growth threshold effects in the relationship between house price and bank instability. In particular, two income growth thresholds are found when changes in house prices index are used, and one income growth threshold is reported when house price deviations from the fundamental values are applied.

First, there exist two income growth thresholds of -5.342% and 3.972% when changes in house price index interact with income growth. Changes in house price index have a significant negative effect on NPLs and the size of the impact depends on the thresholds. When income growth is below -5.342%, NPLs decrease by 0.466% if the changes in house price index increase by 1%, holding

[4] The averages are for the period of 2000–2010. Source of data: Federal Reserve Board.

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

[6] According to the definition by the IMF: "A loan is non-performing when payments of interest and principal are past due by 90 days or more, or at least 90 days of interest payments have been capitalized, refinanced or delayed by agreement, or payments are less than 90 days overdue, but there are other good reasons to doubt that payments will be made in full".

[7] We also consider z-score as an alternative measure of bank instability for commercial banks in U.S. MSAs. However, empirical results using z-score are not significant.

other things equal. When income growth is between −5.342% and 3.972%, the negative impact is smaller with a coefficient of −0.181. When income growth is greater than 3.972%, NPLs decrease by 0.097% if the changes in house price index increase by 1%, holding other factors equal. Overall, our results using percentage changes in house price index are consistent with the collateral value hypothesis: the larger the changes in house price index, the lower the bank instability.

Second, we find single income growth threshold of −4.285% when house price deviations from fundamental values are used. In particular, house price deviations have a significantly positive impact on NPLs with a coefficient of 0.015 when income growth is below −4.285%. This finding is consistent with the deviation hypothesis: the larger the house price deviations, the higher the bank instability. The effect of house price deviations on NPLs is significantly negative but with a smaller coefficient of −0.001 when income growth is above −4.285%. House price appreciations above the long-run equilibrium can slightly lower NPLs when income growth is above the threshold.

Finally, we conduct the same analysis using the non-MSAs sample from 1995Q1 to 2010Q4 for robustness checks. In contrast with the MSAs, we find no common long-run relationship among house prices, personal income, and population growth in the non-MSAs real estate markets. This could be due to the even larger heterogeneity in the housing markets in the non-MSAs. Therefore, house price deviations are not well estimated by the PMG estimator, and we thus proceed to estimate the threshold model using only the house price changes. Single income growth threshold is suggested, and the point estimate is −6.19%. NPLs decrease in response to a positive change in house price index, and the size of the impact depends on income growth threshold. Thus, the collateral value hypothesis is supported, which is consistent with the results for the MSAs.

The remainder of this paper is organized as follows. Section 2 describes the empirical methodologies and data (1) to measure the deviations of house prices from fundamental values and (2) to examine the effects of house price indicators on bank stability under different income growth levels. The empirical results are presented in Section 3. Section 4 reports the robustness results using the non-MSAs sample. Finally, Section 5 concludes and sheds light on some policy implications.

2. Methodology and data

2.1. Deviations of house prices from fundamental values

The behavior of house prices influences business cycle dynamics through their effect on aggregate expenditure and on the performance of financial institutions (Tsatsaronis and Zhu, 2004). Thus, understanding the determinants of house prices is crucial for investors and policy makers. The determinants of house prices include factors that drive the demand for and supply of housing. The major drivers of housing demand are population, income, interest rates, availability of mortgage financing, and house price growth expectations; while the major drivers of housing supply include house prices, construction costs, and the availability of financing (DiPasquale and Wheaton, 1995). However, housing has unique characteristics and the supply side of the real estate market is more rigid due to the shortage of land for housing and the time needed for new construction to be completed (Stepanyan et al., 2010). Therefore, most empirical studies on house price determinants focus on the demand side. Klyuev (2008) applies the fundamental model and the asset pricing approach to examine the dynamics of house prices in the US from 1970 to 2008. He finds there has been a substantial overvaluation in the U.S. housing market since 2001 and that house prices can deviate from their equilibrium value for long periods of time. The changes in the U.S. regional house prices have been more synchronized than before since the early 1990s.

In this paper, we apply the pooled mean-group (PMG) and mean-group (MG) estimators to study house price determinants in the US, using a panel of 286 U.S. MSAs. The PMG and MG estimators introduced by Pesaran and Smith (1995) and Pesaran et al. (1999) are two important methodologies to estimate non-stationary dynamic panels in which the parameters are heterogeneous across groups. As shown in Koetter and Poghosyan (2010), the main difference between the two estimators is that the PMG estimator imposes a homogeneity restriction on the long-run relationship between variables while the MG estimator does not. Such homogeneity restrictions imposed by the theory can be tested empirically using the Hausman test. Following Koetter and Poghosyan (2010), we describe the long-run relationship between house prices and their fundamentals[8] as:

$$HP_{it} = \beta_0 + \beta_{1i} Y_{it} + \beta_{2i} LF_{it} + D + \varepsilon_{it}, \tag{1}$$

where i and t indicate MSA and time, respectively; HP is the log of house price index; Y is the log of personal income per capita; LF is the labor force growth; and D represents a vector of time dummy variables for bank deregulation[9] and the MSA-specific fixed effect. It is argued that if the variables are integrated of order 1 (i.e. $I(1)$) and co-integrated, then the error term ε_{it} is stationary (i.e. $I(0)$) for all i. The autoregressive distributed lags dynamic panel representation of the long-run Eq. (1) is:

$$HP_{it} = \theta_{10i} Y_{it} + \theta_{11i} Y_{it-1} + \theta_{20i} LF_{it} + \theta_{21i} LF_{it-1} + \rho_i HP_{it-1} + \eta D \\ + \varepsilon_{it}. \tag{2}$$

We lag house price determinants by one period[10] and write the error-correction representation of Eq. (2) as:

$$\Delta HP_{it} = \alpha_i (HP_{it-1} - \beta_{0i} - \beta_{1i} Y_{it-1} - \beta_{2i} LF_{it-1}) + \theta_{10i} \Delta Y_{it} \\ + \theta_{20i} \Delta LF_{it} + \varepsilon_{it}, \tag{3}$$

where $\alpha_i = -(1-\rho_i), \beta_{0i} = \frac{\mu_i}{1-\rho_i}, \beta_{1i} = \frac{\theta_{10i}+\theta_{11i}}{1-\rho_i}$, and $\beta_{2i} = \frac{\theta_{20i}+\theta_{21i}}{1-\rho_i}$.

The homogeneity restriction imposed by the PMG estimator is on the coefficients of long-run house price determinants β_1 and β_2, while the intercept β_{0i}, the speed of adjustment parameter α_i and the short-run adjustment coefficients θ_{10i} and θ_{20i} vary across MSAs. We expect a negative speed of adjustment parameter α_i, which suggests that house prices react to disequilibrium in the real estate market: house prices decrease following positive deviations from the long-run equilibrium in the real estate market, while house prices increase following negative deviations from the long-run equilibrium. In particular, the error-correction term $HPD_{it-1} = HP_{it-1} - \hat{\beta}_{0i} - \hat{\beta}_{1i} Y_{it-1} - \hat{\beta}_{2i} LF_{it-1}$ estimated from the PMG estimation represents the temporary deviations of house prices from their fundamental values at the MSA level and can be used as a determinant of non-performing loans in the second-stage analysis, since bank performance or stability is tied to the real estate mortgage quality.

[8] Nominal gross domestic product (GDP) per worker, population growth, and the interest rate are commonly used in the previous literature as the fundamental determinants of house prices. Due to limited data availability at the MSA level, we turn to personal income per capita, labor force growth, and mortgage rate as the proxies for GDP per worker, population growth, and interest rate for the U.S. MSAs, respectively; we decide to exclude mortgage rate in Eq. (1) since the empirical results in Section 3 show that it is insignificant.

[9] There has been significant bank deregulation during the sample period, e.g., the Riegle–Neal Interstate Banking and Branching Efficiency Act of 1994 and the Financial Services Modernization Act of 1999.

[10] We also lag the house price determinants by two, three and four periods, respectively, and obtain the consistent results in Section 3.1. For simplicity, we write down the model here with a one period lag.

