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Real Estate Market and Financial Stability in US Metropolitan Areas: a Dynamic Model with Spatial Effects

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Abstract

This paper investigates spatio-temporal variations in ex-post credit risk in the United States, as a function of real estate prices, loan purchases made by government sponsored enterprises, and a set of local characteristics during the recent housing boom and bust.

We model bank's non-performing loans as a first-order dynamic panel data regression model with group-specific effects and spatial autoregressive errors. To estimate this model, we develop an *ad-hoc* generalized method of moments procedure which consists of augmenting moments

1 Introduction

Since the second half of 2007, the United States experienced a severe …nancial crisis that spread to the …nancial sector of European and Asian economies and triggered a deep, worldwide, recession. The US housing market and its interaction with the …nancial system has been pointed as the main cause of such crisis, through the build-up of a bubble in real estate markets that eventually collapsed.

Housing booms and busts are often associated with systemic …nancial stress (Herring and Wachter (1999), estate prices, GSEs loan purchases, and a set of local, socio-economic characteristics in the United States. We take non-performing loans (NPLs) as proxy for ex-post credit risk. As a proxy for real estate prices we focus on house prices of residential properties, using data from the Federal Housing Finance Agency on loan purchases made by the GSEs Fannie Mae and Freddie Mac. We explore the impact of house prices on NPLs across US metropolitan areas, both in the period of housing boom, in the years 2000 to 2005, and during the house-price bubble bursting, over the years 2006 to 2011. Dividing the sample period into two subsets is also justified by the structural break in house prices observed towards the end of the first sub-period.

Economic theory has formulated a number of hypotheses to explain the relationship between financial stability and real estate prices. Some authors suggest that increases in house prices reduce the risk of real estate financing perceived by banks, thus inducing excessive lending to risky real estate borrowers (Dell'Ariccia and Marquez (2006)). In addition, rising house prices may encourage the riskiest investors to bet on further price increases, leading to a rise in the demand of credit. These factors work in the same direction and tend to increase the bank exposure to risky assets, thus suggesting a positive relationship between NPLs and real estate prices, as increasing bank loans also increase ex-post credit risk. Other theories instead predict a negative relation. For example, the collateral value hypothesis asserts that, in a period of rising house prices, the value of the collateral increases thus improving borrowers' financial position, which in turn reduces the associated risk of default (Koetter and Poghosyan (2010)). During the bursting of the bubble, theoretical models also suggest that, when house prices start to fall below the nominal value of loans, both speculative buyers and owner-occupiers that are unwilling or unung oial pl vth)uth2(b)12(a)6t1s4 t(e)9(r)11((h2(g(b)-16(o) such as personal income and unemployment, that are well known to influence borrowers' balance sheet and their debt servicing capacity. However, we observe that other socio-economic factors may also affect NPLs, such as the degree of urbanization, deprivation and crime, which are notoriously difficult to quantify and are well known to be geographically concentrated. Accordingly, in our empirical model we allow errors to be spatially correlated and assume that they follow a spatial autoregressive process. Ignoring spatial dependence, when this is present in the data, leads to inefficient estimates, which may cause wrong inferences. The availability of reliable models is very important for all market participants, including institutional investors, those who regulate housing, GSEs, mortgage lenders, and related financial institutions. In our regression specification, we also incorporate MSA-specific effects, and control for MSA-specific heteroskedasticity, to allow for heterogeneity in the characteristics of borrowers across different MSAs.

To estimate this model, we develop an *ad-hoc* generalized method of moments (GMM) procedure which consists of augmenting moments proposed by the panel literature to estimate pure dynamic panels, with a set of quadratic conditions in the disturbances. Recent years have witnessed an emerging interest towards the use of GMM for estimating regression models with spatially correlated disturbances. The proposed model is in line with the framework advanced by Mutl (2006). However, the work in Mutl (2006) relays on the restrictive assumption of homoskedastic group-specific effects banks to lend excessively to risky real estate borrowers at unreasonably low rates (Bernanke and Gertler (1995)). According to this view, departures of house prices from their fundamental value increase bank's probability of default. Using data on 78 regional real estate markets in Germany, Koetter and Poghosyan (2010) find evidence that larger departures of house prices from their fundamental value increase the bank's probability of default, as stated in the deviation hypothesis. Gimeno and Martinez-Carrascal (2010) use Spanish data and find evidence that house purchase loans depend positively on house prices. However, they also find evidence for causality from loans to prices when loans depart from their long-run levels. An alternative approach is taken by Mian and Sufi (2009), who investigate the reasons for the rapid expansion in the supply of mortgage credit and increase in house prices in the period 2001 to 2005, and the subsequent mortgage default crisis of 2007, at zip code level, in the US. The authors wish to explore whether the rapid growth in mortgage debt and house price are due to a greater willingness by lenders to assume risk that led to a reduction in the risk premium (*supply* explanation), or rather to increases in productivity or economic opportunities (*demand* explanation). They find that zip codes with high unfulfilled demand (at the beginning of the sample period) experienced a sharp relative decrease in denial rates and a relative increases in mortgage credit and house prices over time, despite the fact that they also experienced negative relative income and employment growth. Results are strongly consistent with the supply hypothesis, also pointing at the important role of securitization in credit expansion.

