Public policy and financial stability: The impact of PCA and TARP on U.S. bank non-performing loans

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Abstract

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This study explores the implications of Prompt Corrective Action (PCA) and the Troubled Asset Relief Program (TARP) on the behavior of non-performing loans (NPLs) and real estate non-performing loans (RELs) in the U.S. over 1984-2015 using a Markov switching framework. We find that NPLs and RELs exhibit pronounced episodic behavior switching between non-stationary and stationary regimes. PCA and TARP have a significant impact on banking sector stability by influencing the probability of switching from non-stationary regimes to stationary regimes and by reducing the level of NPLs and RELs. These results are robust to various model specifications and have important implications for bank regulation as well as for the formulation of macro stress-testing.

Keywords: Prompt Corrective Action (PCA), TARP, banking stability, Markov switching model.

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1. Introduction

During the 1980s U.S. banks operated in a somewhat benign regulatory environment until being shocked by the S&L crisis in the mid-1980s resulting in over 1300 bank failures (Caprio and Klingebiel, 1996). Regulators responded to the aforementioned crisis by adopting Prompt Corrective Action (PCA) in 1992 that aimed at the orderly resolution of troubled banks. From then onwards, there was a general trend toward structural liberalization culminating in the passing of the Financial Services Modernization Act of 1999, repealing the Glass Steagall Act of 1933. The deregulated environment that followed led to an explosion of activity, driven especially by mortgage securitization and the residential property boom. Ultimately, this fed through into the financial crisis which commenced in 2007. As a consequence of the crisis, the U.S. authorities introduced the Troubled Asset Relief Program (TARP) in October 2008 where they made a commitment to purchase the equity and problem assets of banks to preserve stability in the system. The program was regarded (somewhat) of a success and the major banks have generally been successful in building their balance sheets and reducing the level of non-performing loans, although profit levels remain below their pre-crisis peak (De Young, 2014).

Both PCA and TARP have attracted significant attention in the literature. PCA is a key provision of the Federal Deposit Insurance Corporation Improvement Act (FDICIA), which became effective in December 1992 and involved early intervention by regulators. An important, yet unanswered, question refers to whether increasingly stringent regulatory capital standards like PCA stabilize the banking system. This issue is important to governments which, when deciding to intervene, should be aware of whether PCA is effective or not in risk management (Calomiris, 2011). The literature examining the effect of PCA on banking stability is characterized by contradictory theoretical conjectures and very limited, if any, direct empirical evidence. In terms of theory, Calomiris (2011) argues that regulators do rely on capital requirements as a financial instrument for bringing stability, thereby supporting the argument that PCA is indeed effective in risk reduction. In contrast, Blum (1999) contends that capital requirements may entail instability because regulatory capital standards (such as

PCA) cause risk and leverage to become substitutes and banks respond to stringent capital requirements by choosing assets with higher risk. John et al. (2000) argue that a PCA-based system has limited effectiveness in curbing bank risk incentives and creates strong risk incentives even for best capitalized banks. In terms of empirical evidence, Jones and King (1995) found that many banks exhibiting high insolvency risk would not have been considered undercapitalized based on PCA risk-based capital standards, casting doubt on the effectiveness of PCA.

TARP is the largest government bailout program in U.S. history (Bayazitova and Shivdasani, 2011), and is seen as one of the federal government's primary responses to the 2007 financial crisis (Corner, 2013). According to the Treasury Department’s Office of Financial Stability, TARP accomplished several goals (Tae, 2013). It was effective in helping to unfreeze the markets for credit and capital, bringing down the cost of borrowing, restoring confidence in the financial system, and restarting economic growth, and achieved its purpose of injecting capital to financial markets, preventing a collapse in spending and restoring confidence. TARP, however, did receive significant criticism regarding its effectiveness in fulfilling its goals. The Congressional Oversight Panel (COP), in the September 2010 report entitled “Assessing the TARP on the Eve of Its Expiration”, wrote that although TARP “provided critical support to the financial markets at a time when market confidence was in freefall, the program has been far less effective in meeting its other statutory goals, such as supporting home values, retirement savings, and economic growth.” In addition, COP noted the unpopularity of TARP with the public, said that part of the unpopularity was due to “shortcomings in Treasury's transparency and its implementation of TARP programs”, and concluded that while TARP was necessary to stabilize the financial system, it had been mismanaged and could pose significant future costs (Bianco, 2013). In important contributions, Veronesi and Zingales (2010), Hoshi and Kashyap (2010), and Bayazitova and Shivdasani (2011) have illustrated that TARP-like equity infusions may not always be effective in achieving their goals.

Against this backdrop, we empirically examine the impact of PCA and TARP on banking stability by exploring how they affect the dynamics of NPLs in the U.S. over 1984-2015. In particular, we investigate the drivers of the probability of regime transition and the determinants of NPLs allowing for regime specific behavior. We focus on total non-performing loans (NPLs) and real estate non-performing loans (RELs). The latter are considered because domestic banking crises frequently originate from the real estate sector (Reinhart and Rogoff, 2009; Bordo and Jeanne, 2002) and property lending can have a material impact on banks' performance (Zarruk and Madura, 1992; Wheelock and Wilson, 2000).

Non-performing loans (NPLs) have long been widely viewed as an indicator of banking problems and financial stability. Studies, such as Demirgüç-Kunt and Detriagache (1997), Gonzalez-Hermosillo et al (1996), Domaç and Peria (2003), Hoggarth et al. (2002), place strong emphasis on the dynamic behavior of NPLs prior to the banking crises or other periods of fragility. A rise in NPLs reduces the value of banks' assets and increases the 'value at risk' (Sbracia and Zanghini, 2001). When the value of banks assets falls short of the value of liabilities, banks become insolvent and systemic risks increase. NPLs have frequently been used as a proxy for bank asset quality, credit risk and contract quality (de Bock and Demyanets, 2012; Beck et al. 2013) and are key variables used in macro stress-testing.

Our methodology employs a time-series approach which enables us to better capture the large dynamic (both cyclical and seasonal) components of NPLs (Gambera, 2000). In particular, a two-state Markov switching model is used to model the behavior of NPLs (RELs) and to investigate factors explaining such dynamics. Our sample period (1984-2015) witnesses a series of financial crises and widespread regulatory reforms. NPLs can exhibit pronounced episodic behavior switching between non-stationary and stationary regimes and the (non)stationarity of NPLs is employed as evidence of banking (in)stability. By definition, a stationary regime is where the mean and variance of a series do not change over time and follow no trend - implying stability. In contrast, a non-stationary regime has varying mean and variance as well as identifiable trend features, indicating instability. In the literature, the concept of stationarity has been extensively used to characterise the stability of an economic or financial data series. Bremaud and Massoulie (1996) refer to stationarity as a stability property and Lütkepohl (1991) notes that non-stationarity means the non-stability of a series. Several authors have claimed that excessive fluctuations in a series are related to non-stationarity and instability (Shiller, 1979, Rose, 1988).

We find that the dynamics of NPLs are strongly influenced by changes in the regulatory environment as well as other macroeconomic factors and these influences are regime dependent. PCA is more influential in reducing NPLs and RELs in the non-stationary and stationary regime, respectively, while TARP has a more significant impact on both NPLs and RELs in the stationary regime. Allowing for time-varying transition probabilities across different regimes, both PCA and TARP are significant drivers of switching from the non-stationary to stationary regime, although the impact of TARP takes longer to materialize. These results are robust to a variety of model specifications that include various determinants of NPLs/RELs including: federal funds/money market rates, the foreign exchange rate, housing prices, stock prices, the level of unemployment, and average wage rates.

