Journal of Financial Stability 37 (2018) 112–130

Contents lists available at ScienceDirect

Journal of Financial Stability

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

Assessing macroprudential tools in OECD countries within a cointegration framework

Oriol Carreras[a], E. Philip Davis[a,b,*], Rebecca Piggott[a]

[a] NIESR, 2 Dean Trench Street, Smith Square, London, SW1P 3HE, UK
[b] Department of Economics and Finance, Brunel University, Kingston Lane, Uxbridge, Middlesex, UB8 3PH, UK

ARTICLE INFO

Article history:
Received 26 October 2017
Received in revised form 3 April 2018
Accepted 5 April 2018
Available online 7 April 2018

JEL classification:
E58
G28

Keywords:
Macroprudential policy
House prices
Credit expansion
Panel estimation
Robustness

ABSTRACT

Whereas macroprudential policy has come to the fore since the Global Financial Crisis, with many regulators being given responsibility for such policy, the appropriate tools and the effectiveness of such tools remain open questions. We suggest that existing work on effectiveness of macroprudential policy may be vulnerable to bias due to omission of long run cointegration effects. This paper seeks to offer a fresh baseline for work in this area by adopting a cointegration framework which is robust to a variety of alternative techniques and compares favourably with non-cointegrated alternatives. We assess the impact of typical macroprudential policy interventions on house price and household credit growth in up to 19 OECD countries, using three datasets from the IMF and BIS, thus giving both a wider range of control variables and broader coverage of instruments than in most extant work. We find evidence that macroprudential polices remain effective in both short- and long-run at curbing house price and household credit growth even within a cointegration framework, albeit some tools are more effective than others. These include, in particular, taxes on financial institutions, general capital requirements, strict loan-to-value ratios and debt-to-income ratio limits.

1. Introduction

Macroprudential policy is focused on the financial system as a whole, with a view to limiting macroeconomic costs from financial distress (Crockett, 2000), and risk is taken as endogenous to the behaviour of the financial system.[1] Whereas such policies have been widely adopted since the Global Financial Crisis, as noted by Galati and Moessner (2014), "analysis is still needed about the appropriate macroprudential tools, their transmission mechanism and their effect". Theoretical models are in their infancy and empirical evidence on the effects of macroprudential tools is still scarce. Nor has a primary instrument for macroprudential policy emerged. Meanwhile, an examination of the empirical literature shows that the correct modelling of house prices and credit at a macro level is crucial, and existing work on effectiveness of macroprudential policy may be vulnerable to bias due to omission of long run cointegration effects.

In this context, our aim is to advance the empirical evidence on macroprudential tools focused on house prices and credit by adopting a rigorous cointegration framework, which also allows estimation of medium- and long term as well as short term effects of typical policy interventions, thus aiding policymakers in evaluating the tools' effectiveness. Our focus on OECD countries as opposed to global or emerging market samples gives us access to a wider range of control variables than the existing literature; we also include a crisis dummy where appropriate. All of these aspects should reduce omitted variables bias and enhance the accuracy of our results relative to the existing literature that tends to omit cointegration and employ a very simple set of controls. Furthermore, as argued by Cerutti et al. (2017), OECD countries may differ markedly in terms of financial structure and regulation from Emerging Market Economies and Developing Countries, making global pooling as in much of the existing literature potentially problematic.[2] We also undertake a range of robustness checks with a cointegration

* Corresponding author at: Department of Economics and Finance, Brunel University, Kingston Lane, Uxbridge, Middlesex, UB8 3PH, UK.
E-mail addresses: oriolcarreras1@gmail.com (O. Carreras), e_philip_davis@msn.com, philip.davis@brunel.ac.uk, pdavis@niesr.ac.uk (E.P. Davis), r.piggott@niesr.ac.uk (R. Piggott).

[1] Recent overviews of macroprudential policy and instruments are provided inter alia in Bennani et al. (2014), Claessens et al. (2013) and De Nicolò et al. (2012).

[2] They comment "emerging markets have relied more on macro-prudential policies than advanced economies have done. Second, advanced economies tend to have more developed financial systems which offer various alternative sources of finance and scope for avoidance, making it possibly harder for macroprudential policies to be effective. Combined this means that emerging markets and developing countries have been able to use macroprudential policies more effectively." Cerutti et al. (2017) p. 212.

https://doi.org/10.1016/j.jfs.2018.04.004

approach, which underpin the main results, and that have not, to our knowledge, been undertaken in this literature to date. And we compare cointegrated to non-cointegrated estimates of the same dataset to assess the degree to which omitted variables may bias results.

The paper is structured as follows: In Section 2 we survey key recent contributions to the empirical literature on the effectiveness of macroprudential policy. This then forms background to our own modelling exercise which begins in Section 3. We outline the advantages of our cointegra-based approach before estimating panel error correction models for house prices and household sector credit. We then introduce three extant databases of macroprudential tools before testing the additional impact of macroprudential policies using each database in turn. We provide a "ready-reckoner" for the estimated effect of policy over different times horizons which is relevant for regulators. Section 4 features robustness checks within a cointegration framework; first a Vector-Error-Correction (VECM) approach, second using lags of the macroprudential tools, third with fully-modified OLS (FMOLS) and lagged dynamics to better allow for endogeneity of regressors; and finally we adopt a seemingly unrelated regression (SUR) procedure to address a potential concern of weak cointegration underpinning the panel error correction regressions for house prices.[3] In Section 5 we contrast our results with non-cointegrated approaches, including comparison of our baseline with a framework typical of the existing literature for global or emerging market samples, which include mainly economic growth, policy rates and volatility as independent variables and no long run effects, as well as comparing the VECM with a simple VAR which omits cointegration. Section 6 concludes with a summary of results and a number of suggestions for use of the estimates by regulators (for example in calibrating macroeconomic models) as well as suggestions for further empirical work by researchers and policymakers.

2. Empirical research papers on macroprudential policy

As noted in the review by Galati and Moessner (2014), empirical analysis of macroprudential policy is difficult because of lack of established models of real and financial interactions, lack of data and the need for care in distinguishing correlation and causation. This is a matter of concern for policymakers who need to know the impact of policy. A number of approaches to empirical work can be distinguished (for a recent summary, see Carreras et al., 2016). One approach is the event study as for example, Crowe et al. (2011) assess the effects of policies like LTVs on real estate market volatility. A second approach is assessment of authorities or outside observers on effectiveness of macroprudential instruments as in Borio and Shim (2007). Third, macro stress tests can be used to assess responses of the financial system to large shocks, see Drehmann (2009). Fourth, counterfactual analysis seeks to assess what would have happened if macroprudential policies had been applied to past events (see for example Antipa et al., 2010).