2.2. Threshold model

House price appreciations tend to associate with credit growth, while sharp declines in house prices can lead to subprime mortgage crises and increases in non-performing loans in banks. The banks' performance or stability will respond differently to changes in the housing market in an economic boom environment from how it responds in bust circumstances. Different responses to house price deviations can be attributed to bounded rationality, as proposed by Simon (1982), or to local thinking, as introduced by Gennaioli and Shleifer (2010) and Gennaioli et al. (2012). In particular, the Gennaioli and Shleifer (2010) model builds on the notion that agents' decisions are made on the basis of a selected subset of possible events, not on the entire state space. Agents have limited ability to represent uncertainty, and they do not think of all possible states of the risky asset's payoff but only the most likely ones. The neglect of certain risks known as local thinking can lead to over-issuance of new securities and corresponding financial fragility (Gennaioli et al., 2012). Sharp declines in prices can have especially adverse welfare consequences ex post because they cut off lending to new investment and can trigger an economic crisis (Shleifer and Vishny, 2010; Stein, 2012). In an economic bust circumstance, undesirable housing market conditions could significantly deteriorate bank stability. On the other hand, favorable housing market conditions during an economic boom may lessen the impact of house price changes or deviations on banks' instability. Therefore, we expect the effects of house prices on bank instability would be different under various income growth levels.

The issue is how to split the sample along income growth levels. In this paper, we use the threshold estimation technique developed by Hansen (1999), instead of imposing an exogenous criterion on income growth levels and estimating the impact of house prices under each income growth level. Specifically, we estimate NPLs as a function of house price deviations,[11] income growth, and a vector of bank-specific characteristics. The threshold estimation model is given by

$$NPL_{it} = \begin{cases} \alpha_i + \beta_1 HPD_{it-1} + \eta_1 Y_{it-1} + \varphi_1 Z_{it-1} + \eta D + e_{it} & \text{if} \quad Y_{it-1} \leqslant \tau \\ \alpha_i + \beta_2 HPD_{it-1} + \eta_1 Y_{it-1} + \varphi_1 Z_{it-1} + \eta D + e_{it} & \text{if} \quad Y_{it-1} > \tau \end{cases}, \tag{4}$$

where i and t indicate MSA and time, respectively. NPL is the ratio of non-performing loans to total loans of banks in MSA i at time t; HPD_{it-1} is a (lagged) variable measuring the deviations of house prices form their fundamental values at the MSA level; Y_{it-1} denotes the (lagged) growth rate of personal income per capita; Z_{it-1} is a (lagged) vector of bank-specific variables and other explanatory variables; and D represents a vector of time dummy variables for bank deregulation. In this context, the observations are divided depending on whether the threshold variable Y_{it-1} is smaller or larger than the threshold level τ. If the regression slopes, β_1 and β_2, are different, then Eq. (4) is

$$NPL_{it} = \alpha_i + \varphi_1 Z_{it-1} + \beta_1 HPD_{it-1} I(Y_{it-1} \leqslant \tau) + \beta_2 HPD_{it-1} I(Y_{it-1} > \tau) + \eta D + e_{it}, \tag{5}$$

If there exist two threshold levels, τ_1 and τ_2, then Eq. (4) can be represented by

$$NPL_{it} = \alpha_i + \varphi_1 Z_{it-1} + \beta_1 HPD_{it-1} I(Y_{it-1} \leqslant \tau_1) + \beta_2 HPD_{it-1} I(\tau_1 < Y_{it-1} \leqslant \tau_2) + \beta_3 HPD_{it-1} I(\tau_2 < Y_{it-1}) + \eta D + e_{it}, \tag{6}$$

where $I(\cdot)$ is the indicator function.

To determine the number of thresholds, we estimate the fixed effect model allowing for zero, one, two, and three thresholds. We start by looking for one threshold, and estimate τ by least squares. It is the argument of the minimization of the squared residuals from the estimation of Eq. (4). We then test the hypothesis of no threshold effect by H_0:$\beta_1 = \beta_2$. The likelihood ratio test of H_0 is based on statistic $F_1 = \frac{S_0 - S_1(\hat{\tau})}{\hat{\sigma}^2}$, where S_0 and S_1 are respectively the constrained and unconstrained sum of squared residuals, and $\hat{\sigma} = \frac{1}{n(T-1)} \hat{e}^{*\prime} \hat{e}^* = \frac{1}{n(T-1)} S_1(\hat{\tau})$, where $\hat{e}^*$ are the unconstrained residuals at $\tau = \hat{\tau}$. The non-standard asymptotic distribution of the likelihood ratio statistic is attained by a bootstrap procedure, and p-values and confidence intervals are constructed. If the null hypothesis of no threshold is rejected, the likelihood ratio procedure is used to check whether we have one or two thresholds by calculating F_2, and if necessary F_3. The computed likelihood ratio statistics can be plotted as a function of the threshold parameters, and the likelihood ratio will hit the zero axis at a threshold.

We estimate the number of thresholds sequentially. Once the existence of a one-threshold effect is established, we look for a second threshold by first estimating $\hat{\tau}_2$ as the argument of the minimization of the squared residuals amongst values other than the first threshold, and then computing the likelihood ratio statistics for the existence of a second threshold effect F_2. If the null hypothesis is rejected for large values of the statistic, we conclude that our model has one threshold. Otherwise, we expect F_2 to be zero at a certain income growth level other than the first threshold, and thus a second threshold effect exists. We then continue to investigate a third threshold using F_3.[12]

The coefficients of house price indicators gauge the impact of house prices on bank instability under different income growth thresholds and can be used to test the competing collateral value and deviation hypotheses. The collateral value hypothesis argues that rising house prices improve bank stability by increasing the collateral value of the borrowers and reducing the default possibility. This suggests a negative relationship between nominal house price changes and the banks' NPLs. On the other hand, the deviation hypothesis contends that when persistently rising house prices exceed their fundamental values, a reverse correction will follow and banks may be exposed to larger risky assets and higher default rates. Therefore, the deviation hypothesis predicts a positive significant coefficient on house price deviations. In our estimations, we also control for other bank-specific variables to set apart the impact of house price indicators on NPLs from the effect of bank-specific risk or financial conditions.

2.3. Data

To study the U.S. regional real estate markets, data on house prices and macroeconomic variables for the MSAs in the U.S over the period 1990Q1–2010Q4 are drawn from several sources. In contrast to states or census regions, MSAs are defined on the basis of social and economic integration as measured through commuting.[13] We obtain the quarterly house price all-transactions indexes (estimated using sales prices and appraisal data) from the Federal Housing Finance Agency (FHFA). The indexes are based on transactions and appraisals, and are then adjusted for appraisal bias.[14] They are available at the national, regional, and state level, as well as for MSAs.[15]

[11] We also estimate NPLs using percentage changes in house price index instead.

[12] See Hansen (1999) for more details.

[13] The United States Office of Management and Budget defines a Metropolitan Statistical Area as one or more adjacent counties or county equivalents that have at least one urban core area with a population of at least 50,000, plus adjacent territory that has a high degree of social and economic integration with the core as measured by commuting ties.

[14] The FHFA house price indexes include only homes with mortgages that conform to Freddie Mac and Fannie Mae guidelines. Jumbo loans over \$417,000 are not included. These indexes are equally weighted regardless of the value of the house.

[15] The FHFA uses the revised Metropolitan Statistical Areas and Divisions as defined by the Office of Management and Budget in the latest year. These MSAs and Divisions are based on census data.

Table 1a
Summary statistics for MSAs.

	Mean	Sd	Min	p25	p50	p75	Max
MSA-level housing/macro variables							
House price index	133.274	41.272	56.62	102.58	123.14	156.66	348.28
Per capita personal income	26651.1	7587.383	9202	20,592	25883.5	31,767	66,959
Labor force	370,000	819,000	15,810	67,451	123,000	288,000	95,50,000
Unemployment rate	5.597	2.437	0.9	4	5.1	6.6	27.4
Per capita personal income growth	3.87	2.909	−28.135	2.607	4.008	5.437	33.107
Growth rate of labor force	0.294	1.714	−18.706	−0.545	0.272	1.096	17.061
Nominal mortgage rate	7.092	1.362	4.39	6.08	7.04	8.01	10.46
Real mortgage rate	4.46	2.118	−0.022	3.38	4.601	5.558	16.187
Inflation rate	2.632	2.103	−10.337	1.893	2.692	3.648	7.997
HPI percentage changes	0.86	1.85	−15.001	−0.017	0.883	1.755	17.619
House price deviations	25.547	21.238	−52.77	12.398	25.844	38.252	119.135
Bank-specific variables							
Non-performing loans	1.335	1.887	0	0.301	0.772	1.671	86.777
Equity ratio	10.149	3.465	0.179	8.029	9.304	11.365	72.887
Cost-income ratio	77.266	12.298	−32.786	71.224	77.116	82.816	633.333
Return on assets	0.685	0.712	−15.927	0.331	0.631	1.006	14.429
Liquidity	5.49	4.398	0	3.059	4.353	6.362	69.467
z-Score	24.044	10.315	−6.423	16.739	23.499	30.395	80.786

Note: The sample contains 162,960 observations of 1940 U.S. commercial banks in 286 MSAs for the period 1990Q1–2010Q4. Non-performing loan is the ratio of non-performing loans to total loans in commercial banks; equity ratio is the ratio of equity capital to total assets of commercial banks; cost-income ratio is total cost as a share of total income of commercial banks; return on assets (ROA) is the ratio of operating income to equity capital of commercial banks; liquidity is cash as a share of total assets of commercial banks; *z*-score is estimated as ROA + equity/assets)/(standard deviation of ROA).