Exploring the dynamics of NPLs is relevant to several aspects of the empirical banking literature. Our findings provide valuable extensions to the literature linking NPLs with banking sector (in) stability (Meeker and Gray, 1987; Zarruk and Madura, 1992; Reinhart and Rogoff, 2010; De Bock and Demyanets, 2012), and treating NPLs as indicators of bank asset quality (Meeker and Gray, 1987). We also offer a supplementary indirect test for detecting financial (in)stability through four scenarios – (1) low NPLs and stationary, (2) high NPLs and stationary, (3) low NPLs and non-stationary, and (4) high NPLs and non-stationary, where stationarity implies stability.

Our results have important implications for bank regulation as evidence suggests that PCA and TARP have stabilizing effects on NPLs through their impact on the probability of regime switching and on the level of NPLs and RELs. As such this study is related to the debate on the effectiveness of PCA and PCA-type regulatory frameworks in reducing banking risk. Our results also have implications for prudential policy in designing macro-stress-tests. Properly designed regulatory actions are capable of reducing banking sector fragility and incorporating time-varying dynamics into analyses of NPLs. This is also important in stress-testing due to uncertainties surrounding stationarity issues (Hoggarth et al. 2005). We propose that policy makers should consider the time-varying nature of NPLs and RELs, along with the regulatory environment, when examining banking sector fragility.

The structure of the paper is as follows. Section 2 provides a brief synopsis of the PCA and TARP regulatory frameworks. Section 3 describes the econometric methodology and outlines the data and descriptive statistics. Section 4 discusses the results and draws implications for U.S. banking stability. Section 5 concludes.

2. Regulation and stability: PCA and TARP

Following the passage of the Glass-Steagall Act in 1933, the U.S. banking sector experienced relative stability up until a wave of deregulation commencing in the early 1980s. Subsequently, there were major changes in the legislation affecting the banking system.[1] These measures had different purposes, for example, the Competitive Equality Bank Act 1987 was to regulate banks' business activities, and the Financial Institutions Reform, Recovery and Enforcement Act 1989 to create a more efficient, productive and effective base for the industry. Two major deregulation measures – the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994 and the Gramm-Leach-Bliley Act in 1999 – have had significant impacts on banking system structure and activities (DeYoung et al., 2004). While various changes in regulatory, public and market environments (namely, the adoption of Basel capital regulation) may affect bank NPLs, PCA and TARP are two major direct

[1]Bank regulations since 1984 (the first year of our sample period) includes the: Competitive Equality Bank Act 1987; Financial Institutions Reform, Recovery and Enforcement Act 1989; Federal Deposit Insurance Corporation Improvement Act 1991 (PCA); the Riegle-Neal Interstate Banking and Branching Efficiency Act in 1994; Gramm-Leach-Bliley Act in 1999; Financial Services Regulatory Relief Act 2006;Emergency Economic Stability Act 2008; Federal Housing Finance Regulatory Reform Act 2008; American Recovery and Reinvestment Act 2009 (Barth et al., 2010); and the Dodd-Frank Wall Street Reform and Consumer Protection Act 2010.

legislative responses to banking crisis. As such, we focus on examining whether these public policies are effective in restoring financial stability.

PCA was introduced in December 1991 under the Federal Deposit Insurance Corporation Improvement Act (FDICIA) that emphasized the role of capital ratios in diagnosing safety problems in banking. This legislation was a response to the widespread failures that resulted from the S&L crisis in the mid-1980s, and it defined a series of capital thresholds used to determine various supervisory actions aimed at providing a more rapid regulatory response to troubled banks. Under PCA, banks are classified into a category depending on how well they meet capital thresholds based on their tier 1 risk-based capital (T1RBC) ratio. A pictorial representation of T1RBC, as defined in the PCA provision, is given in Figure 1(a). The graph for T1RBC illustrates that there is an increase in the early 1990s, which coincides with the implementation of PCA in 1992 and ongoing implementation of Basel I which was agreed in 1988 but not fully introduced by banks until 1992 (when enforced by law in the Group of Ten (G10) countries.T1RBC is characterized by a switch around 1993 – this observation is in agreement with previous contentions that PCA changed the banking and regulatory playing field representing fundamental prudential reform (Benston and Kaufman, 1997). Furthermore, others have argued that it was the most important U.S. banking legislation since the Glass-Steagall Act of 1933, marking a significant regulatory milestone (Akhigbe and Whyte, 2001). In-line with these views, Covitz et al. (2004) argues that the introduction of PCA marked a regulatory regime switch, classified as a pre-PCA and post-PCA period.

The Troubled Asset Relief Program (TARP), introduced in 2008, was the first program in U.S. history that made government fund injections into private banks. It intended to recapitalize financial institutions by purchasing or guaranteeing up to $700 billion of troubled equity and other assets, which was reduced to $475 billion by the Dodd-Frank Act in July 2010. As of 31 January 31 2015, $427 billion had been disbursed through TARP (with $13 billion in additional projected disbursements). The total estimated cost of TARP amounts to $28 billion (Report on TARP, 2015). As part of the TARP program the U.S. Treasury purchased the preferred stock of some 707 financial institutions, including that of large banking holding companies such as Citigroup, Bank of America and JPMorgan Chase. TARP reversed the declining trend of T1RBC in 2009 (as shown in Figure 1 (a)) and helped stop widespread financial panic and a potential devastating collapse of the financial system. Financial commitments under TARP ended on 3rd Oct 2010. Despite the TARP support program, however, 465 banks failed over 2008 to 2012 (www.fdic.gov), although (with the exception of Washington Mutual in 2008) these were predominantly small bank failures. Some research shows that TARP was effective in increasing lending (Li, 2013), and boosting real economic value (Veronesi and Zingales, 2010; Bayazitova and Shivdasani, 2012). On the other hand, TARP could create moral hazard as this sort of bailout could feed expectations about similar actions in the future. Black and Hazelwood (2013) that report significantly increased risk-taking in large TARP banks but the opposite in small TARP banks, relative to non-TARP institutions. Harris et al. (2013) show a deteriorating pattern in operating efficiency for TARP banks but not for non-TARP banks, which may be attributable to the lack of incentives of bank managers to improve asset quality. Thus, it is by no means clear what the long-term influence of TARP will be on banking risks, although we know these actions went some way to avert a system wide banking sector collapse.

Both PCA and TARP are direct legislative measures aimed at stabilizing the financial system in response to a crisis. PCA establishes capital ratio criteria and sets mandatory and discretionary actions that federal agencies can take to address banking sector problems according to different levels of capital. It aims to resolve failing banks rapidly in order to avoid excessive losses. TARP allows for government investment in private bank's preferred stock therefore boosting capital strength but not diluting ownership rights. The main expectation of TARP is to increase bank lending, reduce "excessive risk-taking" and stabilize the banking system through increased capitalization. An important issue therefore refers to whether increasingly stringent regulatory capital standards in general, and PCA in particular, have aided U.S. regulatory authorities in reducing banking risk. Similarly, it is also interesting to consider how the TARP program has impacted banking sector stability. As credit risk is a major focus of commercial bank prudential regulation, controlling such risks is an important policy issue. This also relates to Basel II and III which rely on mainly credit risk based capital requirements as the main instrument for bank regulation. The following section sets out our approach to gauge the behavior of NPLs (RELs) over 1984-2015 and seeks to examine whether the aforementioned regulatory landmarks have impacted on their behavior.