A fifth approach, on which we focus, is of reduced form regressions, generally using panel data. Appendix Table A1 provides a summary of recent work in this area. Here, the weaknesses are that such regressions may not capture well the interaction of policy, real and financial sectors; there is little experience of macroprudential policy to assess the effect and transmission mechanism; and there is a difficulty in isolating effects from those of monetary policy. Most existing studies use dynamic panel GMM estimation. They also generally estimate over groups of emerging market economies or global samples with a single dataset. Studies typically do not allow for cointegration, and often are purely in differences so do not allow for a long run effect of macroprudential policy. They also often use quite a simple range of control variables, such as GDP growth and short rates. Three studies we consider of particular interest, and hence note in more detail, are as follows:

Kuttner and Shim (2016) assess the effectiveness of nine non-interest rate policy tools, including macro-prudential measures, in stabilising housing market prices and related lending in a global sample of 57 countries quarterly over 1980–2012, using the BIS database shown in Appendix Table A4 and described below. They use panel regressions for growth rates of housing credit and house prices, with controls for lagged growth of the dependent variable, the level of the short rate, the growth in real GDP per capita and the credit/GDP gap, as well as country fixed effects. The finding that credit, house prices and GDP per capita are non-stationary while their differences are stationary is considered to justify this formulation in growth rates (and the level of the interest rate and the gap which are levels-stationary) rather than allowing also for cointegration between the non-stationary variables. There is no banking crisis dummy. The macroprudential tools are measured, as noted in more detail below, at points of tightening (+1) and easing (-1) over 4 lags. Housing credit growth is slowed significantly by adjustments in the maximum debt-service-to-income (DSTI) and housing-related taxes. Furthermore, only a change in housing-related taxes significantly affects house price inflation. General credit policies (reserve requirements, liquidity and credit growth limits) were not found to have a significant effect on house prices or credit growth.

Akinci and Olmstead-Rumsey (2015) construct a quarterly index of domestic macroprudential policies in 57 advanced and emerging (EME) economies covering 2000–2013, partly relying on the IMF survey used in Cerutti et al. (2017) as cited below. Effectiveness of policies in curbing growth in bank credit and house prices is assessed using a dynamic panel data model, where control variables besides lagged growth rates of credit and house prices include real GDP growth, the change in nominal monetary policy rates and the VIX, a measure of the implied volatility of S&P 500 index options. There are no levels of non-stationary variables and accordingly no allowance for possible cointegration. There is also no banking crisis dummy. Findings of the paper are that usage of macroprudential policy has become more active since the global financial crisis, in both advanced countries and EMEs; the main target is the housing market, and they are often related to bank reserve requirements, capital controls and monetary policy. Macroprudential tightening is associated with lower bank credit growth, housing credit growth, and house price inflation and targeted policies are more effective. In EMEs, capital inflow restrictions targeting the banking sector are also associated with lower credit growth, although portfolio flow restrictions are not. Without the measures, credit and asset price growth would have been much higher.

Cerutti et al. (2017) use the first IMF database (see Appendix Table A2 and the description below) of annual macroprudential measures in a global sample[4] of 119 countries, with a panel GMM regression for macroprudential indicators. Independent variables for credit growth and house price growth include GDP growth, the policy rate level, a dummy for banking crises and country fixed effects as well as the macroprudential variables. There are no levels of non-stationary variables and allowance for cointegration. An index summing all types of policy is correlated with lower credit growth, especially in EMEs. Borrower-based policies like LTV and DTI limits, as well as financial-institution based policies like limits

[3] While such a country-by-country approach as SUR tackles successfully the concern of weak cointegration, it has limited scope for econometric inference as the binary nature of the datasets used in this paper becomes a more taxing feature.

[4] Their sample covers 31 advanced countries, 64 emerging market economies and 24 developing countries.

on leverage and dynamic provisioning are shown to be particularly effective in reducing growth in real credit and house prices. Policies work best in the upturn but are less effective in a bust period. Macroprudential policy is weaker in more open and financially deeper economies, suggesting there is evasion cross border or in shadow banking. Countries with more cross border borrowing use macroprudential policies more.

Appendix Table A1 summarises these and other key recent studies. Whatever the context, it is clear that the correct modelling of house prices and credit at a macro level is crucial and is likely to receive increasing attention in the ongoing wake of the sub-prime crisis and recent policy developments; it is to this issue that we turn in the next section.

3. Modelling macroprudential policies within a cointegration framework

3.1. Specification and estimation for house prices and household credit

Our starting point is that many of the reduced-form studies cited above and in Appendix Table A1 have adopted a rather simple dynamic structure[5] (generally growth rates of non-stationary variables and levels of stationary ones) which may be vulnerable to bias. Since variables employed generally show a trend (they are non-stationary), it would be appropriate to test for cointegration and include it in the equation where cointegration is accepted. Indeed, if there is cointegration and it is omitted from the equation, we are losing information over the long run period (Banerjee et al., 1993). Accordingly, a more complex dynamic structure with allowance for cointegration should improve the accuracy of the estimates of the macroprudential tools.

More specifically, the Granger representation theorem (Engle and Granger 1987) states that if the levels are cointegrated then the data generation process can be represented as an error correction model (ECM). The ECM includes lagged levels terms as well as differences. In contrast, a regression in differences, as is typical of the existing literature, omits the lagged levels terms. Omission of cointegration constrains the estimated coefficients on the lagged levels to be zero (entailing bias if they are significant) and under most circumstances will also force the estimated coefficients on the differenced regressors away from the values they would take if the model were correctly specified as an ECM (also entailing bias). This in turn may affect the size and significance of the dummy variables for macroprudential policy, owing to the omitted long run economic effects. We show results consistent with this argument in Section 5 below, where we compare a VECM with a VAR (which omits cointegration), as well as comparing our baseline results with the simpler models typical of the literature that omit the possibility of cointegration.

An additional benefit of cointegration is that it allows both short and long run effects of macroprudential policy to be discerned, that is often not feasible with the existing literature. Furthermore, most existing studies have sought to cover global or emerging market samples, but at a cost of having a rather limited set of control variables for macroprudential tools such as GDP growth, inflation and short term interest rates. We are focusing here on OECD countries, notably in Europe, and accordingly can use a better and more precise set of controls such as real personal disposable income (RPDI), the rate of unemployment, the real stock of housing and gross household financial wealth, that should reduce bias. This is in addition to avoiding potential biases arising from global pooling cited in the introduction. Moreover, a crisis dummy, which is only included in a subset of existing work, ensures that crisis effects are not falsely attributed to the macroprudential tools.

Our chosen target variables, in line with much of the literature, are real house prices and real household sector credit. The macroprudential instrument datasets used are the first and second IMF dataset and the BIS dataset as outlined below, thus offering extensive scope for comparison as compared to existing studies focused on one dataset. Accordingly, we contend that our results are of considerable relevance to policymakers.

Typical estimates for determination of house prices in advanced countries are indeed in error correction format. There is first a cointegrating levels equation which forms an inverted demand function for housing but also includes a supply effect such as the stock of housing which determines the long-run price of housing (Meen (2002), Barrell et al. (2004, 2011), Adams and Füss (2012), Igan and Loungini (2012), Muellbauer and Murphy (2008), Capozza et al. (2002)). This first stage equation constitutes the relationship that drives the long-run properties of the dependent variable and can be written for a country c as the following regression equation:

$$Y^c = X^c\beta^c + \varepsilon^c \tag{1}$$

Where Y is a Tx1 vector containing the dependent variable in log levels, T denotes the time period, c is a country index, X is a TxN matrix of N regressors in log levels including a constant, β is an Nx1 vector of coefficients and ε is the residual term.