Since the variation in house prices differs considerably across the US, it would be better to examine the residential properties at the MSA level. The FHFA reports 344 MSAs; however, data for different MSAs have different starting dates, and some contain missing values. We thus choose 286 MSAs[16] that contain no missing values for the period 1990Q1–2010Q4.

Following the previous literature, we use civil labor force from the Bureau of Labor Statistics (BLS) and per capita personal income from the Bureau of Economic Analysis (BEA) as house price determinants to estimate the house price deviations.[17] We also consider other macroeconomic variables, such as unemployment rates from the BLS and mortgage rates and inflation rates from the Federal Reserve Bank of St. Louis.[18] Details on the data are included in Appendix A.

Table 1 reports the summary statistics. We observe substantial variation in house price percentage changes and house price deviations, as well as macroeconomic variables. Specifically, the average house price percentage change is 0.86%, with a standard deviation of 1.85%, a minimum of −15% (Stockton, CA in 2008Q2), and a maximum of 17.619% (Fairbanks, AK in 1990Q3). The average income growth is 3.87%, with a standard deviation of 2.909%, a minimum of −28.135% (Midland, TX during 2009Q1–Q4), and a maximum of 33.107% (New Orleans-Metairie-Kenner, LA during 2006Q1–Q4).[19] Such large variation suggests that part of the variation in house prices across MSAs can be attributable to the variation in macroeconomic fundamentals. The remaining unexplained part may reflect the deviations of house prices from their fundamental values, which can influence the stability of banks at the MSA level.

To characterize banks' performance, we use Compustat financial accounts data for commercial banks in the US between 1990Q1 and 2010Q4. The raw data at the bank level is sourced from the Call Reports in the Federal Deposit Insurance Corporation. The number of banks without missing values for our sample period is 1940, and the total number of observations is 162,960. To mimic the housing data of 286 MSAs in the US, we aggregate the bank-specific data into the MSA level by taking the simple average of the bank-specific data in the same MSA.[20] We use the ratio of NPLs to total loans as a proxy for bank instability. We also consider *z*-score as an alternative measure of bank instability. The *z*-score of a bank is estimated as the sum of return on assets and capitalization relative to the standard deviation of return on assets of a bank. It is a measure of distance-to-default, which can be a useful tool for regulators in assessing the risk of bank failures. The higher is the *z*-score, the more stable the bank.

We construct the CAMEL measures to approximate banks' capitalization (C), asset quality (A), management skills (M), earnings (E), and liquidity (L). We measure capitalization by the ratio of equity capital to total assets; more capitalization can reduce bank instability. We use the ratio of loans with latent risk to total loans to evaluate asset quality. The larger is the value of this indicator, the lower the asset quality of a bank. We specify cost to income ratio to approximate management quality. Banks with better managerial skills can lower operation expense relative to income, and should be less likely to encounter financial distress, and thus associate with lower NPLs. We measure earnings by return on assets. High earnings indicate that banks are more profitable and are more likely to bear fewer NPLs. Liquidity is measured by the share of cash over total assets. We assess individual explanatory power of the CAMEL covariates and select those covariates with larger explanatory power. The final sample is a balanced panel of 24,024 observations on 1940 U.S. commercial banks in 286 MSAs. We find that banks in the 75 percentile and higher for NPLs are associated with lower *z*-score, lower capital adequacy, lower

[16] List of 286 MSAs is available upon request.

[17] Civil labor force at the MSA level is reported in monthly frequency and we convert monthly to quarterly frequency using the average method in EViews. Per capita personal income at the MSA level is available in yearly frequency and we convert the annual data to quarterly frequency using constant match in EViews.

[18] Unemployment rate at the MSA level is reported in monthly frequency and we convert monthly to quarterly frequency using the average method in EViews. Mortgage rate and inflation rate are available at the census regional level in quarterly frequency and they are identical in the same census region. We experiment with additional macro determinants, such as unemployment rate, mortgage rates, and inflation rates, but they are insignificant. We test the robustness of our results based on this parsimonious model by including such controls in the bank stability equation to avoid forcing all regional macro effects into the house price indicators derived here.

[19] Empirical results remain robust after excluding the extreme values in the sample.

[20] We also tried the geometric mean of the bank-specific data, and our results remain robust.

Table 1b
Summary statistics for non-MSAs.

	Mean	Sd	Min	p25	p50	p75	Max
State non-metropolitan areas housing/macro variables							
House price index	151.422	42.269	97.93	117.92	141.685	177.245	385.05
Per capita personal income	25970.52	6940.843	15,113	21,037	24931.5	29379.5	64,468
Labor force	11,15,105	653180.3	20,677	588,000	10,70,000	15,60,000	30,64,872
Unemployment rate	5.614	1.683	3.5	4.533	5.233	5.867	11.1
Per capita personal income growth	4.053	3.149	−11.22	2.68	4.16	5.67	17.93
Growth rate of labor force	0.615	0.813	−1.33	0.08	0.475	0.97	4.84
Nominal mortgage rate	6.588	1.023	4.39	5.85	6.53	7.31	8.86
Real mortgage rate	4.208	2.234	−0.022	2.731	4.312	5.354	16.187
Inflation rate	2.381	2.154	−10.337	1.636	2.58	3.602	6.232
HPI percentage changes	1.003	1.572	−8.175	0.26	1.026	1.805	12.241
House price deviations	848.486	1714.315	−1639.16	−329.738	459.056	1610.564	8372.017
Bank-specific variables							
Non-performing loans	1.291	1.617	0	0.295	0.806	1.675	16.638
Equity ratio	10.779	3.342	4.102	8.497	10.023	12.088	30.175
Cost-income ratio	76.215	9.877	28.35	70.916	76.219	81.565	235.787
Return on assets	0.711	0.599	−8.672	0.345	0.639	0.998	4.332
Liquidity	5.071	3.805	0	2.822	3.955	5.887	47.58
z-Score	27.41	10.501	0.548	19.523	26.589	33.499	78.228

Note: The sample contains 110,272 observations of 1723 U.S. commercial banks in non-MSAs in 42 states for the period 1995Q1–2010Q4. Non-performing loan is the ratio of non-performing loans to total loans in commercial banks; equity ratio is the ratio of equity capital to total assets of commercial banks; cost-income ratio is total cost as a share of total income of commercial banks; return on assets (ROA) is the ratio of operating income to equity capital of commercial banks; liquidity is cash as a share of total assets of commercial banks; *z*-score is estimated as ROA + equity/assets)/(standard deviation of ROA).

Table 2
Deviation of house prices from fundamentals for MSAs.

House price model	PMG estimation	MG estimation
Long-run coefficients		
Personal income (per capita)	0.569***	0.625
	(0.019)	(1.238)
Labor force growth	0.084*	1.036
	(0.05)	(1.918)
Short-run coefficients		
Speed of adjustment	−0.061***	−0.074***
	(0.003)	(0.006)
Change in personal income per capita	0.045***	0.022**
	(0.007)	(0.009)
Change in labor force growth	0.091***	0.044**
	(0.017)	(0.017)
Dummy94q3	0.003***	0.009***
	(0.0001)	(0.001)
Dummy99q4	0.007***	0.017***
	(0.001)	(0.001)
Intercept	−0.116***	0.142
	(0.006)	(0.218)
Statistics		
Hausman test (*p*-value)	0.74	
Number of observations	24,024	

Notes: PMG is pool mean group estimation and MG is mean group estimation. Both use demeaned data (subtract cross-sectional mean from each variable for each MSA). Standard errors are presented in brackets.
* Significance at 10% level.
** Significance at 5% level.
*** Significance at 1% level.

efficiency, lower returns, and larger stock of liquid assets than banks in the 25 percentile and lower for NPLs. This finding is consistent with our expectation about the relationship between the CAMEL covariates and bank instability.