Endogenous developments in the financial market can greatly amplify the effect of small income shocks, through the so-called *financial accelerator* mechanism (Bernanke, Gertler, and Gilchrist (1996)). In particular, positive shocks to household income translate into wider house price increases in geographical areas where people can borrow against a larger fraction of their housing value (thus having a high loan-to-value) such as in the US and UK, and smaller in countries where such leverage ratios are lower (e.g. Italy). Empirical evidence on such financial accelerator for a set of countries can be found in Almeida, Campello, and Liu (2006).

Empirical research also suggests that banks bad loans are closely related to the economic and determining loan quality and NPLs. We refer to Louzis, Vouldis, and Metaxas (2012) for a review of this literature.

In this paper, to study variations in NPLs over time and across territory, we extend the GMM approach for pure dynamic panels, to allow for spatial dependence in disturbances. Hence, it is of interest to brie‡y introduce the reader to the literature on GMM estimation of panels in the presence of spatial dependence. Kelejian and Prucha (1999) …rst proposed GMM estimation of regression models with spatial autoregressive (SAR) disturbances, in a single cross sectional setting. They suggested the use of three moment conditions that exploit the properties of disturbances entailed by a standard set of assumptions. In the last few years, a sizeable literature has been developed to extend this procedure. Liu, Lee, and Bollinger (2012) and Liu, Lee, and Bollinger (2010) suggested a set of linear and quadratic conditions in the error term, where the matrices appearing in the linear and quadratic forms have bounded row and column norms (see

value, but this is subject to individual banks. Typically, a strong capital base, measured by a large

Assumption 2 *The group-specific effects, μ_i, and the errors, ε_{it}, satisfy:*

$$E(\mu_i) = 0; \; E(\varepsilon_{it}) = 0; \; i = 1, 2, ..., N; t = 1, 2, ..., T; \tag{3}$$

$$E(\varepsilon_{is}\varepsilon_{it}) = 0; \; i = 1, 2, ..., N; s \neq t = 1, 2, ..., T; \tag{4}$$

$$E(\mu_i \varepsilon_{it}) = 0; \; E(x_{it}\varepsilon_{it}) = 0; i = 1, 2, ..., N; t = 1, 2, ..., T. \tag{5}$$

Assumption 3 *The main diagonal elements of* W *are zero. The row and column norms of the matrices* W *and* $(I_N - \lambda W)^{-1}$ *are bounded.*

Assumption 4 $\lambda_0 \in [c_l; c_u]$, *with* $-1 < c_l; c_u < 1$, *and* $(I_N - \lambda W)^{-1}$ *is non-singular for all* $\lambda \in [c_l; c_u]$.

The existence of moments of order higher than four stated in Assumption 1 is needed for applicability of the central limit theorem for triangular arrays by Kelejian and Prucha (2001). In Assumption 2, conditions (4) require serially uncorrelated errors, while (5) exclude the x_{it} process to be endogenously determined. The following assumptions concerning the initial conditions are also taken

$$E(y$$

instruments valid under certain assumptions on the initial conditions of the dynamic process. In particular, suppose that, in addition to (3)-(6), the conditions

$$E(\Delta y_{i1}\eta_i) = 0, \tag{10}$$

hold. Then the following $(T-1)^2/2$ moment conditions are available for the equation in levels, (1):

$$E[\Delta y_{is}(y_{it} - \alpha_0 y_{i,t-1} - \beta_0' x_{it})] = 0, \text{ for } s = 1,\dots,t-1;\ t = 2,3,\dots,T. \tag{11}$$

Further, if regressors, x_{it}, satisfy

$$E(\Delta x_{i1}\eta_i) = 0, \tag{12}$$

then, under strict exogeneity, the T^2 conditions

$$E[\Delta x_{is}(y_{it} - \alpha_0 y_{i,t-1} - \beta_0' x_{it})] = 0,\ s = 1,2,\dots,T;\ t = 1,2,\dots,T, \tag{13}$$

can also be used, while under weak exogeneity, we have the $T^2/2$ moments

$$E[\Delta x_{is}(y_{it} - \alpha_0 y_{i,t-1} - \beta_0' x_{it})] = 0, \text{ for } s = 1,2,\dots,t-1;\ t = 1,2,\dots,T. \tag{14}$$

We observe that, if (7)-(8) (or (9)) and (11), (13) (or (14)) are used jointly, then some of the conditions in (11)-(14) are redundant. In this case, in addition to (7)-(8), only the $(T-1)$ conditions

$$E[\Delta y_{i,t-1}(y_{it} - \alpha_0 y_{i,t-1} - \beta_0' x_{it})] = 0, \text{ for } t = 2,3,\dots,T, \tag{15}$$

and, under either strictly or weakly exogenous regressors,

$$E[\Delta x_{it}(y_{it} - \alpha_0 y_{i,t-1} - \beta_0' x_{it})] = 0, \text{ for } t = 1,2,\dots,T, \tag{16}$$

can be used. Conditions (7)-(8) and (15)-(16) yield the so-called *system* GMM, first proposed by Blundell and Bond (1998) in the context of a pure autoregressive panel data model. It is convenient to rewrite moments (7)-(16) in the compact form:

$$E[Z'(q - G\theta_0)] = 0, \tag{17}$$

where $\theta_0 = (\alpha_0, \beta_0')'$, $q = (q_{1.}', q_{2.}', \dots, q_{N.}')'$, $Z = (Z_{1.}', Z_{2.}', \dots, Z_{N.}')'$ $G = (G_{1.}', G_{2.}', \dots, G_{N.}')'$. The vectors $q_{i.}$ and the matrices $Z_{i.}$, $G_{i.}$ $i = 1,2,\dots,N$, depending on the three possible sets of conditions (and under the further assumption of strictly exogenous regressors), are given by:

(i) Under the *difference moment conditions* (7) and (8):

$$Z_{i.} = \underset{(T-1)\times(1+2k)T(T-1)/2}{Z_{i.}^{d}} = \begin{pmatrix} y_{i0}, x_{i1}', \dots, x_{iT}' & 0 & \cdots & 0 \\ 0 & y_{i0}, y_{i1}, x_{i1}', \dots, x_{iT}' & \cdots & 0 \\ & & \ddots & \vdots \\ 0 & 0 & \cdots & y_{i0}, \dots, y_{i,T-2}, x_{i1}', \dots, x_{iT}' \end{pmatrix}, \tag{18}$$

$$q_{i.} = \underset{(T-1)\times 1}{q_{i.}^{d}} = \begin{pmatrix} \Delta y_{i2} \\ \vdots \\ \Delta y_{iT} \end{pmatrix};\ G_{i.} = \underset{(T-1)\times(k+1)}{G_{i.}^{d}} = \begin{pmatrix} \Delta y_{i1} & \Delta x_{i2}' \\ \vdots & \vdots \\ \Delta y_{i,T-1} & \Delta x_{iT}' \end{pmatrix}. \tag{19}$$

(ii) Under the *level moment conditions* (11) and (13):

$$Z_{i\cdot} = \underset{(T-1)\times[2kT+(T-1)](T-1)/2}{Z^{\ell}_{i\cdot}} = \begin{bmatrix} y_{i1}, \; x'_{i1}, \ldots, \; x'_{i,T} & 0 & \cdots & 0 \\ 0 & y_{i1}, \; y_{i2}, \; x'_{i1}, \ldots, \; x'_{i,T} & \cdots & 0 \\ & & \ddots & \vdots \\ 0 & 0 & \cdots & y_{i1}, \ldots, \; y_{i,T-1}, \; x'_{i1}, \ldots, \; x'_{i,T} \end{bmatrix}, \tag{20}$$

$$q_{i\cdot} = \underset{(T-1)\times 1}{q^{\ell}_{i\cdot}} = \begin{bmatrix} y_{i2} \\ \vdots \\ y_{iT} \end{bmatrix}; \; G_{i\cdot} = \underset{(T-1)\times(k+1)}{G^{\ell}_{i\cdot}} = \begin{bmatrix} y_{i1} & x'_{i2} \\ \vdots & \vdots \\ y_{i,T-1} & x'_{iT} \end{bmatrix}. \tag{21}$$

(iii) Under both *difference and level moment conditions*:

$$Z_{i\cdot} = \underset{2(T-1)\times(T-1)[(1+2k)T/2+(1+k)]}{Z^{sys}_{i\cdot}} = \begin{bmatrix} Z_{d,i} & 0 & & & 0 \\ 0 & y_{i1}, \; x'_{i2} & 0 & \cdots & 0 \\ \vdots & & y_{i2}, \; x'_{i3} & & \\ & & & \ddots & 0 \\ 0 & 0 & 0 & \cdots & y_{i,T-1}, \; x'_{iT} \end{bmatrix}, \tag{22}$$

$$q_{i\cdot} = \underset{2(T-1)\times 1}{q^{sys}_{i\cdot}} = \begin{bmatrix} q^{\ell}_{i\cdot} \\ q^{d}_{i\cdot} \end{bmatrix}; \; G_{i\cdot} = \underset{2(T-1)\times(k+1)}{G^{sys}_{i\cdot}} = \begin{bmatrix} G^{d}_{i\cdot} \\ G^{\ell}_{i\cdot} \end{bmatrix}. \tag{23}$$

In addition to momen

with

$$P_e = \frac{1}{N} \sum_{i=1}^{N} q_{i:} \quad G_{i:}$$

$\boldsymbol{i}$th MSA whose mortgages have been purchased or securitized by Fannie Mae or Freddie Mac.[6] Similarly, $\boldsymbol{GSE_{it}}$ is the number of single-family mortgages purchased by Fannie Mae or Freddie Mac within the $\boldsymbol{i}$