This first stage equation is incorporated into an expanded equation that recognises that actual house prices deviate from their fundamental values in the short-run and typically includes a set of controls in first differences to allow for these dynamics, where the error correction term shows the speed of adjustment to long run equilibrium. For the error correction equation to be meaningful there has to be a cointegrating relationship between the long-run variables (the first stage regression step) and the elements capturing the short-term dynamics must be stationary. This set up allows the examination of factors that drive house price dynamics. The second stage can be written as:

$$\Delta Y^c = \alpha^c + \lambda^c\left(Y^c - X^c\beta^c\right)_{(T-1)} + \gamma^c\Delta Z^c + \epsilon^c \tag{2}$$

Where α denotes a constant, λ is the error correction coefficient, Z is a set of regressors aimed at capturing short-term dynamics of the dependent variable with coefficient vector γ and ϵ is the residual term. The two stages may be combined, as in our work shown below, in a single stage error correction estimation. A similar approach is adopted for household credit.

Following this literature, our modelling started from the panel error-correction approach of Davis et al. (2011), also employed in Armstrong and Davis (2014) using estimated generalised least squares (EGLS). As is normal for panel estimation, the coefficients in (1) and (2) are constrained to be identical for each country, (although we vary this with country-specific coefficients in the seemingly-unrelated regression in Section 4). We estimate an extended house price equation including real house prices (LRPH), real personal disposable income (LRPDI) and the long term real interest rate (LRR) (proxying the user cost as well as impacted by monetary policy)[6] and also the rate of unemployment (U), real gross household financial wealth (LRGW) (as a portfolio balance effect), real housing capital stock (LRKH) (lag only), real household credit (LRLIABS) (lag only) and dummies for financial crises. We estimated

[5] An exception is Vandenbussche et al. (2015) who estimated an error correction equation for house prices in a group of Eastern European countries.

[6] We note that the user cost is also affected by tax deductibility in some countries as well as recurrent property taxes, and mortgages are variable rate in some countries, but we contend that the real long rate is an adequate proxy.

Table 1
Baseline panel-error-correction equations (2000Q1–2015Q4).

Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
C	0.185*** (2.9)	0.373*** (6.0)
DLRPDI	0.129*** (4.8)	0.108*** (4.2)
DLRR	−0.0033** (2.4)	
DLRPH(t-1)	0.397*** (14.6)	
DLRLIABS (t-1)		0.097*** (3.4)
DLRLIABS (t-2)	0.065*** (2.7)	
DLRLIABS (t-3)	0.082*** (3.5)	
LRLIABS (t-1)		−0.019*** (6.1)
LRPH(t-1)	−0.0165*** (5.3)	0.025*** (6.1)
LRPDI(t-1)	0.026*** (3.2)	
LRR(t-1)	−0.0014*** (2.8)	
LRKH(t-1)	−0.035*** (4.8)	−0.021*** (3.5)
DU	−0.0039*** (3.5)	
U(t-1)		−0.0014*** (6.8)
DLRGW	0.059*** (4.2)	0.087*** (6.6)
CRISES	−0.0029*** (2.7)	−0.0042*** (4.7)
R^2	0.56	0.53
SE	0.015	0.012
Observations	1081	1081
KAO	−1.4* (0.08)	−4.3*** (0.0)
Countries	18	18

Notes: Estimation is by EGLS (estimated generalised least squares). Equations include country fixed effects and cross section weights. LRPH is the log of real house price, LRR is the long term real rate, LRPDI is the log of real personal disposable income, LRLIABS is the log of real household credit, LRGW is the log of real gross household financial wealth, LRKH is the log of the real housing capital stock, U is the unemployment rate, and CRISES is a dummy for financial crisis taking a value of 1 when a financial crisis has occurred and 0 otherwise. "D" denotes the variable is in first differences. *T*-stats are reported in parentheses (except for KAO where the p-values are shown in parenthesis). *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

corresponding equations for real household credit, viewing this as a further portfolio balance equation, albeit closely linked to housing.[7]

The Im-Pesaran-Shin panel unit root tests (Pesaran 2007) for the main variables allowing for cross sectional dependence (not illustrated) show the variables, being trended, are non stationary (I(1)) thus justifying an error correction model based approach to estimation. Changes in real house prices were regressed on contemporaneous changes in explanatory variables, and lagged dependent and explanatory variables (both in levels) as well. For our baseline, we used data from 2000Q1-2015Q4 with quarterly observations for up to 18[8] advanced OECD countries from the NiGEM database,[9] the short estimation period being necessitated by the short period covered by the macroprudential databases. The countries are Australia, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Netherlands, Austria, Portugal, Sweden, Spain, the UK and the US.

Panel regression treats all countries as equally important, while the country fixed effects take account of heterogeneity, and we impose cross section weights. In each case we eliminated insignificant variables. The initial estimates are tabulated in Table 1 below. To confirm the existence of the long-term relationship, we also implement the panel cointegration test proposed by Kao (1999) among those variables with significant lagged level terms in a simple levels equation (i.e. the first step of an Engle and Granger (1987) two-step estimation). As shown in the table, the test (denoted KAO) rejects comfortably the null of no cointegration for the panel regressions on real household credit growth, although it barely rejects the null at the 10 per cent significance threshold for real house price growth.

It can be seen in Table 1 that for house prices, the dynamic specification includes real personal disposable income, real long rates, unemployment and real household wealth and also two lagged differences of real household credit. It also includes a lagged house price growth variable as an "accelerator". In the long run, the specification includes the levels of RPDI, long real rates and the housing capital stock, all with correct signs. As regards household credit growth, the dynamic terms are real personal disposable income and real gross financial wealth as well as lagged real household credit growth, while the long term effects arise from house prices, the stock of housing, and the level of unemployment. The crisis variable is significant for both house prices and household credit.

3.2. Datasets of macroprudential tools

Having set out our basic econometric specification, we outline the three publicly available datasets for research on macroprudential tools, one from the BIS and two from the IMF, which are used in some of the research cited above, and which we now go on to employ in our own research. The first IMF dataset, summarised in Appendix Table A2, is set out in Cerutti et al. (2015, 2017). It covers 119 economies with annual data over 2000–2013; it draws on the IMF Global Macroprudential Policy Instruments (GMPI) survey. There are 12 macroprudential instruments in the publicly available dataset, namely General Countercyclical Capital Buffer/Requirement (CTC) (Basel Committee, 2010), Leverage Ratio for banks (LEV), Time-Varying/Dynamic Loan-Loss Provisioning (DP), Loan-to-Value Ratio (LTV), Debt-to-Income Ratio (DTI), Limits on Domestic Currency Loans (CG), Limits on Foreign Currency Loans (FC), Reserve Requirement Ratios (RR), Levy/Tax on Financial Institutions (TAX), Capital Surcharges on SIFIs (SIFI), Limits on Interbank Exposures (INTER) and Concentration Limits (CONC), with zero for "off" and one for "on". Besides the individual tools, they also employ LTV_CAP as the subset of LTV measures used as a strict cap on new

[7] In our modelling strategy, we have substituted certain variables for those typically used in the existing literature on macroprudential instruments (RPDI for GDP and long rate for short rate) as these are more typical in the theoretical and empirical literature on house prices and credit in advanced countries cited in this section. We have also added a number of additional variables in our regressions in the light of that theoretical and empirical literature (such as the rate of unemployment, the real stock of housing and real gross financial wealth). We have calculated the correlation matrix of variables and find these additional variables in our equations have a low correlation with those independent variables used in the existing literature on macroprudential instruments (such as GDP and short rates) and their replacements (RPDI and long rates).