3. Time-varying non-stationarity in bank non-performing loans

In the context of our paper, the (non)stationarity of NPLs is associated with (in)stability of the banking system. We seek to reveal periods of non-stationarity and assess if they correspond to identified periods of banking instability. For this purpose, we need a time-varying regime-switching extension of stationarity testing. Regime switching in unit root testing relates to stochastic unit root processes proposed by Granger and Swanson (1997), Leybourne et al. (1996), and Rahbek and Shephard (2002). Such a process has a unit root that is time-varying, namely it is stationary for some periods and non-stationary for others. Such a process is written as:

$$x_t = b_t x_{t-1} + \varepsilon_t \tag{1}$$

where b_t is allowed to change over time, and ε_t is an iid N(0, σ^2). Equation (1) is re-parameterized as the Dickey Fuller regression as:

$$\Delta x_t = (b_t - 1)x_{t-1} + \varepsilon_t \tag{2}$$

One particular type of time-variation is regime-dependence, under whichequation (2) takes the form:

$$\Delta x_t = b(s_t)x_{t-1} + \varepsilon_t \tag{3}$$

where s_t is an unobservable latent variable which follows a Markov process with a constant probability of transition from regime j to regime i, p_{ij}, $p_{ij} = \Pr(s_{t+1} = i \mid s_t = j)$. We allow parameters of the ADF regression to be time-varying. Specifically, we consider equation (4) which is a Markov switching ADF regression (Hall et al., 1999):[2]

$$\Delta NPL_t = a(s_t) + b(s_t) NPL_{t-1} + \sum_{k=1}^{r} c_k(s_t) \Delta NPL_{t-k} + u_t \text{ , } u_t \sim \text{NID}(0, \sigma^2(s_t)) \tag{4}$$

where ΔNPL_t is the change in *NPL* at time *t*, u_t is the innovation process, and s_t is the regime. It is assumed that s_t follows a first order Markov process with constant, time invariant, transition probabilities p_{ij}, specified as:

$$p_{ij} = \frac{\exp\{\gamma_0^{'}\}}{1 + \exp\{\gamma_0^{'}\}} \tag{5}$$

For parsimony, the number of regimes (*m*) is set equal to 2. We test whether there is regime switching in the ADF regression using the non-standard Likelihood Ratio (LR) bounds test of Davies (1987). The null hypothesis of no regime switching (*m*=1) corresponds to the standard ADF test, and the alternative corresponds to switching across 2 regimes, namely to the Markov ADF model. Maximum likelihood estimation of equation(4) yields the smoothed probabilities representing probabilistic inference that NPL is in regime *i* at date *t*, and the transition probability from regime *i* to regime *i*, p_{ii} ,namely, the probability that regime *i* will prevail over two consecutive periods.

Monte Carlo simulations are used to ensure robustness of the results with regard to the *p*-values of the tests. The *p*-values corresponding to the *t*-tests of the null hypotheses $b(s_t=1)=0$ and $b(s_t=2)=0$ against the respective one-sided alternatives $b(s_t=1)<0$ and $b(s_t=2)<0$ are obtained by first estimating equation(4) under the null ($b(s_t)=0$, $s_t=1,2$), and then generating 10,000 samples that follow the estimated data generating process. For this purpose, 10,000 series for u_t are drawn from the distribution, and the estimates of the parameters under the null are used to generate data for ΔNPL_t . Next, equation (4) is fit to each realization of

2 Hall et al. (1999) propose an approach based on a generalization of the so-called Augmented Dickey Fuller (ADF) unit root test incorporating the class of dynamic Markov-switching models by Hamilton (1989, 1990)

ΔNPL_t, obtaining two series of *t*-statistics for *b*, one for each regime. The resulting *p*-values are the percentage of the generated *t*-ratios below the *t*-values from the estimated model.

To examine factors explaining regime switching, the assumption of constant (time-invariant) transition probabilities, as shown in equation (5), is relaxed. A more general formulation is to assume that transition probabilities are time-varying and dependent upon candidate variables. In this case, the function of the transition probabilities from regime *j* to regime *i* at time *t* is given by:

$$p_{ij,t} = \frac{\exp\{\gamma_0 + \gamma_1 PCA_{t-1} + \gamma_2 TARP_{t-1} + \gamma_3 GDP_{t-1}\}}{1 + \exp\{\gamma_0 + \gamma_1 PCA_{t-1} + \gamma_2 TARP_{t-1} + \gamma_3 GDP_{t-1}\}} \tag{6}$$

Where *i=1, 2… I,PCA*, *TARP* and *GDP* are candidate variables used to explain the evolution of the transition probabilities. Statistical significance of γ_i indicates that its corresponding candidate variable does explain the evolution of transition probabilities. This time-varying specification is derived from the model with fixed transition probabilities given in equation (5) by setting all γ_i jointly equal to 0.

To examine various factors explaining the level of NPLs and RELs, we employ a Markov switching regression model, developed by Hamilton (1989, 1994), that allows for the influence of explanatory variables to be state-dependent. As shown in equation (7), the regression parameters (*βs*) are allowed to change over time according to a particular transition probability and they take-on different values depending on the unobservable latent variable S_t.The transition from one state to another follows a Markov process in discrete-time and space. This approach has been widely applied to economic time series that have dynamic behavior, including: real output, stock returns, corporate bond defaults, credit default swap spreads, interest rates and exchange rates (Hamilton, 1989; Turner et al., 1989; Perez-Quiros and Timmermann, 2000; Taylor, 2004; Cheung and Erlandsson, 2005; Alexander and Kaeck, 2008; Giesecke et al., 2011).

$$Y_t = \beta_0(s_t) + \beta_1(s_t)Y_{t-1} + \beta_2(s_t)PCA_t + \beta_3(s_t)TARP_t + \beta_4(s_t)X_t + \varepsilon\,\varepsilon_t \sim NID(0, \sigma^2_{(st)}) \qquad (7)$$

Where *Y=NPLs* or *RELs*, *PCA*, *TARP* and *X* are candidate variables to explain *NPLs* or *RELs*. Statistical significance of *βs* indicates that the corresponding candidate variables explain NPLs and RELs and are state-specific.

We focus on the impact of the regulatory actions of PCA and TARP and we expect they both affect the probabilities of regime switching and the level of NPLs (RELs). We first control for macroeconomic conditions using real *GDP* growth as the literature suggest that this impacts credit risk (Keeton and Morris, 1987) and more specifically, is negatively associated with NPLs in both cross country studies (Beck et al., 2013; Espinoza and Prasad, 2010; Nkusu, 2011; De Bock and Demyanets, 2012) and those from Spain (Salas and Saurina, 2002) and the U.S. (Keeton and Morris, 1987).

The conditional mean of NPLs (and RELs) may also be affected by other macroeconomic factors. As such, we also test to see how NPLs and RELs are influenced by lending rates (federal funds and money market rates), the nominal effective exchange rate (NEER), housing and stock prices.[3] Higher lending rates may trigger an increase in NPLs due to a rise in debt service costs. Some studies (Beck et al., 2013; Espinoza and Prasad, 2010; Nkusu, 2011) confirm a significant positive relationship, while others (De Bock and Demyanets, 2012) argue that its explanatory power is limited. Based on previous work (Beck et al., 2013; Domaç et al., 2003; De Bock and Demyanets, 2012), we also consider *NEER* to capture the effect of a depreciation of the currency on the dynamics of NPLs. The direction of the effect is unclear as the relationship can depend upon the extent to which the banking sector makes foreign currency loans to unhedged borrowers. On the other hand, currency depreciation that promotes exports and improves borrowers' financial position may reduce NPLs.

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[3]Rapid credit growth potentially undermines asset quality and the literature indicates a positive relationship between lagged credit growth and NPLs (Salas and Saurina, 2002; Espinoza and Prasad, 2010; De Bock and Demyanets, 2012). We find no evidence of a significant impact so this is excluded from our analysis.

Financial and real wealth can act as a buffer for unexpected shocks to borrowers or can be used as collateral to ease access to credit. Empirical evidence indicates that falling asset prices (property and equity prices) are associated with higher NPLs (Nkusu 2011; Rinaldi and Sanchis-Arellano, 2006). In this paper, we employ a housing price index[4] and the SP500 stock market index as proxies for financial and real wealth that may influence NPLs. The literature suggests that employment and income are negatively associated NPLs (Nkusu 2011) and also adversely impact RELs. Thus we also include the unemployment rate and the average wage growth rate in our analysis of RELs.