3. Empirical results

3.1. House price determinants

Table 2 reports the estimation results of the PMG and MG specifications for house prices. The upper panel of the table shows the average long-run coefficient estimates, and the lower panel of the table shows the average short-run adjustment coefficients for all 286 U.S. MSAs. Two time dummy variables (Dummy94q3 and Dummy99q4) are included to control for the impact of bank deregulation during the sample period. Specifically, they represent the Riegle–Neal Interstate Banking and Branching Efficiency Act of 1994 and the Financial Services Modernization Act of 1999.[21] Ample evidence indicates that deregulation led to inter-state and intra-state mergers and acquisitions and generally a broadening geographic scope of banking operation. The geographic expansion implies that different banks might have differed systemically in their risk exposure to different regional real estate disequilibria; specifically, local unitary banks in late-deregulation states would have had less chance to diversify threats from disequilibria in housing markets compared to banks active nationwide.[22] Generally speaking, the two specifications are consistent in terms of the coefficient estimations and statistical significance with minor variation in the statistical significance for the long-run coefficients in the MG estimation. However, the Hausman test with the *p*-value of 0.74 suggests that the PMG estimator is preferable, since we fail to reject the null hypothesis that the difference in coefficients in the two models is not systematic. This suggests a common long-run relationship among house prices, income growth, and labor force growth across 286 U.S. MSAs.

In line with our expectations and the literature, we find a statistically significant positive long-run relationship between personal income per capita and house prices. The income elasticity of house prices is 0.57, which is about two-thirds of the unit elasticity in Holly et al. (2010), who investigate the determination of real house prices in a panel of 49 US states over 29 years. The difference may reveal the heterogeneity of regional real estate markets in the US. The impact of labor force growth is also significant and positive with a magnitude of 0.08, which is roughly half of what Koetter and Poghosyan (2010) obtain for Germany. Overall, our results confirm that equilibrium house prices increase with rising demand, due to income and labor force growth.The coefficient of

[21] The Riegle–Neal Interstate Banking and Branching Efficiency Act of 1994 took into effect on September 29, 1994. The Financial Services Modernization Act of 1999 took into effect on November 12, 1999.

[22] We thank the anonymous referee for this valuable input.

Table 3a
Tests for threshold effects for MSAs (ΔHPI interacts with the income growth).

	Model (A)	Model (B)
Test for single threshold		
F_1	215.7310	224.2191
p-Value	0	0
(10%, 5%, 1% critical values)	(44.8072, 55.3929, 67.8554)	(43.2934, 48.7797, 66.1032)
Test for double threshold		
F_2	120.3634	127.0458
p-Value	0	0
(10%, 5%, 1% critical values)	(53.7835, 61.1712, 81.1006)	(46.7091, 52.0408, 60.3206)
Test for triple threshold		
F_3	33.2293	34.3916
p-Value	0.14	0.09
(10%, 5%, 1% critical values)	(36.0020, 44.2025, 59.4523)	(32.3437, 38.7751, 49.9248)

Table 3b
Tests for threshold effects for MSAs (*HPD* interacts with the income growth).

	Model (A)	Model (B)
Test for single threshold		
F_1	228.7367	167.6834
p-Value	0.06	0.04
(10%, 5%, 1% critical values)	(215.6704, 233.8602, 275.7787)	(130.9787, 161.9784, 241.0721)
Test for double threshold		
F_2	78.0935	40.8002
p-Value	0.25	0.38
(10%, 5%, 1% critical values)	(100.0515, 110.4375, 148.4908)	(65.7310, 76.7664, 92.7219)
Test for triple threshold		
F_3	8.4863	13.5024
p-Value	0.91	0.54
(10%, 5%, 1% critical values)	(37.5000, 46.4205, 74.7960)	(26.4590, 32.0174, 45.7720)

Table 4a
Threshold estimates for MSAs (ΔHPI interacts with the income growth).

	Model (A)		Model (B)	
	Estimate	95% Confidence interval	Estimate	95% Confidence interval
Threshold 1	−5.3421	[−5.3421, −5.3421]	−5.3421	[−5.3421, −5.3421]
Threshold 2	3.9715	[3.9715, 4.0006]	3.9715	[3.9715, 4.0006]

Table 4b
Threshold estimates for MSAs (*HPD* interacts with the income growth).

	Model (A)		Model (B)	
	Estimate	95% Confidence interval	Estimate	95% Confidence interval
Threshold 1	−4.2847	[−4.2847, −4.2847]	−4.28474	[−4.2847, −4.2847]

average speed of adjustment is −0.061, which is statistically significant at the 1% level and suggests that only 6% of the previous quarter's house price deviations from the long-run equilibrium are adjusted this quarter. Following the literature, we calculate the half life of a shock approximated by the ratio $-\ln(2)/\ln(1+\bar{\alpha}_i)$, which is 11.01 quarters (2.75 years). Koetter and Poghosyan (2010) obtain the half life estimate of 6.79 years for the adjustment of house prices to the long-run equilibrium in Germany. Overall, our results provide evidence of a house price adjustment to the long-run equilibrium.

3.2. Threshold estimation results

To test the competing collateral value and deviation hypotheses, we consider two general model specifications: (I) the percentage changes in house price index (ΔHPI) interact with the threshold variable (personal income growth rate); and (II) the house price deviations (*HPD*) interact with the threshold variable. In each general model specification, we consider two models: (A) and (B). The difference between models (A) and (B) is whether the alternative house price indicator is included as an exogenous regressor, so that we can compare the effect of the alternative house price indicator. In model (A), the alternative house price indicator is not considered, whereas in model (B), the alternative house price indicator is added. Tables 3a, 4a and 5a summarize the empirical results for specification (I), and Tables 3b, 4b and 5b are for specification (II).

The test statistics F_1, F_2, and F_3, along with their bootstrap[23] p-values for each model specification are shown in Table 3. In particular, the test statistics F_1 and F_2 are highly significant at the 1% level with a bootstrap p-value of 0 for both single and double threshold effects in models (A) and (B) for specification (I) when ΔHPI interacts with the income growth, and the tests for a triple threshold F_3 are both insignificant at the 5% level in models (A) and (B) as shown in Table 3a. Thus, we conclude that there are two thresholds in the regression relationship when ΔHPI interacts with the income growth.

Table 3b shows that the test statistics for a single threshold F_1 is significant at the 10% level with a bootstrap p-value of 0.06 in model (A) and significant at the 5% level with a bootstrap p-value of 0.04 in model (B) where the lags of ΔHPI are added as exogenous regressors for specification (II) when *HPD* interacts with the income growth. The test statistics for a double threshold F_2 and a triple threshold F_3 are both insignificant at the 10% level in models (A) and (B). Thus, we conclude that there is one threshold in the regression relationship when *HPD* interacts with the income growth. Overall, the existence of threshold effect of house prices on bank instability measured by *NPL* is suggested no matter which house price indicator is used.

Table 4 presents the threshold estimates. The point estimates of the two income growth thresholds are −5.342% and 3.972% when ΔHPI interacts with the income growth as reported in Table 4a. Table 4b shows the point estimate of the single income growth threshold is −4.285% when *HPD* interacts with the threshold variable. The point estimates and the asymptotic 95% confidence intervals are consistent in both models (A) and (B) in the two general model specifications. In particular, the asymptotic 95% confidence intervals are narrower and more precise in the first income growth threshold estimate. Figs. 1a–1c display the computed likelihood ratio statistics as a function of the threshold variable for model (B) when ΔHPI interacts with the income growth and *HPD* is added as an exogenous regressor, confirming the estimates for the first threshold and second threshold. Fig. 2 shows the computed likelihood ratio statistics as a function of the income growth for model (B) when *HPD* interacts with the income growth and ΔHPI is included as an exogenous variable, confirming the estimate for the first threshold.

The estimates, conventional OLS standard errors, and White-corrected standard errors for the double threshold model where ΔHPI interacts with the income growth are reported in Table 5a. The estimates of interest are those on the house price indicators

[23] Three-hundred bootstrap replications are used for each of the three bootstrap tests.

Table 5a
Regression estimates for MSAs: double threshold model for non-performing loans (ΔHPI interacts with the income growth).