6 Estimation results

Tables 6 and 7 present the estimated parameters for the two sub-periods. In both tables, the upper panel presents the estimated parameters for the model using conventional GMM estimation with

to existing empirical literature on nonperforming loans. Differently from previous work, we have used data at metro level, to properly capture the effect of local social, economic and financial conditions on financial stability. Our results point to a significant negative impact of real estate prices on ex-post risk, both during and before the bust of the bubble. In a period of house prices rising fast, this result corroborates the hypothesis that wealth can play the role of a buffer in case of unexpected shocks or that housing wealth can be used as collateral to ease access to credit. During the bursting of the bubble, when house prices start falling below the nominal value of loans, the negative impact of real estate prices on NPLs is explained by an increase in default rates due to speculative buyers and owner-occupiers that are unwilling or unable to repay their mortgages and have difficulties in selling their properties. Our results also indicate a significant positive impact of GSE loan purchases on ex-post risk, only in the period during the bust of the bubble. Hence, in a period of crisis, the activity of GSEs seems to contribute to enhancing financial fragility, rather than working as a economic cushion to mortgage markets. We also found a marked spatial concentration of unobservables, that rises consistently during the bubble bust. Such result may be explained by the worsening of social and economic conditions, which in turn may have accentuated the spatial clustering of poverty and deprivation across the territory in this period.

Another major contribution of this paper has been to extend existing econometric methods adopted to study the determinants of NPLs, to account for possible spatial dependence present in the data. To this end, we have developed an *ad-hoc* GMM procedure to estimate a first-order dynamic panel data regression model with group-specific effects and spatial autoregressive errors. This procedure may be adopted to investigate a large number of economic problems characterised by both spatial and temporal patterns. For instance, they may be useful for estimating cross-country growth regressions as in Caselli, Esquivel, and Lefort (1996), studying spatio-temporal patterns in consumption behaviour (see, for example, Browning and Collado (2007)), or exploring the dynamics in the production of firms as in Blundell and Bond (2000).

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Appendices

In these appendices we first introduce the GMM estimator of the SAR coefficient, and prove its consistency and asymptotic normality. We then provide results for a small Monte Carlo exercise. For our statistical derivations, it is useful to introduce the following lemma.

Lemma 1 *Let* $\varepsilon = (\varepsilon'_{1\cdot}; \varepsilon'_{2\cdot}; \ldots; \varepsilon'_{N\cdot})'$, $\varepsilon_{i\cdot} = (\Delta\varepsilon_{i2}; \ldots; \Delta\varepsilon_{iT})'$, *be a* $N(T-1)$*-dimensional vector with* ε_{it} *satisfying Assumption 1, and let* A_ℓ, *for* $\ell = 1; 2; \ldots; r$, *be non-stochastic matrices with zero diagonal elements. We have, for* $\ell = 1; 2; \ldots; r$,

10.9091 Tf 7.575 05 -1.777 Td [(`)]TJ/F24 10.9091 Tf 6.382 1d6t58777 Td [

$$\frac{1}{2N(T-1)}E\left[\varepsilon'(A_\ell \otimes I_{T-1})\varepsilon\right] = 0; \qquad (.45)$$

$$Var\left[\frac{1}{2N(T-1)}\varepsilon'(A_\ell \quad I_\ell \quad I$$

To prove (A.1), note that

$$
\begin{aligned}
& \frac{1}{2N(T\quad 1)} \quad \hat{\ }(\ )'(A\grave{}\quad I_{T-1})\quad \hat{\ }(\ ) \\
= \; & \frac{1}{2N(T\quad 1)}(\hat{\ }\qquad {}_0)'G^{d\prime}\;(I_N\qquad W)'A\grave{}(I_N\qquad W)\quad I_{T-1}\;G^{d}(\hat{\ }\qquad {}_0) \\
& + \frac{2}{2N(T\quad 1)}(\hat{\ }\qquad {}_0)'G^{d\prime}\;(I_N\qquad W)'A\grave{}P(\ )\quad I_{T-1}\qquad '' \\
& + \quad ''(\ )'(A\grave{}\quad I_{T-1})\quad ''(\ ) \\
= \; & \frac{1}{2N(T\quad 1)}(\hat{\ }\qquad {}_0)'G^{d\prime}(B\grave{}\quad I_{T-1})\,G^{d}(\hat{\ }\qquad {}_0) \\
& + \frac{2}{NT}(\hat{\ }\qquad {}_0
\end{aligned}
$$

6 Td [(2)]TJ/F40 10.9091 Tf.(7.134 -2.62 Td [(0)]TJ/F8 10.9091 Tf 4.732 2.62 Td [(6 T

Let $B_\ell = P(\ )' A_\ell P(\ )$ with elements $b_{ij;\ell}$, and note that the diagonal elements of $(B_\ell \quad D)$ are $2b_{ii;\ell}$, for $i = 1, 2, \ldots, N; t = 1, 2, \ldots, T$. Then the variance of (A.6) satisfies

$$Var \quad 1$$

Proof. Consistency and asymptotic normality of ^ can be proved using results from Proposition and following the same lines of reasoning as in Moscone and Tosetti (2011). See also Kelejian and Prucha (1999), Liu, Lee, and Bollinger (2010), Lee (2007), and Kelejian and Prucha (2009) for further details on consistency of GMM estimators of spatial models. ■

The e¢ cient GMM estimator can be obtained by imposing, in (A.10), the optimal weights given by $Q = Q^{*} = V^{-1}$ (see Greene (2002) on this). Notice that the `th element of d is (see Appendix A.1)