All variables span the period 1984 Quarter 1 – 2015 Quarter 2, giving a total of 126 quarterly observations. All data are from public sources and details are given in Table A1 in the Appendix. We consider the percentage of total non-performing loans past due 90+ days plus non-accrual to total loans for all U.S. banks, denoted as NPLs. We also consider the percentage of total real estate loans 30-89 days past due to total loans, denoted as RELs. A graphical representation of some variables is given in Figure 1. In Figure 1 (b), we observe a switch in the mean of NPL and RELs around the end of 1992with the commencement of PCA. The two policy variables of main interest are defined as step dummies – *PCA* takes a value of 1 for all periods from 1991Q4 to 2008Q3 (when TARP was introduced) and 0 otherwise; *TARP* takes a value of 1 for all periods from 2008Q4 onwards and 0 otherwise.

Descriptive statistics are reported in Table 1. NPLs are non-stationary under the Phillips-Perron (PP) test (1990) that fails to reject the null hypothesis of non-stationarity, but they are stationary under both the ADF and DF-GLS tests (Elliott et al., 1996). Similarly, RELs are non-stationary under the Phillips-Perron test but stationary using the ADF and DF-GLS tests. As the Phillips–Perron test underperforms the ADF in finite samples (Davidson and MacKinnon, 2004), we conclude that NPLs and RELs are stationary. Most macroeconomic variables are non-stationary and they enter in first differences in regressions

[4] Housing price index is obtained from Federal Housing Finance Agency. It is an all-transaction index estimated using sales prices and appraisal data.

[Table 1 around here]

4. Empirical findings

4.1 Dynamics of non-performing loans

The first step is to test whether regime switching is present in the dynamics of NPLs and RELs using the non-standard LR test of Davies (1987).[5] The null hypothesis refers to no regime switching. Results are reported in Table 2. As shown in this Table, the null of no regime switching is strongly rejected. The log-likelihood value of the regression under the alternative hypothesis is significantly higher than the likelihood value under the null, suggesting that the null is rejected even by invoking the upper bound of Davies (1987). Thus, for both measures of loan-losses there is evidence of regime switching suggesting that the regime-dependence should be allowed for in modelling their dynamics.

[Table 2 around here]

Having established that regime switching is present in NPLs and RELs, we proceed to characterize the different regimes. We seek to identify the differences in the dynamics across regimes. This is achieved in Table 3, which reports the mean-reversion parameter estimates with standard errors under the two regimes, the resulting t-statistics under the two regimes, the conditional standard deviation conditional on being in each regime, and the estimates of the probabilities that NPLs and RELs are stationary. For NPLs, the mean-reversion parameter is -0.076 in regime 1 and -0.074 in regime 2. The standard error of the estimate of the reversion parameter in regime 1 is 0.018 and in regime 2 is 0.032. The t-statistics of the mean-reversion parameters are -4.16 in regime 1 and -2.31 in regime 2. For RELs, Table 3 shows that the mean-reversion parameters are -0.115 in regime 1 and -0.33 in regime 2. Based on the standard errors of the estimates (0.024 for regime 1 and 0.13 for regime 2), the ADF statistics are -4.68 and -2.53. These results reveal that for both NPLs and RELs the null hypothesis of non-stationarity is rejected in regime 1, but cannot be rejected in regime 2. This

[5]The lags in (4) are determined using the general-to-specific procedure discussed in Hall (1994).

is further supported by the p-values for the ADF test obtained through the Monte Carlo simulations discussed in the previous section. The simulation-based p-values for regime 1 are both less than 0.01, thereby supporting that in regime 1 the null is strongly rejected. We conclude that non-performing loan dynamics are characterised by two regimes, a stationary regime (regime 1) and a non-stationary regime (regime 2). The transition probabilities reported in Table 3 reflect regime persistence. For NPLs, the probability of transition from regime 1 to regime 1 (namely, the probability that NPLs will remain in the 'stationary' regime, p_{11}) is 98.25%, whilst the probability that NPLs will remain in the non-stationary regime, p_{22}, is 96.24%. Thus, the stationary regime is more persistent than non-stationary regime. Similar results are obtained for RELs.

[Table 3 around here]

The next step is to chronologically identify the two regimes using smoothed probabilities and to link the (non)stationarity of regimes to stability. Figure 2 portrays the dates that the stationary regime prevails. The results are interesting. The non-stationary regime (regime 2) prevails mainly in the pre-1993 period and in the post-2007 period till 2011Q4. The characterisation of the pre-1993 period as a non-stationarity period coincides with the characterisation by Caprio and Klingebiel (1996) of the period 1984-1991 as a banking crisis period[6].And the latter period unsurprisingly corresponds to the timing of the global financial crises.

We argue that the (non)stationarity of non-performing loans provides a simple and supplementary indirect test for banking sector (in)stability. As summarized in Table 4, there are four scenarios – (1) low NPLs and stationary, (2) high NPLs and stationary, (3) low NPLs and non-stationary, and (4) high NPLs and non-stationary. Scenario (1) implies stability. Low levels of NPLs means higher performing assets that impact positively on bank profits and capital strength. Higher NPLs, of course, means the opposite – larger credit losses and

[6] This is a period of U.S. banking turmoil with more than 1300 banks failing (Caprio and Klingebiel, 1996).

diminished profitability. NPLs are relatively low and stationary over the periods of 1994Q4-2006Q3 and after 2014Q1. Scenario (2) represents a transitional period from instability to stability, signalling stability. A high level of NPLs implies adverse factor(s) dominate and that regulators and bank managers are expected to intervene to reduce the level of bad loans. If such regulatory actions succeed, NPLs are expected to decrease and move back towards mean values that are more likely to be stationary. The periods of 1993Q4-1994Q4 and 2012Q1-2013Q4 represent this case. If such regulatory attempts are yet to take effect or fail, NPLs are out of control and more likely to continue to grow in a relatively dramatic manner and become non-stationary. This is the case in scenario (4) typically indicating instability as characterized in the periods of 1984Q1-1993Q3 and 2008Q1-2011Q4. Such periods require policy action aimed at reducing bank loan losses. In scenario (3) non-stationarity is caused by adverse forces that set in and tend to drive NPLs upwards, presenting an early warning of instability. NPLs switch to the non-stationary regime in 2006Q4 at a low level of 0.86% and increased gradually until they had doubled by 2007Q4.

[Table 4 around here]

5.2. What factors are driving regime switching in NPLs and RELs?

As shown in Figure 2, the stationary regime prevails over 1993-2007 and after 2011, roughly coinciding with the adoption of PCA in 1992 and after most of the implementation of TARP. It is graphically evident that the timing of the implementation of regulatory actions appears to match the timing of NPLs switching to the stationary regime. We seek to extend the above analysis by empirically examining factors that drive NPL dynamics – switching from one regime to another. In particular, we explore whether the regulatory actions of PCA and TARP affect the probability of regime switching by influencing the conditional mean of NPLs (and RELs).

The results are reported in Table 5 for NPLs and for RELs. In-line with the results in Table 3, the ADF test statistics for NPLs are -6.62 in regime 1 and -2.63 in regime 2, and those for RELs are -9.51 and 1.17. Based on both standard critical values and on Monte Carlo p-values, these findings suggest that regime 1 is still the stationary regime and regime 2 is the non-stationary regime. In terms of the variables that significantly affect the switching between regimes, both γ_1 (the parameter reflecting the effect of PCA) and γ_2 (the parameter reflecting the effect TARP) are statistically significant for both NPLs and RELs, while γ_3 (the parameter reflecting the macroeconomic environment) is significant for RELs but not for NPLs.