[8] Note that we include Norway in the SUR estimation below. None of our samples include Korea, that Kuttner and Shim (2016) found a potentially problematic outlier in their work.

[9] https://nimodel.niesr.ac.uk/.

loans; and RR_REV as the subset of reserve ratio (RR) measures that impose a specific wedge on foreign currency deposits or are adjusted countercyclically. The tools are aggregated (MPI) in total and then in two subgroups, borrower related (LTV_CAP and DTI) (MPIB) and those others which are aimed at financial institutions' assets or liabilities (MPIF). The dataset covers the whole period the policy operates on an annual basis, but with no judgement of intensity or whether they are binding.

The second IMF dataset (Cerutti et al., 2016, see Appendix Table A3) focuses also on changes in the intensity in the usage of several widely used prudential tools by cumulation of policy actions, taking into account both macro-prudential and micro-prudential objectives. The database aggregates information from primary sources (e.g., central bank reports) and secondary sources (e.g., the Global Macroprudential Policy Instruments [GMPI] as mentioned above). The database covers 64 countries, and has quarterly data for the period 2000Q1-2014Q4. The five types of prudential instruments in the database are: capital buffers, interbank exposure limits, concentration limits, loan-to-value (LTV) ratio limits, and reserve requirements. A total of nine prudential tools are then constructed since some further decompositions are presented: Capital buffers are divided into four sub-indices: general capital requirements, real estate credit specific capital buffers, consumer credit specific capital buffers, and other specific capital buffers. Reserve requirements are divided into two sub-indices: domestic currency reserve requirements and foreign currency reserve requirements. However, it does omit some of the tools included in the earlier database, not least taxes on financial institutions.

The BIS dataset (Appendix Table A4) is focused on policy actions for housing markets, covering 57 economies worldwide monthly from 1990 to 2012 (Kuttner and Shim 2016). The database covers policy actions by central banks and financial authorities, including monetary policy measures and also prudential measures (both microprudential and macroprudential). The focus is on the direction of change of such measures. For monetary policy measures, this includes reserve requirements, credit growth limits and liquidity requirements. These have a general effect on lending for the private sector in general, including for housing and are also summed as a "general credit" variable. As regards macroprudential measures, these include loan-to-value (LTV) limits; debt-service-to-income limits (DSTI); adjustable risk weights on housing loans; specific and general loan loss provisioning on housing loans; housing related taxes; and limits on bank exposures to the housing sector. Each measure is then classified as tightening, loosening or neutral. The dataset incorporates 1111 non-interest monetary and prudential policy measures. The dataset initially is purely qualitative but is made quantitative by the authors attaching values of 1 for measures of tightening and −1 for measures of loosening. Hence, unlike the IMF datasets, there is zero during periods when policy is unchanged, whether or not a policy is in operation.

An important issue is that all of these datasets employ categorical rather than numerical variables, generally with zero for "policy off" and one for "policy on/policy tightened". Reasons for this are set out inter alia in Kuttner and Shim (2016) who note that data heterogeneity is a key problem necessitating such a simplification "Even with the application of uniform selection criteria, the specifics of policy actions differ across countries and over time. For example, the dataset includes the introduction of a maximum LTV ratio as well as the subsequent reductions and increases in the ratio. Also, in some economies total household income is used in calculating the DSTI ratio, while in others the borrower's income is used. Including these data in a regression model therefore requires some degree of standardization and aggregation." (Ibid: 36). Cerutti et al. (2017) note "while the level/thresholds of each instrument may change over time, these may not capture the degree to which the instruments are actually binding, again especially hard to measure consistently across a large set of countries. Similarly, without knowing whether instruments bind, it is difficult to code the variations in the use of instruments objectively as a tightening or a loosening. We therefore construct simple binary measures of whether the instruments were in place." (Ibid:206). The use of categorical variables means that our estimates, in line with the existing literature, show the effect of typical policy interventions in each case.

3.3. *Assessing the tools within the cointegration framework*

We tested the macroprudential variables in each dataset one by one in the specifications set out in Table 1. To obtain quarterly data for the macroprudential instruments, we transformed the annual and monthly data of the first IMF and BIS databases respectively to quarterly data. The second IMF database is already quarterly so could be used directly. The data periods for regression with the macroprudential variables are accordingly 2000Q1–2013Q4 for the first IMF dataset, 2000q1–2014q4 for the second IMF dataset and 1990q1–2012q2 or 2000q1–2012q2 for the BIS dataset. Omission of some variables in the following tables compared with the lists in Appendix Tables A2–A4 reflects near singularity of the matrix in estimation.

Starting with the first IMF dataset, we see in Table 2 that house prices are affected significantly[10] by the summary variables MPI (which aggregates all macroprudential variables) and MPIB (aggregating macroprudential variables affecting the borrower), as well as LTV (loan-to-value ratio), DTI (debt-to-income ratio), TAX (taxes on financial intermediaries) and LTV_CAP (the subset of LTV measures used as a strict cap on new loans). Household credit growth is affected by MPI, MPIF (aggregating macroprudential policies which are aimed at financial institutions' assets or liabilities), DTI (with the wrong sign), TAX, and INTER (limits on interbank lending). In assessing the coefficients, note that since the dependent variable is in logs, they show the immediate percentage change when a typical policy intervention is introduced (so for example the coefficient on DTI of −0.004 implies a first quarter fall in real house prices of 0.4%). Longer term changes require calculation via the lag structure as set out in Table 5.

We went on to test the second IMF database (Table 3). There are significant results for an effect on house prices of cumulated concentration rules, cumulated general prudential controls and cumulated general capital requirements. For household credit there are significant results for non-cumulated general prudential limits, non-cumulated general capital requirements and non-cumulated interbank exposure limits as well as cumulated prudential limits, cumulated interbank exposure limits, cumulated concentration limits and cumulated capital requirements. There are also significant variables with the wrong sign in the case of non-cumulated reserve requirements bearing on local currencies[11] for credit and non-cumulated changes in the loan-to-value ratio cap (LTV_CAP) for credit and housee prices.

We estimated similarly with the 2016 BIS database (Table 4), taking the policy dummies over one year (lag 1 to lag 4) as in

[10] Policies are shown to be effective by significant coefficients on the policy tools, and underpinned by the econometric specifications. A summary of results for various cointegrating specifications is given in Table 13. Further information is given in Table 5 below, which shows not only the immediate effect of a typical policy intervention but also after 8 quarters and in the long term, feeding through the lag structure of the equations and in some cases allowing for interactions between effects on credit and house prices.

[11] The difficulty in getting "right signs" for reserve requirements may link to their dual role as an instrument of monetary policy and of macroprudential policy. See for example Izquerido et al. (2013) on related issues in Latin America.

Table 2
Results with the first IMF dataset using baseline equations.

Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
All variables aggregated in total (MPI)	−0.002** (2.4)	−0.0016** (2.3)
Borrower related instruments (MPIB)	−0.0023** (2.3)	0.0018 (1.5)
Instruments aimed at financial institutions' assets or liabilities (MPIF)	−0.0013 (0.9)	−0.0031*** (3.8)
Loan-to-Value Ratio (LTV)	−0.0023* (1.7)	−0.0023 (1.3)
Debt-to-Income Ratio (DTI)	−0.004** (2.0)	0.0043* (1.8)
Limits on Foreign Currency Loans (FC)	0.007 (0.7)	−0.0036 (1.0)
Levy/Tax on Financial Institutions (TAX)	−0.0039* (1.7)	−0.0074*** (4.7)
Limits on Interbank Exposures (INTER)	0.0006 (0.2)	−0.0045*** (2.7)
Concentration Limits (CONC)	−0.004 (0.6)	0.0026 (0.6)
Subset of LTV measures used as a strict cap on new loans (LTV_CAP)	−0.0047** (2.4)	0.0024 (1.1)

Notes: For further information see Appendix Table A2. *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

Table 3
Results with second IMF database using baseline equations.

Variables	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
Change in sector specific capital buffer: Real estate credit.(SSCB_RES)	0.0003 (0.1)	−0.0037 (0.8)
Change in sector specific capital buffer: Other sectors (SSCB_OTH)	0.004 (0.2)	0.00167 (0.2)
Change in sector specific capital buffer: Consumer credit (SSCB_CONS)	0.0043 (0.2)	0.0016 (0.2)
Sum of changes in sector-specific capital buffers across the residential, consumer, and other sectors (SSCB)	0.0006 (0.1)	−0.0011 (0.4)
Change in reserve requirements on local currency-denominated accounts (RR_LOCAL)	−0.001 (0.4)	0.0073*** (3.1)
Country index by time t and country c, equal to 1 if the sum of the 9 instruments is >=1 and −1 if the sum of the instruments is < = −1, 0 otherwise. In this case, all individual instruments are adjusted to have maximum and minimum changes of 1 and −1 (PRUC2)	−0.0006 (0.4)	−0.002* (1.7)
Country index by time t and country c, equal to 1 if the sum of the 9 instruments is >=1 and −1 if the sum of the instruments is < = −1, 0 otherwise (PRUC)	−0.0006 (0.4)	−0.002* (1.7)
Change in the loan-to-value ratio cap. Limits on loans to residential borrowers (LTV_CAP)	0.0039* (1.8)	0.0053** (2.4)
Change in interbank exposure limit. Limits banks exposures to other banks (IBEX)	−0.00028 (0.1)	−0.0075*** (3.1)
Change in concentration limit. Limits banks' exposures to specific borrowers or sectors (CONCRAT)	−0.0047 (1.3)	0.0016 (0.4)
Change in capital requirements. Implementation of Basel capital agreements (CAP_REQ)	−0.0004 (0.3)	−0.008*** (4.2)
Cumulative change in sector specific capital buffer: Real estate credit (CUM_SSCB_RES)	0.0009 (0.4)	0.0001 (0.1)
Cumulative change in sector specific capital buffer: Other sectors (CUM_SSCB_OTH)	−0.001 (0.2)	0.0024 (0.9)
Cumulative change in sector specific capital buffer: Consumer credit (CUM_SSCB_CONS)	−0.001 (0.2)	0.0024 (0.9)
Cumulative change in the aggregate sector-specific capital buffer instrument (CUM_SSCB)	0.0003 (0.2)	0.0005 (0.6)
Cumulative change in reserve requirements on local currency-denominated accounts (CUM_RR_LOCAL)	0.0021 (1.3)	0.0048*** (3.7)
Sum of the cumulative version of the 9 instruments by country c and time t. In this case, all individual instruments are adjusted to have maximum and minimum changes of 1 and −1 (CUM_PRUC2)	−0.0007* (1.7)	−0.0013*** (3.5)
Sum of the cumulative version of the 9 instruments by country c and time t (CUM_PRUC)	−0.0007* (1.7)	−0.0013*** (3.5)
Cumulative change in the loan-to-value cap (CUM_LTV_CAP)	0.0011 (1.3)	0.0003 (0.3)
Cumulative change in interbank exposure limit (CUM_IBEX)	−0.0009 (0.7)	−0.0031*** (3.3)
Cumulative change in concentration limit (CUM_CONCRAT)	−0.0019 ** (2.1)	−0.0045*** (3.4)
Cumulative change in capital requirements (CUM_CAP_REQ)	−0.0015* (1.9)	−0.003*** (3.9)

Notes: For further information on variables see Appendix Table A3. *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

Kuttner and Shim (2016). Given the longer time period available, we also include results beginning in 1990 as well as the 2000 start-date used in Tables 2 and 3. It can be seen that debt service to income limits (DSTI) and to a lesser extent loan-to-value limits

Table 4
Results with BIS database using baseline equations.

Variables	Real house price growth (DLRPH)		Real household credit growth (DLRLIABS)	
Period	1990–2012	2000–2012	1990–2012	2000–2012
Reserve requirements (RR)	0.0012* (1.8)	0.0046*** (3.0)	−0.011* (1.8)	0.0016 (1.1)
Liquidity requirement (LIQ)	0.0061* (1.8)	0.0072 (1.5)	−0.0016 (0.4)	0.00013 (0.1)
Credit growth limit (CRG)	−0.00001 (0.1)	−0.0046 (0.8)	−0.00022 (0.1)	−0.012* (1.8)
Loan-to-value limit (LTV)	−0.0025* (1.9)	−00025* (1.6)	0.002 (1.3)	0.001 (0.7)
Debt service to income limit (DSTI)	−0.0047** (2.3)	−0.0041** (2.0)	−0.0004 (0.1)	0.0004 (0.2)
Risk weighting related to housing (RW)	−0.00075 (0.3)	0.0013 (0.5)	−0.0015 (0.5)	−0.00001 (0.1)
Provisioning related to housing (PROV)	−0.00046 (0.1)	−0.0024 (0.6)	−0.0009 (0.2)	−0.0038 (1.0)
Exposure limit related to housing (EXPO)				
Housing related tax (TAX)	−0.0008 (0.9)	−0.0004 (0.4)	−0.0019** (2.1)	−0.0009 (1.0)
Sum of RR+LIQ+CRG (GENERAL CREDIT)	0.0012* (1.9)	0.004*** (2.9)	−0.0011* (1.8)	0.0008 (0.6)

Notes: For further information see Appendix Table A4. *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold. The variables are taken as the sum of the first four lags of each instrument.

Table 5
Cumulative levels effects of sustained typical macroprudential policy interventions (first IMF dataset using baseline equations).

Variable	Real house prices			Real household credit		
Effect over	Impact	8 quarters	Long run	Impact	8 quarters	Long run
All variables aggregated in total (MPI)	−0.2%	−2.2%	−10.0%	−0.2%	−1.1%	−21.4%
Borrower related instruments (MPIB)	−0.2%	−2.2%	−11.6%			
Instruments aimed at financial institutions' assets or liabilities (MPIF)				−0.3%	−2.3%	−16.7%
Loan-to-Value Ratio (LTV)	−0.2%	−2.2%	−12.1%			
Debt-to-Income Ratio (DTI)	−0.4%	−3.4%	−20.4%	0.4%	2.9%	−1.1%
Limits on Foreign Currency Loans (FC)						
Levy/Tax on Financial Institutions (TAX)	−0.4%	−4.6%	−19.8%	−0.7%	−5.6%	−56.2%
Limits on Interbank Exposures (INTER)				−0.5%	−3.3%	−25.8%
Concentration Limits (CONC)						
Subset of LTV measures used as a strict cap on new loans (LTV_CAP)	−0.5%	−4.5%	−23.5%			

Notes: The calculations for TAX and DTI, where the macroprudential variables are significant in both equations, allow for interactive effects of the variables in each equation following the intervention (i.e. we allow for an impact of policy on house prices both directly and via that on household credit and vice versa).