Dependent variable: Non-performing loans	Model (A)			Model (B)		
Regressors	Coefficient estimate	OLS SE	White SE	Coefficient estimate	OLS SE	White SE
Equity ratio$_{it-1}$	−0.0663	0.0133	0.0210	−0.0671	0.0133	0.0210
Equity ratio$_{it-2}$	0.0701	0.0133	0.0213	0.0712	0.0133	0.0213
Return on assets$_{it-1}$	0.0003	0.0002	0.0004	0.0000	0.0002	0.0002
Return on assets$_{it-2}$	0.0002	0.0002	0.0004	0.0004	0.0002	0.0006
Liquidity$_{it-1}$	0.0151	0.0049	0.0070	0.0127	0.0050	0.0071
Liquidity$_{it-2}$	−0.0209	0.0050	0.0073	−0.0197	0.0050	0.0073
G_PIPC$_{it-1}$	−0.0350	0.0037	0.0045	−0.0235	0.0044	0.0057
G_PIPC$_{it-2}$	−0.0153	0.0036	0.0042	−0.0240	0.0040	0.0051
HPD$_{it-1}$				0.1610	0.0080	0.0112
HPD$_{it-2}$				0.0386	0.0080	0.0113
Unemployment rate$_{it-1}$	0.1499	0.0077	0.0110	−0.1412	0.0164	0.0155
Unemployment rate$_{it-2}$	0.0518	0.0077	0.0108	0.0896	0.0159	0.0152
Nominal mortgage rate$_{it-1}$	−0.1428	0.0163	0.0157	−0.0354	0.0035	0.0042
Nominal mortgage rate$_{it-2}$	0.1023	0.0157	0.0154	0.0018	0.0038	0.0045
Inflation rate$_{it-1}$	−0.0378	0.0035	0.0042	0.0390	0.0075	0.0110
Inflation rate$_{it-2}$	−0.0009	0.0037	0.0045	−0.0410	0.0075	0.0110
Dummy94q3	−0.2345	0.0224	0.0232	−0.2364	0.0223	0.0233
Dummy99q4	0.1284	0.0193	0.0151	0.1442	0.0204	0.0164
HPI percentage change (g_pipc ⩽ th1)	−0.4171	0.0221	0.0472	−0.4656	0.0237	0.0491
HPI percentage change (th1 < g_pipc ⩽ th2)	−0.1402	0.0049	0.0071	−0.1813	0.0088	0.0130
HPI percentage change (th2 < g_pipc)	−0.0580	0.0050	0.0049	−0.0968	0.0088	0.0117

Notes: th1 and th2 denote the corresponding first and second threshold estimates in the double threshold models. Models (A) and (B) use housing price index (HPI) percentage changes to interact with personal income growth; Model (B) also includes house price deviations (*HPD*) as a regressor. G_PIPC = the growth rate of personal income per capita.

Table 5b
Regression estimates for MSAs: single threshold model for non-performing loans (*HPD* interacts with the income growth).

Dependent variable: Non-performing loans	Model (A)			Model (B)		
Regressors	Coefficient estimate	OLS SE	White SE	Coefficient estimate	OLS SE	White SE
Equity ratio$_{it-1}$	−0.0622	0.0136	0.0215	−0.0614	0.0132	0.0203
Equity ratio$_{it-2}$	0.0791	0.0136	0.0219	0.0606	0.0132	0.0206
Return on assets$_{it-1}$	0.0005	0.0002	0.0005	0.0003	0.0002	0.0004
Return on assets$_{it-2}$	0.0000	0.0002	0.0003	0.0000	0.0002	0.0003
Liquidity$_{it-1}$	0.0177	0.0051	0.0073	0.0132	0.0049	0.0071
Liquidity$_{it-2}$	−0.0236	0.0051	0.0075	−0.0173	0.0050	0.0074
G_PIPC$_{it-1}$	−0.0154	0.0039	0.0042	−0.0073	0.0038	0.0040
G_PIPC$_{it-2}$	−0.0284	0.0037	0.0043	−0.0223	0.0036	0.0041
HPI percentage change$_{it-1}$				−0.0864	0.0037	0.0046
HPI percentage change$_{it-2}$				−0.0886	0.0038	0.0045
Unemployment rate$_{it-1}$	0.1703	0.0079	0.0110	0.1324	0.0077	0.0104
Unemployment rate$_{it-2}$	0.0604	0.0079	0.0107	0.0553	0.0077	0.0101
Nominal mortgage rate$_{it-1}$	−0.1362	0.0167	0.0163	−0.1129	0.0163	0.0156
Nominal mortgage rate$_{it-2}$	0.0931	0.0162	0.0164	0.0564	0.0158	0.0156
Inflation rate$_{it-1}$	−0.0366	0.0035	0.0043	−0.0264	0.0035	0.0041
Inflation rate$_{it-2}$	0.0153	0.0038	0.0046	−0.0008	0.0038	0.0044
Dummy94q3	−0.1675	0.0228	0.0236	−0.2453	0.0222	0.0231
Dummy99q4	0.1256	0.0208	0.0164	0.1413	0.0202	0.0162
HPD (g_pipc ⩽ th1)	0.0179	0.0014	0.0024	0.0151	0.0014	0.0023
HPD (g_pipc > th1)	−0.0018	0.0006	0.0007	−0.0013	0.0006	0.0006

Notes: th1 denotes the corresponding first threshold estimates in the single threshold models. Models (A) and (B) use house price deviations (*HPD*) to interact with personal income growth; Model (B) also includes house price index (HPI) percentage changes as a regressor. G_PIPC = the growth rate of personal income per capita.

interacting with the threshold variable. In both models (A) and (B), ΔHPI has a significantly negative effect on *NPL* with various magnitudes according to the two thresholds. In particular, the coefficient in model (B) equals −0.466 when income growth is below −5.342%, −0.181 when income growth is between −5.342% and 3.972%, and −0.097 when income growth is above 3.972%. Overall, this is consistent with the collateral value hypothesis: larger positive house price index percentage changes are associated with lower *NPL* and improve bank stability. Moreover, the negative impact of ΔHPI on *NPL* is stronger as the economy experiences a recession with severe negative income growth. The coefficients on the two lags of *HPD* as shown in model (B) are both significantly positive, which implies that *HPD* has a significantly positive effect on *NPL*. Finally, the two control dummy variables for the impact of bank deregulation, Dummy94q3 and Dummy99q4, are both significant, confirming that bank deregulation can influence banks' responses to house price changes.

Table 5b displays the estimates, conventional OLS standard errors, and White-corrected standard errors for the single threshold model where *HPD* interacts with the threshold variable. The coefficient estimation and statistical significance on *HPD* interacting with the income growth in models (A) and (B) are consistent. For instance, when ΔHPI is added as exogenous variable in Model (B), *HPD* has a significantly positive effect on *NPL* (when *HPD* increases by 1%, *NPL* increases by 0.015%), if income growth is below −4.285%. This is consistent with the deviation hypothesis: the lar-

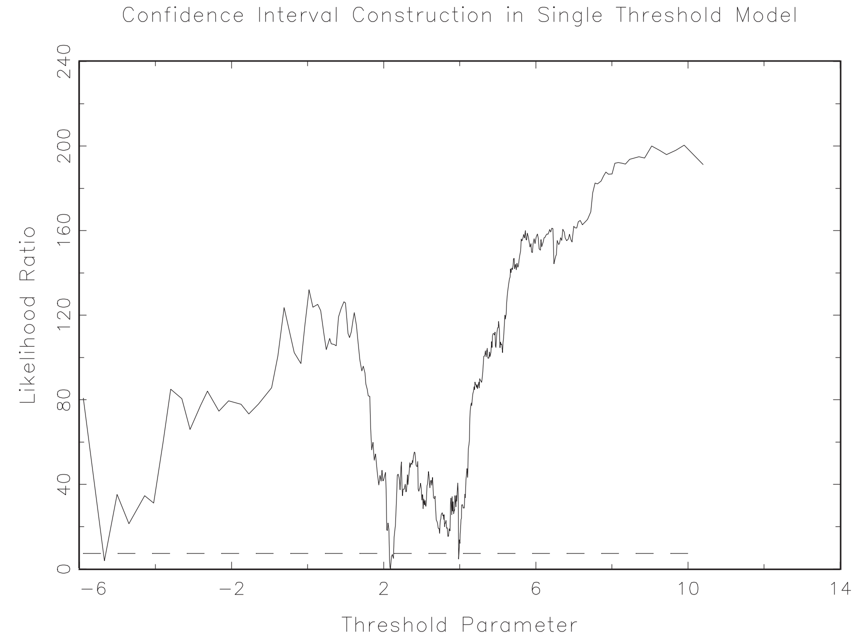

Fig. 1a. Confidence interval construction in single threshold model for MSAs (Δ*HPI* interacts with the income growth).