-3732(10.9691 Tf 341(v-278(= eleme04)27(ts)-340(.8.7d8(1(the)-340(and)-387 -1.636 Td 3F4
54d8.836e

$$d_{\ell} = \lim_{N\to\infty} \frac{1}{N} Tr \quad A_{\ell} + A'_{\ell} \;\; W (I_N \quad {}_0 W)^{-1} \; : \qquad \text{(A.12)}$$

Since Q^{*} and d depend on ${}_0$, they can be proxied by $Q^{*} = Q^{*}$ ^ , and d = d ^ , where ^ =

54d8.836e d9]TJ/F49 eleme04ts .4 TT3 [(d9]TJ/F4100(and)-340(deriv)27(e)1eriv)the eleme1 Td [(T)]TJ/F4

^; $\frac{1}{2(T-1)} \sum_{t=1}^{T} (\;\; _{1t})^2$; [redacted]

54d8.836e d9]TJ/F49 eleme04ts .4 TT3 [(d9]TJ/F4100(and)-340(deriv)27(e)1eriv)the eleme1 Td [(T)]TJ/F4

A.1 The eleme [redacted]

[redacted] t $\frac{@}{@} M_{NT}(\;)$ = ! $\lim_{N\to\infty} E$ [redacted] ( ) = , and derive the elements of the v1d+at

B Monte Carlo evidence

We consider the following data generating process

$$y_{it} = {}_i(1 \quad) + y_{i;t-1} + x_{it} + u_{it}; \; t = m + 1; \; m + 2; \ldots; 0; 1; \ldots; T; \tag{B.1}$$

$$y_{i;-m} = {}_i + x_{i;-m} + u_{i;-m}; \tag{B.2}$$

with

$$u_{it} = \sum_{j=1}^{N} w_{ij} u_{jt} + "_{it}; \; t = m; \; m + 1; \; m + 2; \ldots; 0; 1; \ldots; T; \tag{B.3}$$

and $"_{it} \quad IIDN(0; {}^2_i); \; {}^2_i \quad IIDU(0{:}05; 0{:}95); \; t = m; \; m + 1; \ldots; 0; 1; \ldots; T$. We assume the spatial weights matrix W is a row standardised regular lattice of 1st order, with elements $w_{ij} = 1$ if units i and j are contiguous and $w_{ij} = 0$ otherwise. The spatial weight matrix is de…ned in a circular fashion, whereby the …rst cross section unit is placed adjacent to the last unit. We discard the …rst m

B.1 Results

Table 1 shows results for the conventional, one-step GMM-DIF estimator of and , for the GMM-DIF estimator corrected for spatial correlation using formulas (32), (41), and for the corresponding estimated SAR parameter. The bias and RMSE of conventional GMM-DIF are small, and decrease as N gets large, for all values of , corroborating the theoretical results provided in the first part of Theorem 1. When $= 0$, the conventional GMM-DIF for and is correctly sized for all choices of N, while it is subject to size distortions when > 0. The over-rejection tendency is due to the use of inappropriate standard errors, and appears to be substantial in the case where the true value of spatial parameter is relatively large ($= 0.7$). In contrast, the GMM-DIF estimator corrected for spatial dependence is correctly sized, reflecting the fact that the estimated variance is a consistent estimator of the true variance.

Tables 2, 3 and 4 provide results for the conventional GMM-DIF, GMM-LEV and GMM-SYS estimators using optimal weights, for the GMM-DIF, GMM-LEV and GMM-SYS estimators corrected for spatial correlation using formulas (43)-(44) (i.e., $\hat{}_{e}^{II}$), and for the corresponding estimated SAR parameters. The first panel of these tables shows that, when $= 0$, the conventional GMM estimators with optimal weights for and are correctly sized for large N. However, they show some size distortions when $N = 300$. This result is in line with existing findings in the literature, indicating that the estimated asymptotic standard errors of the conventional two-step GMM estimator are downward biased in small samples. The second and third panels in Tables 2-4 show that, when > 0, the conventional GMM estimators, ignoring spatial dependence, are severely oversized even when N is large. In contrast, the empirical sizes of the GMM estimators corrected for spatial dependence are very close to the nominal size, for all values of the spatial parameters, for large N. Tables 1-4 also show that the GMM estimators for are always correctly sized, for any sets of moments taken to compute the slope parameters, and for all choices of N.

To conclude, our results indicate that, for the combination of N and T in our empirical study ($N = 366$ and $T = 6$), the proposed GMM estimators performs quite well.

Table 1: Monte Carlo results for the conventional GMM-DIF estimator and the two-step GMM-DIF estimator corrected for spatial correlation