[Table 5 around here]

We therefore conclude that PCA was successful in driving bank loan performance away from the non-stationary regime (pre-1993 period) characterised by bank failures and banking fragility until the onset of the 2007 crisis. PCA was not effective in averting the effects of this crisis, which caused a switch back to the non-stationary regime. TARP stepped in and brought bank loan performance (after a few years) back to the stationary regime. These successes reflect the ability of PCA and TARP in bringing stability to U.S. banking through their effect on the probabilities of switching across regimes. PCA takes two years (1992Q1 – 1993Q4) to bring NPLs to the stationary regime, while it takes TARP three years and a quarter (2008Q4 – 2012Q1). This perhaps reflectsthe severity of the 2007-09 crises as well as the varying naturesof PCA and TARP.Moreover, we also test for whether other macroeconomic variables (such as the federal funds rate and money market rates for the NPL model, and house prices and the unemployment rate for the RELs model) influence the probability of transition. Results, however, were either non-convergent or only weakly converging, thus we ignore these in our analysis.

5.3. What factors are explaining NPLs and RELs?

We further extend the analysis by examining factors that explain NPLs and RELs, allowing for their effects to be regime-dependent. Results for NPLs and RELs are reported in Table 6 and Table 7, respectively. The coefficient estimates differ substantially between the two regimes and these regimes are quite persistent with a high likelihood of staying in the same regime – the probability of remaining in regime 1 is 98% for both NPLs and RELs, and for regime 2 is 86% for NPLs and 93% for RELs. The results confirm the episodic nature of NPL (REL) dynamics and justify our use of the Markov switching framework.

[Table 6 around here]

[Table 7 around here]

For NPLs, our baseline model (model 1) focuses on the effect of PCA and TARP after controlling for the effects of the macroeconomic environment (GDP), while other models examine whether these effects are sensitive to the lending rate, assets prices and the foreign exchanges rate.[7] As expected, PCA has a significant impact on reducing NPLs, which is stronger in regime 2 (non-stationarity) with a coefficient of -0.35 compared with -0.076 in regime 1 (stationarity). This finding is robust across the board with the inclusion of other macroeconomic variables as illustrated in models 2-5. TARP is effective in bringing down the level of NPLs in regime 1 but has little impact in regime 2 in the baseline model. However, this effect appears to be sensitive to the inclusion of interest rate and exchange rate variables in models 3-5 and it becomes stronger in regime 2 than in the regime 1. The macroeconomic environment (GDP) has a positive impact on lowering NPLs, regardless of the model specification, and consistent with evidence from the empirical banking literature (Beck et al., 2013; Espinoza and Prasad, 2010; Nkusu, 2011; De Bock and Demyanets, 2012; Salas and Saurina, 2002). The coefficients on the changes in lending rates, proxied by the federal funds rate in model 3 and the money market rate in model 4, are negative and significant, suggesting that a decrease in interest rates (an expansionary monetary policy) drives NPLs upward. It is worth noting that this effect is especially strong during unstable periods (regime

[7] Some macroeconomic factors are correlated (exchange and interest rate (0.6) in Table 6, and the mortgage rate and housing price index (-0.67) in Table 7). This may lead to some coefficients becoming insignificant in a full specification with all key macroeconomic. As our main focus is two policy variables of PCA and TARP, we don’t report results from the full specification but they are available from the authors on request.

2). We find little evidence that asset prices or the nominal exchange rate have any influence on NPLs.

For RELs (results reported in Table 7), the baseline model (model 1) focuses on the effect of PCA and TARP, while other specifications (models 2-6) examine whether these effects are sensitive to the mortgage rate, assets prices (S&P500 and house prices), unemployment and the average wage rate.[8] Both PCA and TARP have a significant impact on reducing RELs and (like in the case for NPLs) they are more effective during stable periods (regime 1). While stock market performance has little impact, changes in housing prices are negatively associated with the level of RELs in regime 1 only. Consistent with expectations, higher housing prices result in lower RELs during financially stable periods. Falling mortgage rates appear to lead to higher RELs, especially during unstable periods (regime 2), similar to the effect of the federal funds and money market rates on NPLs. The unemployment rate and average wage rate have little impact on RELs in regime 1 (stable period), but in regime 2 they increase.

To sum up, we conclude that the PCA-based capital adequacy regulation and the TARP framework have affected the dynamics of NPLs and RELs. They have been successful in mitigating their upward (non-stationary) movement in the pre-1992 period as well as following the 2007 crisis. Our results suggest that regulatory measures are preferred over expansionary monetary policy as a tool to improve loan quality.

5.4. Discussion

Our results can be interpreted from a number of perspectives that includes areas covering credit risk, banking stability, the quality of bank assets, and macro stress testing methodologies. NPLs have extensively been used in the empirical banking literature as a proxy for credit risk, our results can be interpreted as evidence that PCA and TARP helped stabilize credit risk in the U.S. banking system. This is important because NPLs (and credit

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[8] We test for the effect of macroeconomic condition (GDP) and its impact is insignificant across all specifications, thus we exclude it from our analysis.

risk) were increasing prior to 1992, and after the 2007 crisis. Our evidence suggests that PCA and TARP were successful in stopping the increasing stochastic trend (captured by non-stationarity) of NPLs (and credit risk) and in bringing stability (stationarity) to the banking system. This interpretation is consistent with earlier findings on PCA by Aggarwal and Jacques (2001) and Akhigbe and White (2001).

Our results are also related to the strand of literature examining credit quality and the stability of bank loan portfolios. Given that non-performing loans have been used as a variable to measure bank asset quality, our results suggest that changes in NPL dynamics imply that bank asset quality is also time-varying. This interpretation is consistent with Beck et al. (2013), and echoes Wojnilower's (1962) argument that the changing quality of bank loans contribute to cyclical movements in the economy. On the basis of this conjecture, it would be interesting to explore whether macroeconomic fluctuations can be attributed to the dynamic behavior of NPLs. Our finding that PCA and TARP brought about stationarity in NPLs suggests that these actions could bring stability in bank asset quality and help isolate the macro-economy from bank asset variations.

Time-varying NPL dynamics and changing bank asset quality are also linked to banking sector stability. Several studies have associated bank balance sheets, and NPLs with banking crises and fragility (Bongini et al., 2002; Gonzalez-Hermosillo et al., 1996).In particular, Demirgüç-Kunt and Detragiache (2002) use NPLs as a proxy for defining a banking crisis and find that weak macroeconomic environments, deposit insurance, and lax legal enforcement increase the probability of banking crises. Our finding that PCA and TARP are associated with NPLs switching from non-stationary to stationary regimes suggests that PCA and TARP enhanced banking stability. As such, regulatory actions seem to be capable of reducing the probability of a banking crisis and as such, these types of regulatory actions may provide a guide for policies aimed at reducing the probability of crises (Caprio and Peria, 2002, Demirgüç-Kunt and Detragiache 2002, and FSOC, 2011).

Finally, NPLs have played a central role in macro stress tests of banking systems. Amongst the various methodologies used are Vector Autoregressive (VAR) systems and impulse response analysis (Hoggarth et al., 2005). Correct application of the above methodologies is based on the assumption of stationarity of the variables in the VAR. If, however, the behavior of NPLs is episodic, then there is a question over the reliability of such tests. Importantly, Kim (1999) explored the prediction implications of models which are near-stationary, highlighting the importance of ensuring stationarity in forecasting. In the case that stationarity of NPLs itself is questionable, it may have effects upon econometric inference and policy implications (Singh and Ullah, 1985). In this case, researchers should consider non-parametric approaches to system and VAR estimation (Singh and Ullah, 1985), such as the methods suggested by Smith and Kohn (2000) and Hardle et al., (1998). This conjecture carries important practical implications as such tests have been recently employed by bank supervisors and regulators in the EU, the U.S. and the UK (Bank of England, 2008; Board of Governors of the Federal Reserve System, 2009; Committee of European Banking Supervisors, 2010; European Banking Authority, 2011). In addition, as NPLs are characterized by time-varying dynamics, we conclude that using NPLs in stress tests should move away from static stress testing approaches (Cihak, 2007) and closer to dynamic approaches (Jakubik and Schmieder, 2008; Schmieder et al., 2011). Thus, our results are supportive of this recent trend in macro stress test specification and calibration.