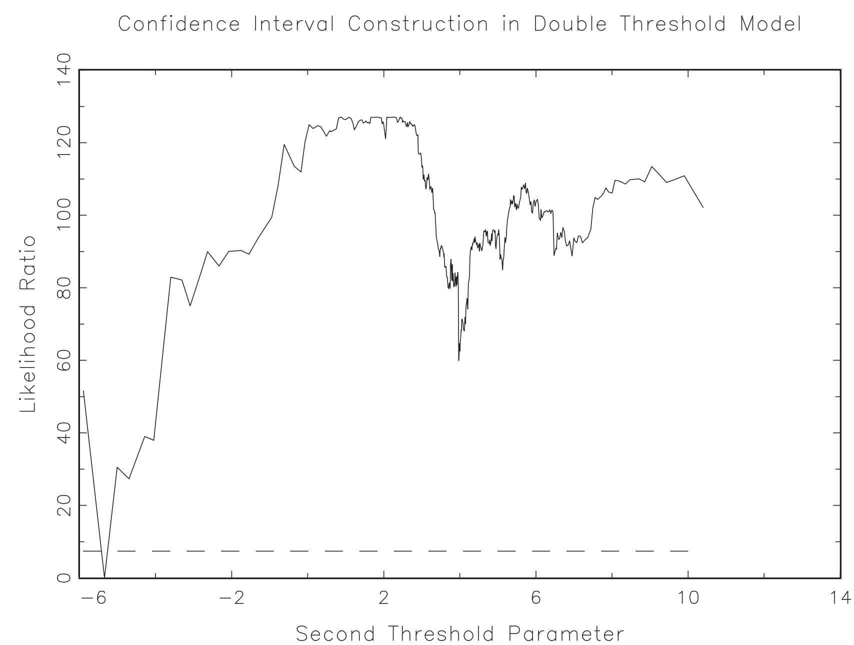

Fig. 1b. Confidence interval construction in double threshold model for MSAs (Δ*HPI* interacts with the income growth).

ger are the house price deviations, the higher the bank instability. However, *HPD* has a significantly negative effect on *NPL*, but the impact is smaller with a coefficient of −0.001, if income growth is above −4.285%. Moreover, the two lagged Δ*HPI* have significantly negative effects on *NPL*. The two time dummy variables for bank deregulation are again both significant.To summarize, our results reveal that the impact of percentage changes in house price index (Δ*HPI*) and house price deviations (*HPD*) on bank instability varies with income growth levels. When Δ*HPI* interacts with the threshold variable (income growth), double threshold effects are suggested and the collateral value hypothesis is supported. When *HPD* interacts with the income growth, single threshold effect is suggested and the deviation hypothesis is supported when income growth is below −4.285%.

4. Robustness check using non-Metropolitan Statistical Areas

We further study non-MSAs as a comparison. However, the house price all-transactions indexes for non-MSAs are available only at the state level since 1995Q1 from the FHFA. Per capita personal income and population for non-MSAs are available at the state level from the BEA. After eliminating missing values, the final

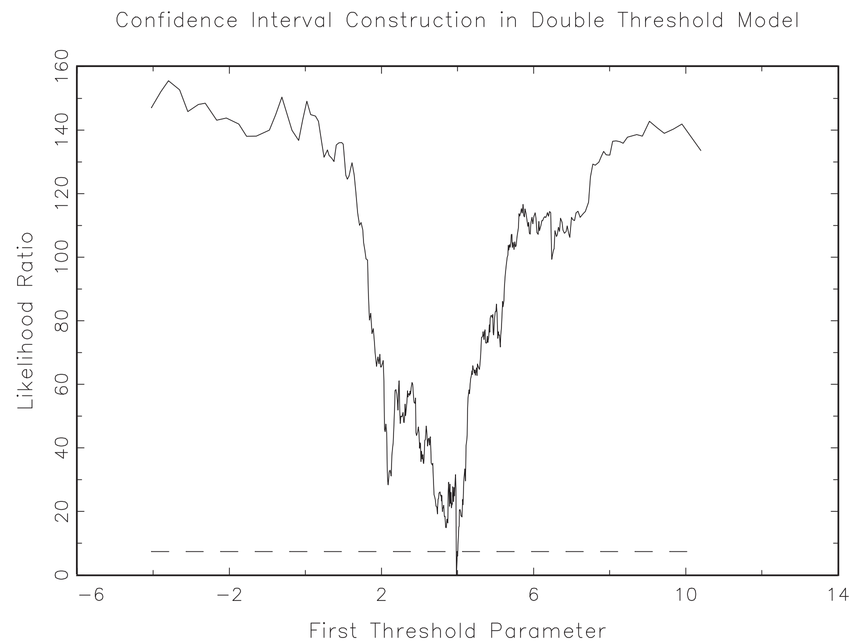

Fig. 1c. Confidence interval construction in double threshold model for MSAs (ΔHPI interacts with the income growth).

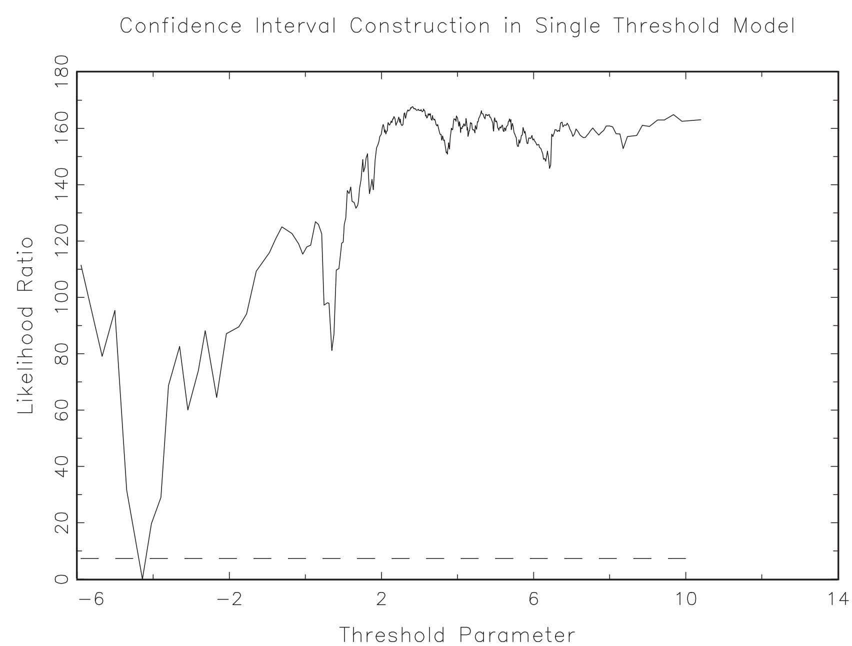

Fig. 2. Confidence interval construction in single threshold model for MSAs (*HPD* interacts with the income growth).

sample contains 2688 observations for 42 states[24] for the period 1995Q1–2010Q4. Details on the data are included in Appendix A.

Table 1b reports the summary statistics for the variables used in the estimations. For instance, the average income growth is 4.05%, with a standard deviation of 3.149%, a minimum of −11.22% (non-MSAs in Wyoming during 2009Q1–Q4), and a maximum of 17.93% (non-MSAs in North Dakota during 2008Q1–Q4). It is noteworthy that non-MSAs exhibit much larger variation in house price deviations than MSAs, suggesting enormous heterogeneity in the real estate markets in the non-MSAs.

Financial accounts data for the commercial banks between 1995Q1 and 2010Q4 are drawn from Compustat. The raw data at the bank level is sourced from the Call Reports in the Federal Deposit Insurance Corporation. The number of banks without missing values for the sample period is 1723, and the total number of observations is 110,727. To mimic the housing data of non-MSAs in 42 states without missing values, we aggregate the bank-specific data into the state level by taking the simple average of the bank-specific data in the same state.[25] NPLs range from 0% to 16.64%, with a mean of 1.29% and a standard deviation of 1.617%.

Table 6 summarizes the results from the PMG and MG estima-

[24] List of 42 states is available upon request.

[25] We also tried the geometric mean of the bank-specific data, and our results remain robust.

Table 6
Deviation of house prices from fundamentals for non-MSAs.

House price model	PMG estimation	MG estimation
Long-run coefficients		
Personal income (per capita)	−3.091***	−0.021
	(0.551)	(1.356)
Population growth	19.95***	5.138
	(2.284)	(7.653)
Short-run coefficients		
Speed of adjustment	−0.006	−0.024**
	(0.004)	(0.01)
Change in personal income per capita	−0.003	−0.015
	(0.011)	(0.016)
Change in population growth	0.095	0.068
	(0.100)	(0.129)
Dummy99q4	0.008***	0.010***
	(0.001)	(0.002)
Intercept	−1.316	−0.799
	(0.900)	(2.365)
Statistics		
Hausman test (*p*-value)	0.02	
Number of observations	2688	

Notes: PMG is pool mean group estimation and MG is mean group estimation. Both use demeaned data (subtract cross-sectional mean from each variable for each non-MSA). Standard errors are presented in brackets.
* Significance at 10% level.
** Significance at 5% level.
*** Significance at 1% level.

Table 7a
Tests for threshold effects for non-MSAs (ΔHPI interacts with the income growth).