		$_0$= 0:3				$_0$= 0:7			
N	Par.	Bias	RMSE	Size	Power	Bias	RMSE	Size	Power
		$_0$= 0:0				$_0$= 0:0			
300	^	-0.026	0.063	0.053	0.583	-0.040	0.081	0.053	0.530
500		-0.013	0.054	0.057	0.650	-0.022	0.063	0.053	0.600
300	^''	-0.025	0.063	0.050	0.580	-0.039	0.081	0.057	0.533
500		-0.012	0.054	0.057	0.643	-0.022	0.063	0.053	0.590
300	^	0.034	0.184	0.050	0.573	-0.025	0.186	0.050	0.457
500		0.028	0.158	0.050	0.593	0.004	0.139	0.050	0.450
300	^''	0.033	0.184	0.050	0.573	-0.024	0.186	0.053	0.463
500		0.028	0.158	0.053	0.593	0.004	0.139	0.057	0.450
300		-0.002	0.047	0.033	0.593	-0.001	0.047	0.043	0.557
500		0.002	0.038	0.056	0.747	0.003	0.038	0.050	0.750
		$_0$= 0:3				$_0$= 0:3			
300	^	-0.027	0.065	0.097	0.597	-0.043	0.086	0.127	0.537
500		-0.014	0.055	0.093	0.697	-0.024	0.066	0.113	0.587
300	^''	-0.024	0.062	0.053	0.590	-0.038	0.080	0.050	0.523
500		-0.012	0.053	0.050	0.643	-0.022	0.062	0.050	0.597
300	^	0.037	0.196	0.080	0.580	-0.025	0.198	0.083	0.647
500		0.031	0.165	0.077	0.593	0.002	0.147	0.077	0.640
300	^''	0.029	0.180	0.053	0.560	-0.026	0.185	0.050	0.663
500		0.027	0.155	0.053	0.580	0.004	0.137	0.053	0.650
300		-0.007	0.041	0.047	0.750	-0.006	0.040	0.043	0.733
500		-0.002	0.032	0.057	0.917	0.000	0.032	0.060	0.903
		$_0$= 0:7				$_0$= 0:7			
300	^	-0.034	0.086	0.223	0.693	-0.065	0.122	0.290	0.650
500		-0.019	0.064	0.223	0.727	-0.037	0.086	0.230	0.630
300	^''	-0.024	0.062	0.053	0.603	-0.037	0.079	0.057	0.510
500		-0.012	0.052	0.050	0.643	-0.022	0.060	0.050	0.613
300	^	0.055	0.300	0.130	0.517	-0.040	0.320	0.120	0.763
500		0.049	0.236	0.110	0.513	-0.008	0.233	0.100	0.727
300									

Table 2: Monte Carlo results for the conventional GMM-DIF estimator using optimal weights and the two-step GMM-DIF estimator corrected for spatial correlation

		$_0 = 0{:}3$				$_0 = 0{:}7$			
N	Par.	Bias	RMSE	Size	Power	Bias	RMSE	Size	Power
		$_0 = 0{:}0$				$_0 = 0{:}0$			
300	$\hat{\ }_e$	-0.025	0.067	0.080	0.567	-0.037	0.086	0.110	0.507
500		-0.012	0.055	0.050	0.630	-0.020	0.064	0.073	0.580
300	$\hat{\ }^{II}_e$	-0.024	0.068	0.057	0.557	-0.036	0.088	0.060	0.503
500		-0.012	0.055	0.053	0.623	-0.019	0.064	0.063	0.580
300	$\hat{\ }_e$								

Table 3: Monte Carlo results for the conventional GMM-LEV estimator using optimal weights and the two-step GMM-LEV estimator corrected for spatial correlation

		$_0 = 0{:}3$				$_0 = 0{:}7$			
N	Par.	Bias	RMSE	Size	Power	Bias	RMSE	Size	Power
		$_0 = 0{:}0$				$_0 = 0{:}0$			
300	$\hat{}_e$	0.000	0.065	0.100	0.467	0.002	0.045	0.063	0.713
500		0.012	0.047	0.057	0.517	0.005	0.031	0.057	0.860
300	$\hat{}^{\prime\prime}_e$	-0.002	0.066	0.090	0.490	0.001	0.046	0.067	0.717
500		0.011	0.047	0.053	0.513	0.005	0.032	0.050	0.853
300	$\hat{}_e$	-0.001	0.173	0.060	0.647	-0.003	0.138	0.060	0.783
500		-0.017	0.133	0.050	0.663	0.000	0.105	0.047	0.703
300	$\hat{}^{\prime\prime}_e$	0.004	0.175	0.060	0.637	-0.002	0.140	0.060	0.780
500		-0.015	0.133	0.053	0.663	0.001	0.105	0.047	0.710
300		-0.001	0.047	0.053	0.580	-0.001	0.047	0.040	0.567
500		0.003	0.038	0.057	0.747	0.003	0.038	0.057	0.750
		$_0 = 0{:}3$				$_0 = 0{:}3$			
300	$\hat{}_e$	-0.002	0.065	0.097	0.487	0.001	0.046	0.090	0.723
500		0.011	0.047	0.090	0.567	0.005	0.032	0.077	0.857
300	$\hat{}^{\prime\prime}_e$	-0.002	0.065	0.070	0.490	0.001	0.046	0.067	0.710
500		0.011	0.047	0.063	0.523	0.005	0.032	0.047	0.873
300	$\hat{}_e$	0.003	0.180	0.083	0.640	-0.002	0.145	0.080	0.780
500		-0.014	0.141	0.067	0.667	0.002	0.111	0.063	0.700
300	$\hat{}^{\prime\prime}_e$	0.004	0.170	0.063	0.630	0.001	0.139	0.080	0.780
500		-0.016	0.131	0.053	0.670	0.000	0.104	0.057	0.710
300		-0.007	0.041	0.057	0.740	-0.004	0.040	0.057	0.733
500		-0.001	0.033	0.057	0.903	0.001	0.032	0.057	0.900
		$_0 = 0{:}7$				$_0 = 0{:}7$			
300	$\hat{}_e$	-0.009	0.080	0.230	0.583	-0.004	0.058	0.180	0.690
500		0.005	0.055	0.177	0.667	0.004	0.044	0.160	0.803
300	$\hat{}^{\prime\prime}_e$	-0.001	0.062	0.060	0.467	0.002	0.045	0.060	0.693
500		0.012	0.047	0.050	0.500	0.006	0.032	0.050	0.880
300	$\hat{}_e$	0.022	0.249	0.143	0.777	0.011	0.214	0.113	0.747
500		0.000	0.186	0.113	0.773	0.007	0.161	0.093	0.757
300	$\hat{}^{\prime\prime}_e$	0.000	0.162	0.050	0.730	0.002	0.134	0.057	0.783
500		-0.016	0.128	0.057	0.773	-0.001	0.100	0.043	0.720
300		-0.007	0.025	0.050	1.000	-0.004	0.023	0.053	1.000
500		-0.002	0.019	0.053	1.000	0.000	0.019	0.057	1.000