5. Conclusion

We find empirical evidence that U.S. bank loan performance over the period 1984-2015 is characterized by time-varying episodic dynamics. NPLs are non-stationary during the pre-1992 period and during the post-2007 period up to 2011. Evidence also confirms that the regulatory actions of PCA and TARP have been successful in bringing stability to the banking sector by influencing both the probability of switching from non-stationary to stationary regimes and lowering the level of NPLs and RELs. Both PCA and TARP yield similar effects on bank loan-losses but the influence of the latter takes longer to take effect. These finding are robust to an array of model specifications and have key implications for calibrating time series-based macro stress tests, as well as designing capital adequacy regulation to support banking sector stability.

Figure 1: Graphical presentation of series (1984Q1-2015Q2)

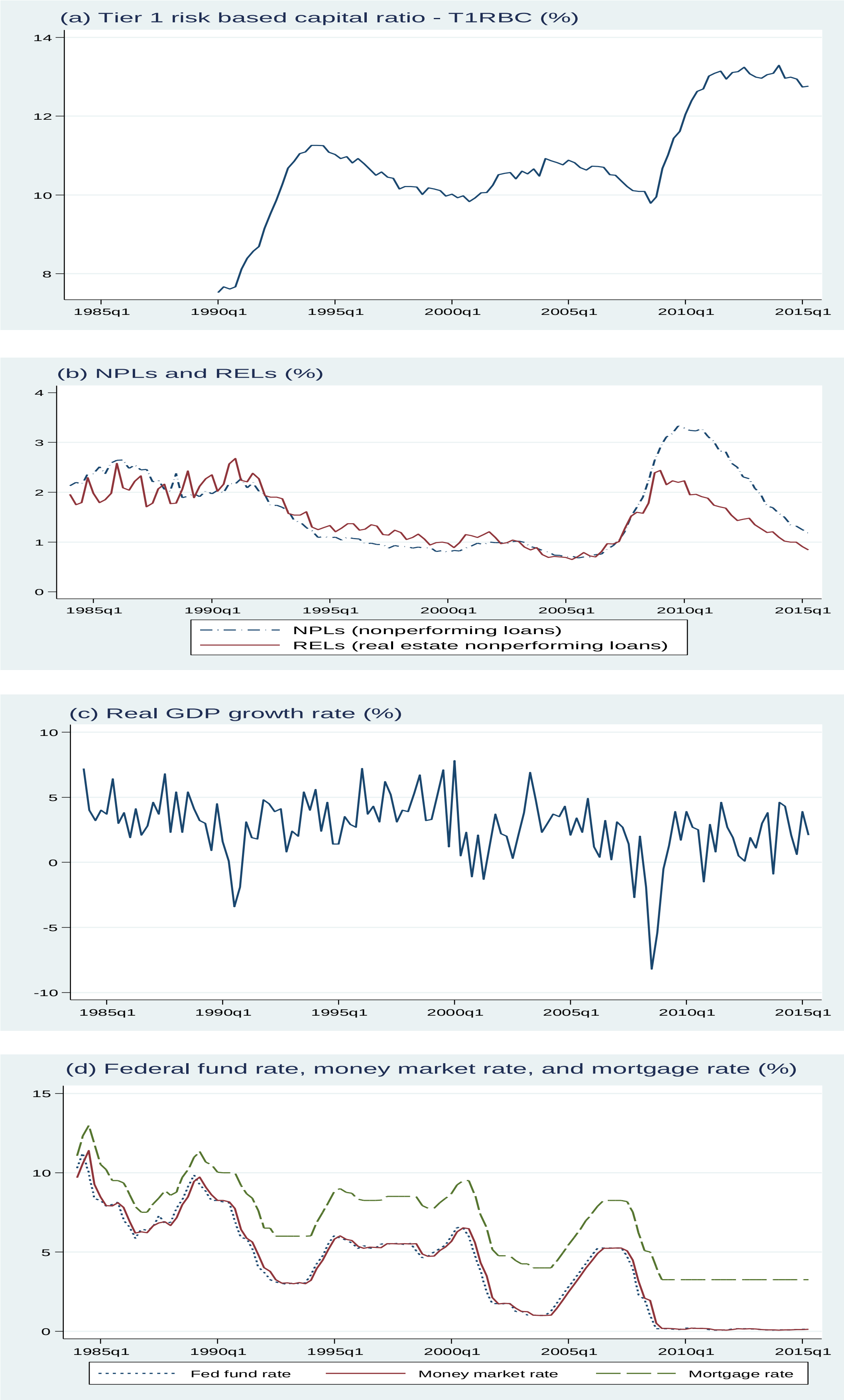
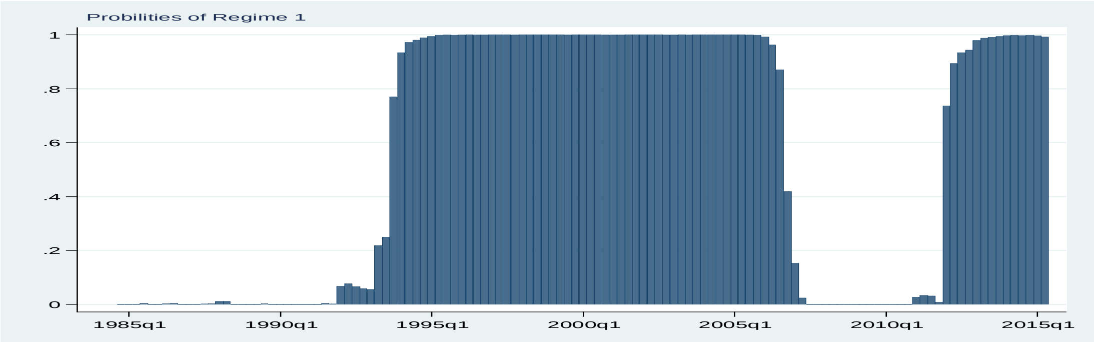
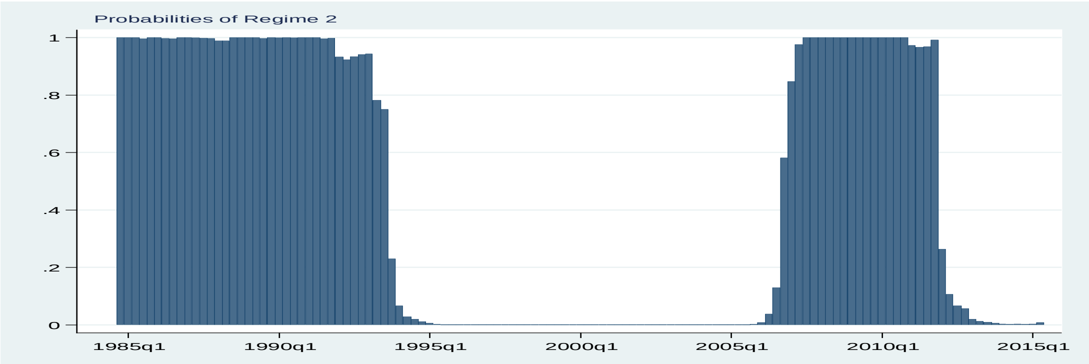