	Model (A)
Test for single threshold	
F_1	86.4114
p-Value	0.03
(10%, 5%, 1% critical values)	(34.1121, 55.6113, 176.0056)
Test for double threshold	
F_2	16.4581
p-Value	0.43
(10%, 5%, 1% critical values)	(30.2277, 35.1304, 42.4314)
Test for triple threshold	
F_3	15.7625
p-Value	0.09
(10%, 5%, 1% critical values)	(14.5484, 17.9886, 24.2053)

Table 7b
Threshold estimates for non-MSAs (ΔHPI interacts with the income growth).

	Model (A)	
	Estimate	95% Confidence interval
Threshold 1	−6.19	[−6.19, −6.19]

tions for the non-MSAs sample. First, the impact of the Financial Services Modernization Act of 1999 (Dummy99q4) is positively significant in both estimations. The Hausman test with the *p*-value of 0.02 suggests that the MG estimator is preferable; in other words, there is no common long-run relationship among house prices, income growth, and labor force growth across non-MSAs. In particular, the coefficient of average speed of adjustment from the MG estimation is −0.024, which is statistically significant at the 1% level and suggests that only 2.4% of the previous period's house price deviations from the long-run equilibrium are adjusted this period, only one-third of that for MSAs. However, long-run coefficients on personal income per capita and population growth are insignificant. Moreover, the coefficient of average speed of adjustment from the PMG estimation is −0.006 but is insignificant. This may suggest that house price deviations from the long-run

Table 7c
Regression estimates for non-MSAs: Single threshold model for non-performing loans (ΔHPI interacts with the income growth).

Dependent variable: Non-performing loan Regressors	Model (A)		
	Coefficient estimate	OLS SE	White SE
Equity ratio$_{it-1}$	−0.0886	0.0378	0.0547
Equity ratio$_{it-2}$	0.0287	0.0375	0.0553
Return on assets$_{it-1}$	0.0002	0.0006	0.0006
Return on assets$_{it-2}$	0.0019	0.0006	0.0005
Liquidity$_{it-1}$	−0.0279	0.0141	0.0183
Liquidity$_{it-2}$	−0.0324	0.0142	0.0176
G_PIPC$_{it-1}$	0.0045	0.0057	0.0073
G_PIPC$_{it-2}$	−0.0120	0.0055	0.0072
Unemployment rate$_{it-1}$	0.3767	0.0477	0.0588
Unemployment rate$_{it-2}$	−0.1850	0.0485	0.0649
Nominal mortgage rate$_{it-1}$	−0.0624	0.0339	0.0343
Nominal mortgage rate$_{it-2}$	0.0266	0.0342	0.0314
Inflation rate$_{it-1}$	−0.0164	0.0061	0.0066
Inflation rate$_{it-2}$	0.0019	0.0066	0.0069
Dummy99q4	−0.0849	0.0351	0.0361
HPI percentage change (g_pipc ⩽ th1)	−0.7417	0.0687	0.3615
HPI percentage change (th1 < g_pipc)	−0.1104	0.0087	0.0111

Notes: th1 denotes the corresponding first threshold estimate in the single threshold model. Model (A) uses housing price index (HPI) percentage changes to interact with personal income growth. G_PIPC = the growth rate of personal income per capita.

equilibrium for the non-MSAs are not well estimated by the PMG estimation based on the sample we have. The non-MSAs might exhibit more heterogeneity across states and the long-run relationship between housing and macroeconomic variables may not be coherent. Therefore, we proceed to estimate the threshold model using only ΔHPI for the non-MSAs. Tables 7a–7c report the results.

Table 7a shows that the test statistics for a single threshold F_1 is significant at the 5% level with a bootstrap *p*-value of 0.03. However, the test statistics for a double threshold F_2 and a triple threshold F_3 are both insignificant at the 5% level. Thus, we conclude that there is one threshold in the regression relationship for the non-MSAs. Table 7b reports that the point estimate of the single income growth threshold is −6.19%. The estimates, conventional OLS standard errors, and White-corrected standard errors for the single threshold model are summarized in Table 7c. ΔHPI has a significantly negative effect on *NPL*, supporting the collateral value hypothesis where larger positive house price percentage changes are associated with lower *NPL* and improve bank stability. In particular, the coefficient equals −0.742 when income growth is below −6.19%, and −0.11 when income growth is above −6.19%. The dummy variable for the impact of bank deregulation, Dummy99q4, is significant. Bank deregulation does indeed influence banks' responses to the housing markets. Fig. 3 displays the computed likelihood ratio statistics as a function of the income growth, confirming the estimate for the first threshold.

To summarize, our results based on the non-MSAs sample from 1995Q1 to 2010Q4 suggest the existence of income growth threshold effects in the relationship between house prices and bank instability and support the collateral value hypothesis.

5. Conclusion

This paper applies the threshold model to examine the effect of income growth on the relationship between house prices and bank stability using the house prices and bank variables for 286 U.S. MSAs from 1990Q1 to 2010Q4. In the empirical study, we choose non-performing loans to measure bank instability and consider two house price indicators: the percentage changes in house price

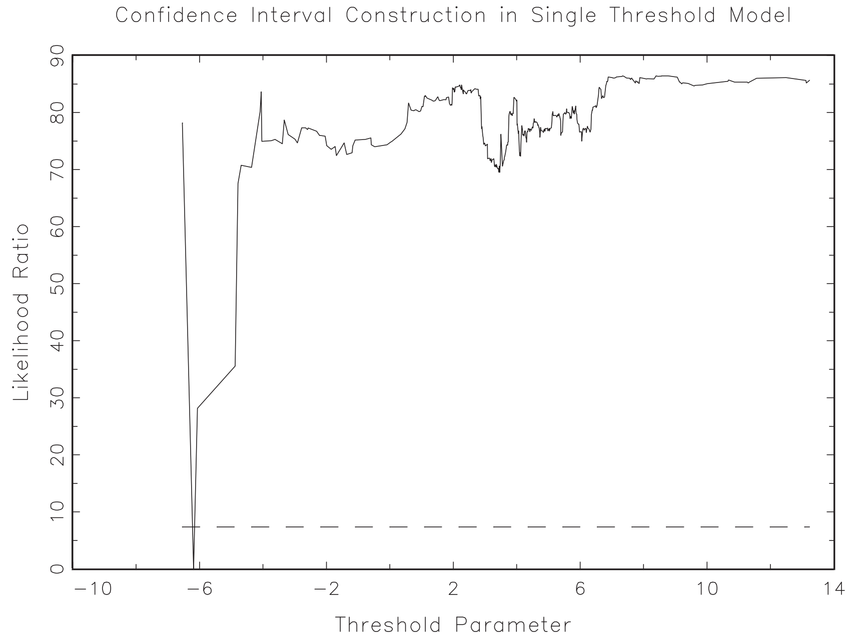

Fig. 3. Confidence interval construction in single threshold model for non-MSAs. ΔHPI interacts with the income growth).

index and house price deviations from their long-run fundamental values. Following Koetter and Poghosyan (2010), we apply the pooled mean-group and mean-group estimators to estimate house price determinants in the US. Our results confirm that the equilibrium house prices increase with rising demand due to income and labor force growth and provide evidence of a house price adjustment to the long-run equilibrium.

Personal income growth rate is considered as the threshold variable which interacts with the house price indicators in the threshold models. Empirical results show the existence of the income growth thresholds in the relationship between house prices and bank instability. In particular, two income growth thresholds (−5.342% and 3.972%) are found in the models where the percentage changes in house price index (ΔHPI) interact with the personal income growth rate; additionally, one income growth threshold (−4.285%) is suggested in the models where the house price deviations (*HPD*) are used. On one hand, our results suggest that ΔHPI has a significantly negative effect on NPLs, which is consistent with the collateral value hypothesis. Moreover, the negative impact is stronger as the economy experiences a recession with severe negative income growth. On the other hand, house price deviations have a significant positive effect on NPLs when income growth is below −4.285%, which is consistent with the deviation hypothesis. When the economy experiences a recession with income growth below the threshold, house price deviations could deteriorate bank stability. However, the impact is opposite when income growth is above the threshold.

For comparison purposes, we conduct the same analysis using the non-MSAs sample from 1995Q1 to 2010Q4 for robustness checks. We find no common long-run relationship among house prices, personal income, and population growth in the real estate markets. This finding is not surprising due to the even larger heterogeneity in the housing markets for non-MSAs. Therefore, house price deviations for non-MSAs are not well estimated by the PMG estimator. We thus apply ΔHPI in the threshold model and find a single income growth threshold of −6.19%. Consistent with the results for MSAs, the collateral value hypothesis is supported where NPLs decrease in response to a positive change in ΔHPI.