We compute $\hat{}_e = \left(\hat{}_e; \; _e\right)^{\prime}$ using equation (3.2) in Arellano and Bover (1995), and $\hat{}^{\prime\prime}_e = \left(\hat{}^{\prime\prime}_e; \; ^{\prime\prime}_e\right)^{\prime}$ using equation (43), and (44) for its variance.
We compute $\hat{}$ using residuals $\hat{u}_{it}$

Table 4: Monte Carlo results for the conventional GMM-SYS estimator using optimal weights and the two-step GMM-SYS estimator

		$_0 = 0{:}3$				$_0 = 0{:}7$			
N	Par.	Bias	RMSE	Size	Power	Bias	RMSE	Size	Power
		$_0 = 0{:}0$				$_0 = 0{:}0$			
300	$\hat{\ }_e$	-0.002	0.034	0.120	0.920	-0.002	0.031	0.130	0.950
500		0.005	0.026	0.073	0.973	0.002	0.024	0.090	0.993
300	$\hat{\ }_e^{II}$	-0.001	0.034	0.120	0.907	-0.001	0.032	0.140	0.940
500		0.005	0.026	0.073	0.967	0.002	0.024	0.083	0.993
300	$\hat{\ }_e$	0.000	0.058	0.083	0.867	0.000	0.055	0.073	0.933
500		-0.001	0.046	0.073	0.860	0.000	0.042	0.057	0.917
300	$\hat{\ }_e^{II}$	0.000	0.059	0.083	0.873	0.001	0.056	0.083	0.927
500		-0.001	0.047	0.077	0.850	0.000	0.042	0.067	0.913
300		-0.001	0.048	0.040	0.560	-0.001	0.048	0.040	0.557
500		0.003	0.039	0.057	0.733	0.003	0.039	0.063	0.737
		$_0 = 0{:}3$				$_0 = 0{:}3$			
300	$\hat{\ }_e$	-0.003	0.035	0.063	0.910	-0.004	0.032	0.060	0.950
500		0.005	0.026	0.063	0.970	0.002	0.024	0.063	0.990
300	$\hat{\ }_e^{II}$	-0.001	0.034	0.063	0.923	-0.001	0.032	0.057	0.940
500		0.005	0.026	0.050	0.977	0.002	0.023	0.060	0.993
300	$\hat{\ }_e$	-0.001	0.061	0.063	0.843	0.000	0.059	0.060	0.997
500		-0.001	0.048	0.050	0.823	0.000	0.044	0.053	0.997
300	$\hat{\ }_e^{II}$	-0.001	0.059	0.057	0.860	0.001	0.055	0.057	0.920
500		-0.001	0.046	0.053	0.867	0.000	0.041	0.050	0.940
300		-0.001	0.040	0.057	0.707	-0.001	0.040	0.057	0.700
500		0.002	0.032	0.053	0.890	0.002	0.032	0.053	0.883
		$_0 = 0{:}7$				$_0 = 0{:}7$			
300	$\hat{\ }_e$	-0.008	0.051	0.240	0.850	-0.011	0.049	0.230	0.893
500		0.002	0.035	0.167	0.920	-0.001	0.035	0.170	0.950
300	$\hat{\ }_e^{II}$	0.000	0.033	0.060	0.913	-0.001	0.030	0.067	0.940
500		0.005	0.025	0.057	0.980	0.002	0.023	0.053	0.993
300	$\hat{\ }_e$	-0.001	0.087	0.117	0.837	-0.003	0.098	0.167	0.970
500		-0.002	0.064	0.077	0.840	-0.001	0.069	0.113	0.967
300	$\hat{\ }_e^{II}$	-0.002	0.059	0.063	0.800	-0.001	0.055	0.063	0.847
500		0.000	0.044	0.050	0.873	0.001	0.040	0.053	0.980
300		-0.001	0.023	0.045	0.997	-0.001	0.023	0.049	0.997
500		0.001	0.018	0.053	1.000	0.001	0.018	0.057	1.000