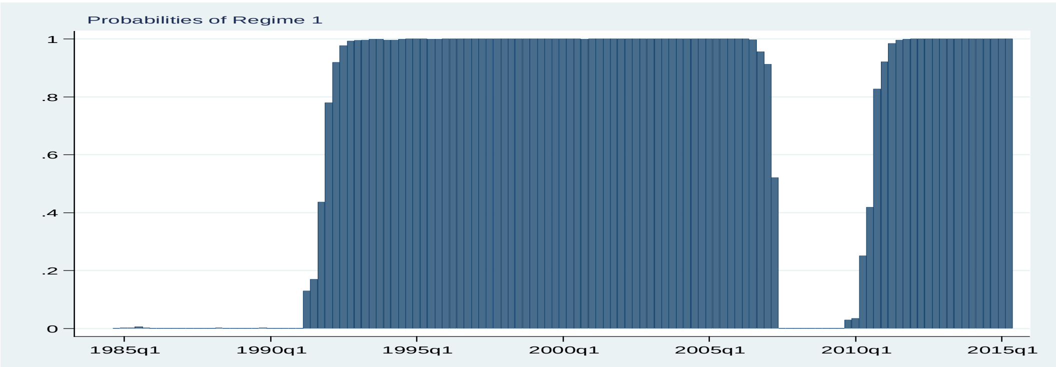
Figure 2: Dating of regimes

(a) Non-performing loan ratio (NPLs)





(2) Real estate non-performing loans ratio (RELs)



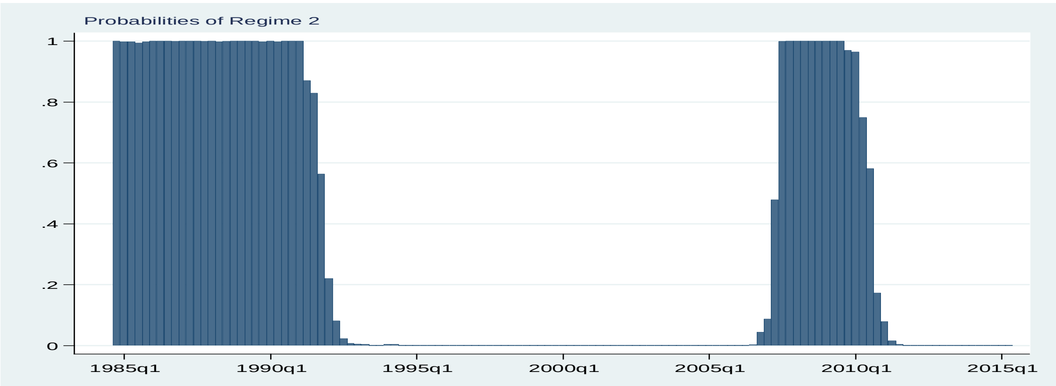


Table 1. Descriptive statistics for U.S. banks (1984Q1-2015Q2)

Variable	Mean	Std. Dev.	Min	Max	Tests for stationarity		
					ADF	PP	DF-GLS
NPL	1.66	0.77	0.68	3.33	-3.47**	-1.42	-2.74***
REL	1.50	0.53	0.65	2.68	-2.505**	-1.64	-1.98**
PCA	0.53	0.50	0.00	1.00			
TARP	0.22	0.42	0	1			
Real GDP growth	2.71	2.42	-8.20	7.80			
SP500 index	910.77	517.83	150.66	2103.84			
Housing price index	241.34	84.22	122.17	400.58			
Nominal effective exchange rate (NEER)	116.83	16.84	91.82	171.04			
Federal funds rate	4.08	2.97	0.07	11.23			
Money market interest rate	4.13	2.98	0.07	11.39			
Mortgage rate	6.86	2.59	3.25	12.99			
Unemployment	6.16	1.46	3.80	10.00			
Average wage growth rate	0.32	0.47	-1.99	1.96			
Number of observation	126						

Notes: (1) NPL denotes the percentage of total nonperforming loans to total loans, and REL denotes total nonperforming real estate loans to total outstanding real estate loans; (2) PCA denotes Prompt Corrective Action and TARP denotes Troubled Asset Relief Program; (3) ADF denotes the augmented Dickey-Fuller (DF) test, PP is the Phillips-Perron test, and DF-GLS is the modified DF test proposed by Elliott, Rothenberg, and Stock (1996); The 5% critical values are -2.88 for the ADF (-1.658 for RELs with drift) and the PP tests, and -1.95 for the DF-GLS test; (4) * , **, *** denotes the rejection of the null hypothesis of non-stationarity at the significance level of 10%, 5% and 1%, respectively.

Table 2. Testing for Markov switching in the ADF regression for U.S. bank loan performance

Loan performance measure	Lags (r)	H_0: No Markov regime switching in *a* and *b* H_A: Markov switching in *a* and *b*		
		Log likelihood (H_0)	Log likelihood (H_A)	Davies
NPL	2	104.7	143.24	0.000
REL	2	34	91.08	0.000

Notes: (1) NPL denotes the percentage of total nonperforming loans to total loans, and REL denotes total nonperforming real estate loans to total outstanding real estate loans; (2) The estimated model under the H_0 is: $\Delta y_t = a + by_{t-1} + \sum_{k=1}^{r} c_k \Delta y_{t-k} + u_t$ and the estimated model under the H_A is: $\Delta y_t = a(s_t) + b(s_t) y_{t-1} + \sum_{k=1}^{r} c_k \Delta y_{t-k} + u_t$, u_t ~NID(0, σ^2 (s_t)), where s_t is the unobserved stochastic regime which evolves as a Markov chain of 1st order, and y_t =NLP, REL; (3) the lag order r was chosen using the general-to-specific approach (Hall, 1994); (4) The entries in the last column entitled 'Davies' report the p-values for the Davies (1987) test.

Table 3. Markov switching unit root tests

	ΔNLP		ΔREL	
	Regime 1	Regime 2	Regime 1	Regime 2
a	0.06***	0.17***	0.094***	0.73***
	(3.84)	(2.26)	(3.04)	(2.77)
c_1	-0.12	0.08	-0.003***	-0.05
	(-1.31)	(0.70)	(-0.02)	(-0.4)
c_2	0.40***	0.50***	-0.46***	-0.4***
	(3.92)	(4.34)	(-5.12)	(-3.08)
b	-0.076 ***	-0.074	-0.11	0.33
[standard error]	[0.018]	[0.032]	[0.024]	[0.13]
ADF test statistic	**-4.16*** **	**-2.31**	**-4.68*** **	**-2.53**
Standard error	0.039	0.14	0.07	0.22
Transition probabilities	p_{11}=98.25%	p_{22}=96.24%	p_{11}=98.71%	p_{22}= 95.12%
Probability that bank loan performance is stationary	68.23%	31.76%	79.01%	20.91%

Notes:(1) The estimated model is: $\Delta y_t = a(s_t) + b(s_t) y_{t-1} + \sum_{k=1}^{y} c_k \Delta y_{t-k} + u_t$, u_t ~NID(0, $\sigma^2(s_t)$) ,where s_t is the unobserved stochastic regime which evolves as a Markov chain of 1st order, $y_t =$ NPL, REL. The entries in columns 2 and 3, entitled 'Regime 1' and 'Regime 2' are the values of the t-statistic of $b(s_t = 1)$ and the t-statistic of $b(s_t = 2)$, i.e. the regime-dependent ADF statistics in regime 1 and in regime 2, respectively. (2) p_{11} and p_{22} denote the probability of transition from regime 1 to regime 1, and from regime 2 to regime 2, respectively; (3) The probabilities that NLP and REL will be in the stationarity regime at any year within the sample period were calculated using the formula $P(s_t = 1) = [(1 - p_{22})/(2 - p_{11} - p_{22})]$, where regime 1 stands for the stationary regime, and regime 2 stands for the non-stationary regime. (4)*, **, *** denotes the rejection of the null hypothesis of non-stationarity at the significance level of 10%, 5% and 1%, respectively.