In summary, this paper finds evidence to support our conjecture that the responses of NPLs to house prices vary under different levels of income growth using disaggregated housing and bank data which better reveal the heterogeneity of regional real estate markets and commercial banks in the US. Moreover, this paper verifies the collateral value hypothesis in the literature when using house price changes in the threshold model for both MSAs and non-MSAs, suggesting that the larger are the changes in house prices, the lower the bank instability.

Our study provides new evidence on the relationship between house prices and bank stability and can shed light on some policy implications. First, heterogeneity across the regional real estate markets in the US should be taken into account when making policies. We find that a common positive long-run relationship among house prices, personal income, and labor force growth does exist in MSAs but not in non-MSAs. Policies that promote personal income and labor force growth should help appreciate house prices in the long run in MSAs, but may not have a substantial impact in non-MSAs. Based on these findings, we propose that different policies should be applied to MSAs and non-MSAs, respectively.

Second, banks' responses to house prices are asymmetric during economic booms and busts. In an economic boom, with favorable housing market conditions, the impact of house price deviations on banks' performance or stability will be less severe because house price changes or deviations are supported by strong economic growth. However, when economic growth is sluggish, undesirable housing market conditions could significantly deteriorate bank stability. Thus, policies for promoting housing market recovery would be a priority in an economic recession.

The recent financial crisis in the US has been associated with a sharp decline in house prices, widespread bank failures, and sluggish economic growth. Our results are based on the US data for the period 1990Q1–2010Q4. Therefore, further study about the real estate-financial fragility-economic growth nexus applying longer time series in the future to fully capture the effects of financial crisis would be desirable. Moreover, empirical evidence from other countries at various levels of economic and financial developments would be of great interest.

Acknowledgements

The authors would like to thank the anonymous referee for the valuable comments and suggestions that vastly improved the paper.

Appendix A. Data sources and coverage

Series	Source	Frequency [a]	Time period	Number of observations
Metropolitan Statistical Areas				
House price all-transactions indexes	FHFA	Q	1990Q1–2010Q4	24,024
Labor force	BLS	M	1990M1–2010M12	24,024
Per capita personal income	BEA	A	1990–2010	24,024
Unemployment rate	BLS	M	1990M1–2010M12	24,024
State non-metropolitan areas				
House price all-transactions indexes	FHFA	Q	1995Q1–2010Q4	2688
Population	BEA	A	1995–2010	2688
Per capita personal income	BEA	A	1995–2010	2688
Unemployment rate	BLS	M	1995M1–2010M12	2688
Census regions				
Mortgage rate (30-year fixed rate)	FRED	Q	1990Q1–2010Q4	336
Inflation rate [b]	BLS	M	1990M1–2010M12	336
Banks				
Non-performing loan	Compustat	Q	1990Q1–2010Q4	162,960 for MSAs; 110,272 for non-MSAs
Equity ratio	Compustat	Q	1990Q1–2010Q4	162,960 for MSAs; 110,272 for non-MSAs
Cost-income ratio	Compustat	Q	1990Q1–2010Q4	162,960 for MSAs; 110,272 for non-MSAs
Return on assets	Compustat	Q	1990Q1–2010Q4	162,960 for MSAs; 110,272 for non-MSAs
Liquidity	Compustat	Q	1990Q1–2010Q4	162,960 for MSAs; 110,272 for non-MSAs
z-Score	Compustat	Q	1990Q1–2010Q4	162,960 for MSAs; 110,272 for non-MSAs

Note: FHFA is Federal Housing Finance Agency; BLS is Bureau of Labor Statistics; BEA is Bureau of Economic Analysis; FRED is Federal Reserve Economic Data from Federal Reserve Bank of St. Louis. The four census regions include Northeast, Midwest, South, and West, which are grouping of 50 states and the District of Columbia defined by the U.S. Census Bureau.
Frequency and Time Period are for the raw data.
[a] M represents monthly; Q represents quarterly; and A represents annual. If the raw data is reported in monthly frequency, we convert monthly to quarterly frequency using the average method in EViews. If the raw data is reported in yearly frequency, we convert the annual data to quarterly frequency using constant match in EViews.
[b] We do Census X12 multiplicative seasonal adjustment for consumer price indexes (CPI), and then calculate the annual rate of inflation based on the CPI.

References

Bhattacharya, R., Kim, S.W., 2011. Economic fundamentals, subprime lending and housing prices: Evidence from MSA-level panel data. Housing Studies 29 (6), 897–910.
Cebula, R., Koch, J., Fenili, R., 2011. The bank failure rate, economic conditions and banking statutes in the U.S., 1970–2009. Atlantic Economic Journal 39 (1), 39–46.
Chiarella, C., 1992. The dynamics of speculative behavior. Annals of Operations Research 37, 101–123.
Chiarella, C., Dieci, R., Gardini, L., 2002. Speculative behaviour and complex asset price dynamics: a global analysis. Journal of Economic Behavior and Organization 49, 173–197.
Daglish, T., 2009. What motivates a subprime borrower to default? Journal of Banking and Finance 33, 681–693.
Day, R., Huang, W., 1990. Bulls, bears and market sheep. Journal of Economic Behavior and Organization 14, 299–329.
De Grauwe, P., Grimaldi, M., 2006. Exchange rate puzzles: a tale of switching attractors. European Economic Review 50, 1–33.
De Grauwe, P., Dewachter, H., Embrechts, M., 1993. Exchange Rate Theory – Chaotic Models of Foreign Exchange Markets. Blackwell, Oxford.
Dieci, R., Westerhoff, F., 2012. A simple model of a speculative housing market. Journal of Evolutionary Economics 22 (2), 303–329.
Dipasquale, D., Wheaton, W.C., 1995. Urban Economics and Real Estate Markets, first ed. Prentice Hall.
Gennaioli, N., Shleifer, A., 2010. What comes to mind. Quarterly Journal of Economics 125 (4), 1399–1433.
Gennaioli, N., Shleifer, A., Vishny, R., 2012. Neglected risks, financial innovation, and financial fragility. Journal of Financial Economics 104 (3), 452–468.
Gerlach, S., Peng, W., 2005. Bank lending and property prices in Hong Kong. Journal of Banking and Finance 29, 461–481.
Hansen, B., 1999. Threshold effects in non-dynamic panels: estimation, testing, and inference. Journal of Econometrics 93, 345–368.
Holly, S., Pesaran, M., Yamagata, T., 2010. A spatio-temporal model of house prices in the US. Journal of Econometrics 158, 160–173.
Kahneman, D., Slovic, P., Tversky, A., 1986. Judgment Under Uncertainty: Heuristics and Biases. Cambridge.
Kauko, K., 2012. External deficits and non-performing loans in the recent financial crisis. Economics Letters 115 (2012), 196–199.
Klyuev, V., 2008. What Goes up must Come Down? House Price Dynamics in the United States. IMF Working Paper WP/08/137.
Koetter, M., Poghosyan, T., 2010. Real estate prices and bank stability. Journal of Banking and Finance 34, 1129–1138.
Niinimaki, J.-P., 2009. Does collateral fuel moral hazard in banking? Journal of Banking and Finance 33, 514–521.
Nkusu, M., 2011. Nonperforming Loans and Macrofinancial Vulnerabilities in Advanced Economies. IMF Working Paper WP/11/161.
Pesaran, H., Smith, R., 1995. Estimating long-run relationships from dynamic heterogenous panels. Journal of Econometrics 68, 79–113.
Pesaran, H., Shin, Y., Smith, R., 1999. Pooled mean group estimation of dynamic heterogenous panels. Journal of the American Statistical Association 68, 621–634.
Shleifer, A., Vishny, R., 2010. Unstable banking. Journal of Financial Economics 97 (3), 306–318.
Simon, H., 1982. Models of Bounded Rationality, vols. 1 and 2. MIT Press.
Sinai, T., 2012. House Price Moments in Boom-bust Cycles. NBER Working Paper No. 18059.
Smith, V., 1991. Papers in Experimental Economics. Cambridge.
Stein, J., 2012. Monetary policy as financial stability regulation. Quarterly Journal of Economics 127 (1), 57–95.
Stepanyan, V., Poghosyan, T., Bibolov, A., 2010. House Price Determinants in Selected Countries of the Former Soviet Union. IMF Working Paper WP/10/104.
Tsatsaronis, K., Zhu, H., 2004. What Drives Housing Price Dynamics: Cross-country Evidence. Bank for International Settlements Quarterly Review, March.
Von Peter, G., 2009. Asset prices and banking distress: a macroeconomic approach. Journal of Financial Stability 33, 298–319.
Zabel, J., 2012. Migration, housing market, and labor market responses to employment shocks. Journal of Urban Economics 72, 267–284.