We compute $\hat{\ }_e = \left(\hat{\ }_e;\ _e\right)'$ using equation (3.2) in Arellano and Bover (1995), and $\hat{\ }_e^{II} = \left(\hat{\ }_e^{II};\ _e^{II}\right)'$ using equation (43), and (44) for its variancgtsWe compute

Figure 2: Quantile distribution of real house prices in US MSAs, in the years 2000 to 2005 (left) and 2006 to 2011 (right)

Figure 3: Quantile distribution of non performing loans in US MSAs, in the years 2000 to 2005 (left) and 2006 to 2011 (right)

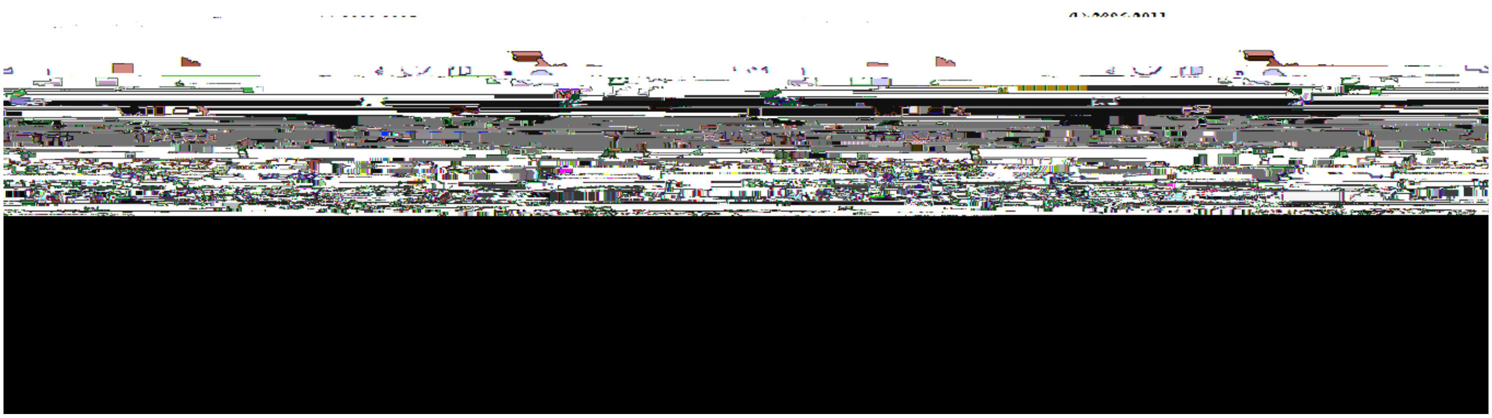

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Table 7: Determinants of non-performing loans in the period of the bubble bursting (2006 to 2011)

	(I): GMM-DIF		(II): GMM-LEV		(III): GMM-SYS	
	CONVENTIONAL GMM					
	Par.	S.E.	Par.	S.E.	Par.	S.E.
$y_{i;t-1}$	0.225*	0.020	0.496*	0.028	0.369*	0.015
HP_{it}	-0.734*	0.240	-1.015*	0.176	-0.689*	0.138
GSE_{it}	0.184	0.099	0.424	0.257	0.325	0.242
$INCOME_{it}$	-0.707*	0.497	-1.075*	0.098	-1.379*	0.057
$URATE_{it}$	0.957*	0.064	0.569*	0.092	1.051*	0.046
$IRATE_{it}$	0.031*	0.011	-0.022	0.013	-0.049*	0.008
POP_{it}	3.444*	0.936	0.121*	0.043	0.044	0.038
$EQASS_{it}$	-0.547*	0.081	-0.430*	0.126	-0.652*	0.068
HHI_{it}	-0.204*	0.058	-0.008	0.051	-0.183*	0.036
	SPATIAL GMM					
$y_{i;t-1}$	0.240*	0.021	0.502*	0.029	0.391*	0.015
HP_{it}	-0.674*	0.278	-1.135*	0.216	-0.778*	0.159
GSE_{it}	0.204*	0.082	0.348*	0.069	0.236*	0.046
$INCOME_{it}$	-0.845*	0.514	-1.055*	0.101	-1.315*	0.059
$URATE_{it}$	0.906*	0.090	0.548*	0.119	0.871*	0.070
$IRATE_{it}$	0.047*	0.015	-0.014	0.030	-0.022	0.017
POP_{it}	3.445*	0.977	0.158*	0.052	0.112*	0.043
$EQASS_{it}$	-0.514*	0.083	-0.419*	0.138	-0.653*	0.072
HHI_{it}	-0.246*	0.062	-0.026*	0.009	-0.189*	0.038
	0.574*	0.131	0.720*	0.078	0.702*	0.101
AR(1)	-7.01	[0.00]	-6.00	[0.00]	-7.7	[0.00]
AR(2)	1.11	[0.30]	1.56	[0.56]	1.12	[0.26]
Hansen	230.54	[0.31]	130.16	[0.11]	335.94	[0.34]

Notes: (*) denote 5 per cent signi...cance level respectively.
Standard errors are reported in in round brackets, while ***p***-value are shown in square brackets