Table 4. Stationarity of NPL and financial stability

Scenario	Stationarity	NPLs	Stability	Periods identified	Policy implication
1	Stationary	Low	Stability	1994Q4-2006Q3; 2014Q1-2015Q2	Keep best practice
2	Stationary	High	Stability	1993Q4-1994Q4; 2012Q1-2013Q4	A transitional period from instability to stability, signalling stability, continue current regulatory actions
3	Nonstationary	Low	Instability	2006Q4-2007Q3	Early warning that adverse factor(s)may start to set in, close monitoring
4	Nonstationary	High	Instability	1984Q1-1993Q3; 2007Q4-2011Q4	Require policy attention to take steps or keep monitoring those measures undertaken yet to take effect to reduce NPLs

Table 5: Explaining the probability of regime transition of bank loan performance

	ΔNLPs		ΔRELs	
	Regime 1	Regime 2	Regime 1	Regime 2
ADF regression				
b	-2.15	0.02	-0.23	-0.034
Standard error	0.32	0.008	0.0025	0.028
ADF test statistic	**-6.62*****	**-2.63***	**-9.51*****	**-1.17**
Transition probabilities regression				
Constant (γ_0)	-3.45		-22.81***	
PCA_{t-1}(γ_1)	-23.7***		-7.17**	
$TARP_{t-1}$(γ_2)	-24.25***		-4.63***	
GDP_{t-1}(γ_3)	0.39		-0.61***	

Notes:(1) The estimated model is: $\Delta y_t = a(s_t) + b(s_t) y_{t-1} + \sum_{k=1}^{y} c_k \Delta y_{t-k} + u_t$, u_t ~NID(0, σ^2 (s_t)) with $p_{ij,t} = \frac{\exp\{\gamma_0 + \gamma_1 PCA_{t-1} + \gamma_2 TARP_{t-1} + \gamma_3 GDP_{t-1}\}}{1 + \exp\{\gamma_0 + \gamma_1 PCA_{t-1} + \gamma_2 TARP_{t-1} + \gamma_3 GDP_{t-1}\}}$, where s_t is the unobserved stochastic regime which evolves as a Markov chain of 1st order, $y_t =$ non-performing loans (NPLs), real estate non-performing loans (RELs). The entries in columns 2 and 3, entitled 'Regime 1' and 'Regime 2' are the values of the t-statistic of $b(s_t = 1)$ and the t-statistic of $b(s_t = 2)$, i.e. the regime-dependent ADF statistics in regime 1 and in regime 2, respectively; (2) *, **, *** denotes the significance level of 10%, 5% and 1%, respectively.

Table 6 The impact of regulations on U.S. non-performing loans (NPLs) over 1984Q1-2015Q2

	Model 1		Model 2		Model 3		Model 4		Model 5	
	Regime1	Regime2	Regime1	Regime2	Regime1	Regime2	Regime1	Regime2	Regime1	Regime2
NPL_{t-1}	0.94***	0.90***	0.93***	0.90***	0.93***	0.95***	0.93***	0.90***	0.94***	0.92***
PCA	-0.076**	-0.35***	-0.079**	-0.32***	-0.08**	-0.44***	-0.084***	-0.54***	-0.072**	-0.42***
TARP	-0.11***	-0.24	-0.11***	-0.25	-0.10***	-0.35***	-0.11***	-0.35***	-0.11***	-0.31**
GDP	-0.01**	-0.023*	-0.01**	-0.025*	-0.008*	-0.021**	-0.009**	-0.015	-0.010**	-0.036***
ΔSP500			-0.001	0.003						
ΔFEDrate					-0.059***	-0.093*				
ΔMMrate							-0.045***	-0.14***		
ΔNEER									0.0015	-0.011
Constant	0.16***	0.68***	0.17***	0.66***	0.16***	0.61***	0.17***	0.76***	0.15***	0.68***
Sigma (ln)	0.086		0.085		0.082		0.082		0.085	
p11	0.98		0.98		0.98		0.98		0.98	
p21	0.14		0.14		0.12		0.12		0.14	
Observations	125		125		125		125		125	

Notes:(1) this table provides results from the Markov switching model, $NPL = \beta_0(s_t) + \beta_1(s_t)NPL_{t-1} + \beta_2(s_t)PCA + \beta_3(s_t)TARP + \beta_4(s_t)GDP + \beta_5(s_t)X + \varepsilon$, for the determinants of U.S. non-performing loans under a constant transition probabilities over the period from the first quarter of 1984 to the second quarter of 2015; (2) PCA denotes Prompt Corrective Action, TARP denotes Troubled Asset Relief Program, FEDrate denotes the federal fund rate, MMrate denotes the money market rate, NEER denotes nominal effective exchange rate; (3) p11 and p21 denote the probability of transition from regime 1 to regime 1, and from regime 2 to regime 1, respectively; (4)* , **, *** denotes the rejection of the null hypothesis of non-stationarity at the significance level of 10%, 5% and 1%, respectively.

Table 7 The impact of regulations on real estate non-performing loans (RELs) over 1984Q1-2015Q2

	Model 1		Model 2		Model 3		Model 4		Model 5		Model 6	
	Regime1	Regime2	Regime1	Regime2	Regime1	Regime2	Regime1	Regime2	Regime1	Regime2	Regime1	Regime2
ΔREL_{t-1}	0.30**	0.42**	0.24*	0.37**	0.28***	0.61***	0.28**	0.18	0.31*	0.089	0.39*	0.24*
PCA	-1.00***	-0.51***	-0.99***	-0.50***	-0.91***	-0.44***	-1.00***	-0.45***	-1.09***	-0.62***	-1.14***	-0.61***
TARP	-0.82***	-0.30**	-0.82***	-0.28***	-0.77***	-0.37***	-0.82***	-0.22**	-0.84***	-0.31***	-0.95***	-0.42***
$\Delta SP500_{t-1}$			0.005	0.01								
ΔHousing					-0.041***	-0.0093						
ΔMortgage rate							-0.21***	-0.52***				
$\Delta Unemployment_{t-1}$									0.16	0.42***		
$Wager_{t-1}$											-0.050	-0.11
$Wager_{t-2}$											-0.13	-0.27***
Constant	2.04***	2.31***	2.02***	2.26***	2.12***	2.36***	2.03***	2.16***	2.05***	2.18***	2.15***	2.28***
lnsigma	0.22		0.22		0.18		0.19		0.22		0.21	
p11	0.98		0.98		0.98		0.98		0.97		0.97	
p21	0.07		0.07		0.08		0.07		0.05		0.03	
Observations	124		124		124		124		124		124	

Notes:(1) this table provides results from the Markov switching model, $REL = \beta_0(s_t) + \beta_1(s_t)REL_{t-1} + \beta_2(s_t)PCA + \beta_3(s_t)TARP + \beta_4(s_t)X + \varepsilon$,for the determinants of U.S. real estate non-performing loans under a constant transition probabilities over the period from the first quarter of 1984 to the second quarter of 2015; (2) PCA denotes Prompt Corrective Action, TARP denotes Troubled Asset Relief Program, Wager denotes growth rate of average wages; (3) p11 and p21 denote the probability of transition from regime 1 to regime 1, and from regime 2 to regime 1, respectively; (4)* , **, *** denotes the rejection of the null hypothesis of non-stationarity at the significance level of 10%, 5% and 1%, respectively.

Appendix

Table A1. Data sources

Indicator	Source
Tier 1 risk based capital ratio	Federal Deposit Insurance Corporation (FDIC)
Non-performing loans (NPLs)	Federal Reserve Bank of St Louis
Real estate loans (RELs): 30-89 days past due	Quarterly Reports for U.S. commercial banks of the Federal Insurance Deposit Incorporation (FDIC)
Real Gross Domestic Product	Federal Reserve Bank of St Louis
Lending rate - federal funds	Federal Reserve Bank of St Louis
Lending rate - money market	International Monetary Fund – International Financial Statistics
Lending rate - mortgage	International Monetary Fund – International Financial Statistics
Bank credit	Federal Reserve Bank of St Louis
Nominal effective exchange rate-NEER (narrow indices)	Bank of International Settlements
House price index (all-transactions)	Federal Housing Finance Agency
Industrial Production	Federal Reserve Bank of St Louis
CPI	Federal Reserve Bank of St Louis
Unemployment	Federal Reserve Bank of St Louis

Note: We cross check data with other sources, such as World Bank.

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