(LTV) are effective in limiting growth in house prices and housing-related tax, reserve requirements and the general credit variable in limiting household credit growth, albeit not consistently across estimation periods. There are wrong signs for reserve requirements and general credit in house prices, as well as liquidity in the longer period.

One question that may be asked, notably by practitioners and policymakers, in the light of our results is the economic impact of the macroprudential policies. What do the equations show regarding the actual effect of introducing and sustaining the different policies over time? Is there a larger long run than short run effect? To address this issue we show below a "ready-reckoner" table showing the cumulative estimated effect on levels of real house prices and real household credit, of the policies shown in Table 2 as having a significant impact on the dependent variable. The effects (of raising the macroprudential variable from zero to one) are then fed through the lag structure to show not only the impact effect as shown by the sign and size of the significant coefficient but also the effects after 8 quarters and if the policy is sustained permanently. We include interactions between equations in the cases of the debt-to-income, tax policies and the summary variable MPI since they are significant in both equations and as shown in Table 1, there are lagged differences of household credit in the house price equation and a lagged level of house prices in the household credit equation.

The ready reckoner table highlights the difference with the existing literature in that the latter, being generally specified in first difference, only allows for a short run response. Hence the long run responses are direct additions to the literature which are available by using cointegration and show more realism in terms of the responses. They are quite different from the estimated short run responses. These outcomes are new, we simply could not know what these long run responses to macroprudential policy are using the existing literature. There are also limitations; in effect, the ready-reckoner gives helpful further information within the confines of the data available for all of the existing literature, which does not include numerical as opposed to categorical values for the macroprudential policies (i.e. they mostly show simply whether the policy is applied). We are showing the effectiveness of tools as applied in practice across the countries concerned, given the typical intervention undertaken, both in the short and long term and including in some cases interactions between household credit and house prices. We noted above the difficulties faced by those devising the datasets which led them to use a categorical approach, such as heterogeneity of policies and difficulties of judging whether a given policy is binding. Nonetheless, progress in this area would be helpful.

As shown in Table 5, the impact effect reflects directly the size of the coefficient since the dependent variable is in logs and we are raising the macroprudential variable from zero to one (so for example a coefficient of −0.004 gives rise to a percentage change of −0.4%). The effect of the policy builds gradually, but is nonetheless already sizeable in a number of cases after 8 quarters. For example, a tax on financial institutions reduces house prices by 4.6% and household credit by 5.6%, allowing for inflation. The subset of LTV measures used as a strict cap on new loans reduce real house prices by 4.5% over the same period, while debt-to-income limits reduce real house prices by 3.4%. Meanwhile the long run effects are quite sizeable, but owing to the lag structure this requires a prolonged period to be effective (for example after 10 years, the effect of debt-to-income limits on house prices is only 70% of the long run), and hence the shorter period may be more relevant for policy purposes. The interaction effects for debt-to-income, tax and the summary variable MPI lead to rather different results from a single-equation evaluation which ignores the cross effects.[12] Similar "ready reckoners" could easily be calculated for other results in the paper. Note in interpreting the table that whereas the individual variables are simply 0–1 variables, the summary variables MPI, MPIB and MPIF can rise above 1 if multiple policies are introduced.

Our interim conclusion is that macroprudential tools remain a significant determinant of house prices and household credit growth in OECD countries even when using an error correction framework and including a detailed set of regression variables. A number of macroprudential tools are shown as effective, notably loan-to-value limits, debt-to-income limits and taxes on financial institutions for house prices and taxes on financial institutions, interbank exposure limits and capital requirements for household credit growth.

4. Variants to test for robustness within the cointegration framework

To validate our results, and underpin their usefulness for policymakers, it is essential to test for robustness in various ways. We undertake four main tests, each using a cointegration framework, using in each case the first IMF dataset (Appendix Table A2) as a testbed.

First, we estimate a panel vector-error-correction model (VECM) including both house prices and household credit, which can overcome the difficulty of reduced form estimation of capturing

[12] For real house prices, this enhances the short run negative effect of the policy in the case of tax and MPI and reduces it in the case of debt-to-income compared with a single equation evaluation, although the long run effect is unchanged (since credit enters as a difference it does not affect the long run). For real credit, the tax policy and MPI again show an enhanced short run negative effect but also a greater long run decline since house prices enter as a level. For debt-to-income, where the sign of the macroprudential policy in the single equation is positive, the negative effect on house prices mean the positive effect is less after 8 quarters than it would be as a single equation, and the effect becomes mildly negative in the long run as the effect arising from house prices exceeds the direct effect on credit.

Table 6
Panel vector error correction model (2000q1-2015q4).

Cointegrating Equation:				
LRPH(-1)	1.000000			
LRPDI(-1)	0.0327 (0.6)			
LRR(-1)	0.0878*** (3.6)			
LRLIABS(-1)	−0.0431 (0.8)			
Error Correction equations:	DLRPH	DLRPDI	DLRR	DLRLIABS
Cointegrating residual	−0.0141*** (5.7)	−0.00274 (1.2)	0.0634* (1.6)	0.00461** (2.1)
DLRPH(-1)	0.329*** (11.2)	0.0968*** (3.7)	−0.0447 (0.1)	0.0777*** (3.0)
DLRPDI(-1)	−0.039 (1.1)	−0.0388 (1.3)	−0.488 (0.9)	−0.0177 (0.6)
DLRR(-1)	−0.00106 (0.6)	−0.0037** (2.2)	0.283*** (9.5)	−0.000129 (0.1)
DLRLIABS(-1)	0.108*** (3.5)	0.0231 (0.8)	0.341 (0.7)	0.388*** (14.1)
C	0.00439*** (6.0)	0.00421*** (6.4)	−0.0561*** (4.8)	0.008*** (12.3)
CRISES	−0.0108*** (8.4)	−0.00456*** (4.0)	0.0827*** (4.0)	−0.00737*** (6.4)
R^2	0.329	0.0665	0.124	0.297
SE	0.0161	0.0144	0.255	0.0142
F-statistic	89.6	13.03	26.0	77.2
Akaike AIC	−5.41	−5.64	0.114	−5.66
Observations	1104	1104	1104	1104
Countries	18	18	18	18
Determinant residual covariance (Dof adjusted)	6.16E-13			
Determinant residual covariance	6.00E-13			
Akaike information criterion	−16.73211			

Note: *T*-stats are reported in parentheses. For variable definitions see footnotes to Table 1. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold. Dof denotes degrees of freedom.

Table 7
Results with a panel VECM, First IMF database.

Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
All variables aggregated in total (MPI)	−0.00076* (1.8)	−0.00038 (1.1)
Borrower related instruments (MPIB)	−0.0032*** (2.6)	−0.0001 (0.1)
Instruments aimed at financial institutions' assets or liabilities (MPIF)	−0.0005 (1.0)	−0.0005 (1.3)
Loan-to-Value Ratio (LTV)	−0.0034*** (2.7)	−0.0006 (0.6)
Debt-to-Income Ratio (DTI)	−0.0068** (2.2)	−0.0024 (0.9)
Limits on Foreign Currency Loans (FC)	0.0058 (1.5)	−0.0078** (2.3)
Levy/Tax on Financial Institutions (TAX)	−0.0002 (0.1)	−0.0055*** (4.0)
Limits on Interbank Exposures (INTER)	0.0003 (0.2)	−0.0007 (0.7)
Concentration Limits (CONC)	−0.0011 (1.0)	0.0005 (0.5)
Subset of LTV measures used as a strict cap on new loans (LTV_CAP)	−0.0039** (2.3)	0.0007 (0.5)

Notes: *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

interaction of policy, real and financial sectors. Second, we simply lag the macroprudential variables to reduce the risk of reverse causality. Third, we address potential endogeneity in the error correction specification by use of fully-modified OLS (FMOLS) in the long run and lagged dynamics and macroprudential variables in the short run. And finally, we undertake extensive tests using seemingly unrelated regressions (SUR), given in particular the fact the Kao test for cointegration is only passed at the 90% level for house prices. Apart from the lag, all of these are new to the literature on macroprudential instruments and hence warrant close consideration in and of themselves for research and policy purposes.

Accordingly, we first estimated a **simple panel vector error correction model** (VECM) with endogenous variables being log real house prices, log real household credit, log RPDI and long real rates, with one lag. Exogenous variables are dummies for crises and the macroprudential variables from the IMF database, the latter introduced one at a time while the crisis effects are present for each estimate. The Johansen trace tests showed that there is one cointegrating vector present and this is shown in Table 6 below. We contend that this approach can overcome the difficulty of reduced form estimation of capturing interaction of policy, real and financial sectors. To our knowledge, such an approach has not been used in the literature on macroprudential policy to date. Note that the cointegrating residuals are most significant for house prices and household credit, and show quite a slow adjustment to equilibrium, which is turn is driven largely by the relationship between house prices and real interest rates. The short run effects show a large number of significant variables in the VECM, crises having a particular impact as is also the case elsewhere.

As shown in Table 7 below, there are a number of significant effects for house prices comparable to Table 2, including all variables aggregated (MPI) and borrower related instruments (MPIB), as well as loan-to-value ratios (LTV), the subset of LTV measures used as a strict cap on new loans (LTV_CAP) and debt-to-income ratios (DTI). The levy/tax on financial institutions (TAX) however is not significant. For household credit, the positive results are sparser as compared the baseline in Table 2, but include TAX as a significant restraint on household credit growth, given the other included variables, as well as limits on foreign currency loans (FC) that was not significant in Table 2.

The second variant takes **the first lag of the macroprudential dummies** in the context of the baseline equation, to allow for possible reverse causality, as for example did Akinci and Olmstead-Rumsey (2015).[13] Results for macroprudential tools as shown in Table 8 are broadly similar to those for the level in Table 2, although loan-to-value ratios (LTV) and levy/tax on financial institutions (TAX) are not now significant for house prices (the subset of LTV

[13] Results of estimation are not shown but are available from the authors on request.

Table 8
Results with first lag of macroprudential variables, baseline equations, First IMF database.

Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
All variables aggregated in total (MPI) (t-1)	−0.0017** (2.0)	−0.0013* (1.9)
Borrower related instruments (MPIB) (t-1)	−0.002** (2.0)	0.002* (1.7)
Instruments aimed at financial institutions' assets or liabilities (MPIF) (t-1)	−0.001 (0.7)	−0.0028*** (3.4)
Loan-to-Value Ratio (LTV) (t-1)	−0.0018 (1.3)	−0.0019 (1.1)
Debt-to-Income Ratio (DTI) (t-1)	−0.0038* (1.8)	0.005** (2.0)
Limits on Foreign Currency Loans (FC) (t-1)	0.005 (0.6)	−0.0042 (1.3)
Levy/Tax on Financial Institutions (TAX) (t-1)	−0.002 (0.9)	−0.0063*** (3.9)
Limits on Interbank Exposures (INTER) (t-1)	0.0001 (0.1)	−0.0044*** (2.6)
Concentration Limits (CONC) (t-1)	−0.007 (1.1)	0.003 (0.8)
Subset of LTV measures used as a strict cap on new loans (LTV_CAP) (t-1)	−0.0039** (2.0)	0.0029 (1.3)

Notes: Estimation is by EGLS (estimated generalised least squares). *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

measures used as a strict cap on new loans (LTV_CAP) remains significant).

The third variant is to address a potential difficulty with the panel error correction model that we use, which is potential endogeneity of the regressors. We considered an alternative cointegration approach which retains the single-equation approach capturing both short and long run effects, but corrects for the potential endogeneity for example between house prices, household credit and real personal disposable income. The correction is twofold, firstly in a cointegrating regression we employ the **pooled fully-modified ordinary least squares (FMOLS) approach**. This approach, as noted inter alia by Afonso and Jalles (2012) and Cho and Ramirez (2016), corrects for endogeneity bias as well as serial correlation and allows for normal inference, providing unbiased estimates of the cointegrating coefficients that can then be used as long run elasticities in the dynamic equation. Then, secondly, **in the dynamic equation we included thelagged FMOLS residual and also lagged all of the dynamic terms** and the macroprudential policy tools in order to further reduce issues of endogeneity. This approach has not to our knowledge been used in the literature on macroprudential data to date.

Accordingly, we re-estimated the panel error correction model with these corrections for endogeneity, starting from the specification shown in Table 1. As shown in Table 9 below, the cointegrating regressions are similar to the long run of the EGLS estimates for the error correction models, except that the stock of housing and unemployment in the credit equation have different signs (we attribute this to the absence of fixed effects in the first stage regression). The lagged cointegrating residual (error correction term) is highly significant in the dynamic equations. In the dynamic equation, similar effects are present when terms are lagged, except that the short term income effect and short term interest rate effect no longer appear in house prices (they are however, present in the long run). The credit equation has the dynamic term in income at the second lag.

As shown in Table 10, we have again many of the same significant results for the lagged macroprudential variables in these equations as in Table 2, with all variables aggregated (MPI) and borrower related instruments (MPIB) significant for both house prices and household credit while the house price equation also shows a significant effect for loan-to-value ratios (LTV), debt-to-income ratios (DTI) and the subset of LTV measures used as a strict cap on new loans (LTV_CAP), while the household credit equation has significant effects from LTV, levy/tax on financial institutions (TAX) and LTV_CAP.

Table 9
Baseline equations with FMOLS and lagged dynamics (2000Q1-2015Q4).

Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
FMOLS (pooled) Cointegrating Equation	Dependent variable: LRPH (Constant included)	Dependent variable: LRLIABS (Constant included)
LRPH		0.712 (11.2)***
LRPDI	1.0 (8.9)***	
LRR	−0.031 (5.0)***	
LRKH	−0.23 (2.3)**	1.33 (13.1)***
U		0.021 (6.0)***
R^2	0.674	0.999
SE	0.115	0.124
Observations	1109	1133
Countries	18	18
Error correction Equation	Dependent variable: DLRPH	Dependent variable: DLRLIABS
Cointegrating residual	−0.0175 (5.3)***	−0.0168 (4.6)***
C	0.0011 (1.8)*	0.008 (13.9)***
DLRPDI(t-2)		0.09 (3.2)***
DLRR (t-1)		
DLRPH(t-1)	0.45 (16.6)***	
DLRLIABS (t-1)		0.38 (13.5)***
DLRLIABS (t-2)	0.094 (3.7)***	
DLRLIABS (t-3)	0.124 (4.9)***	
DU(t-1)	−0.0022 (2.0)*	
DLRGW(t-1)		−0.03 (2.2)**
CRISES(t-1)	−0.0049 (4.5)***	−0.006 (6.2)***
R^2	0.517	0.417
SE	0.015	0.014
Observations	1092	1071
Countries	18	18

Notes: Dynamic equations include country fixed effects and cross section weights. For variable definitions see Table 1. *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

Table 10
Results with equations using FMOLS and lagged dynamics, First IMF database.

Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
All variables aggregated in total (MPI) (t-1)	−0.0019 *** (2.7)	−0.0014 ** (2.3)
Borrower related instruments (MPIB) (t-1)	−0.0026 *** (3.5)	−0.0018 * (1.7)
Instruments aimed at financial institutions' assets or liabilities (MPIF) (t-1)	−0.0003 (0.2)	−0.0014 (1.6)
Loan-to-Value Ratio (LTV) (t-1)	−0.0023 * (1.9)	−0.004 ** (2.5)
Debt-to-Income Ratio (DTI) (t-1)	−0.0055 *** (3.6)	−0.0034 (1.6)
Limits on Foreign Currency Loans (FC) (t-1)	0.0048 (0.5)	−0.005 (1.4)
Levy/Tax on Financial Institutions (TAX) (t-1)	−0.002 (0.9)	−0.0034 ** (2.1)
Limits on Interbank Exposures (INTER) (t-1)	0.002 (0.8)	−0.001 (0.6)
Concentration Limits (CONC) (t-1)	−0.0043 (0.7)	0.0016 (0.4)
Subset of LTV measures used as a strict cap on new loans (LTV_CAP) (t-1)	−0.0046 *** (3.1)	−0.0033 * (1.7)

Notes: *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

The final variant is **Seemingly Unrelated Regressions**. As shown in Table 1, the Kao panel cointegration test of the long-run components of the regression specification (the variables in levels) delivers a strong rejection of the null of no cointegration for real household credit growth and a weak rejection for real house price growth. To address the concern that the long-run components may fail to cointegrate, we adopt a different strategy and estimate the long-run components on a country-by-country basis rather than in a panel framework, thus allowing the coefficients of the long-run regressions to be different across countries. The main focus is on house price growth given the panel cointegration result, we include results for household credit growth for completeness.

The long-run relationships were estimated as shown in Appendix Table A5, and there are indeed differences between countries. We take the residuals and combine them with other short-term dynamics to produce a set of country by country regressions in error correction form using a seemingly unrelated regression (SUR) estimation procedure (Appendix Tables A6 and A7). Again, the speed of adjustment as shown by the error correction coefficient differs between countries. Although the coefficients that result from the SUR estimates do not benefit from the panel dimension of the data, the variance-covariance of the estimates still make use of the panel dimension by allowing the possibility that the error terms of the different countries are correlated. We note that this approach has to our knowledge not been used in the literature on macroprudential policy to date.

The main advantage of this approach is that it tackles the concern of weak cointegration of the long-run components of the error correction equation for house prices. It also enables individual country effects of the tools to be estimated. The drawback is a loss of data. Our macroprudential dataset is composed of dummy variables and some of the countries in our sample have variables that take the same value for the whole sample. While this variable can be included within the context of a panel regression, it can no longer be used in a SUR procedure as it would produce a singular regressor matrix.

The set of regressions presented in Appendix Tables A5–A7 constitute our baseline specifications upon which we add, one at a time, each of the macroprudential variables from the first IMF dataset. We have excluded in each set of regressions all countries for which the macroprudential variable was constant, as it generates a singular matrix. In addition, we omit the results of the regressions for which the coefficient on the macroprudential variable is not significantly different from zero for any of the countries in the sample for either regression. Tables 11 and 12 report the estimates of the effects of each macroprudential variable on real house price growth and real household credit growth, respectively. In both Tables 11 and 12 we observe that whenever the coefficient is statistically different from zero, the effect goes, in most instances, in the expected direction: macroprudential variables reduce house price and household credit growth. However, a large number of estimates are not statistically different from zero; a phenomenon that may be product of the binary nature of the underlying data.

Table 13 provides a summary of results from the robustness section as compared to the baseline. The VECM, which has quite a limited set of variables, omits some of the main results. The lag variant and the FMOLS variant are similar to the level baseline results, while SUR highlights specific countries with significant results, namely Canada, Norway, the Netherlands, Sweden and Austria for house prices, and Finland, France, the Netherlands, Norway, Austria, Portugal for household credit growth, in all but one case with a negative sign. Overall, the robustness checks underpin the main results.

5. Comparing results with non-cointegration specifications

To assess the difference made to results by cointegration and a wider range of control variables, in the light of the arguments presented at the beginning of Section 3, we assessed how results would differ on our dataset with non-cointegrating specifications. First we compare the baseline panel error correction model (Tables 1 and 2) with a more simple specification that is typical of the literature; second, we compare the VECM results above with a simple VAR that omits cointegration. Since we use the same dataset, this is a more accurate comparison that comparing different studies with different datasets, country and time coverage.

Starting with the simpler specification, as in Akinci and Olmstead-Rumsey (2015), effectiveness of policies in curbing growth in bank credit and house prices is assessed using a dynamic panel data model where control variables besides a lagged dependent variable include real GDP growth, the change in nominal monetary policy rates (R3 M) and the VIX volatility measure based on US share prices. It does not, however, allow for the long run or cointegration, nor for the wider range of control variables that we employ. This specification has the advantage of enabling developing and emerging market countries that have relatively sparse macroeconomic data to be included in the regression. In contrast, our baseline specification (Table 1) could not readily cover a wider range of countries. As for Table 1, we use country fixed effects and cross section weights. The simpler specification for the same 18 countries is depicted in Table 14 below; as can be seen, the main impact arises from growth in GDP and the lagged dependent, although the volatility measure is also relevant for house price growth. Note this is not a direct comparison with Akinci and Olmstead-Rumsey (2015) since we are using EGLS for comparability with our baseline rather than GMM as in their work (although they note in footnote 13 of their paper that a specification similar to ours gave them similar results); also we are using a different credit measure and different datasets of macroprudential variables. Rather, comparing this simple specification with our own enables us to assess the impact of using a richer range of independent variables and dynamic specification in tests of macroprudential policies

Table 11
Real house price growth: impact of macroprudential variables, First IMF database, SUR equations.

Variable	Australia	Belgium	Canada	Denmark	Finland	France	Germany	Greece	Ireland	Italy
All variables aggregated (MPI)			−0.0026* (1.9)		−0.0101 (1.4)	0.0008 (0.2)				
Borrower related instruments (MPIB)			−0.0026* (2.0)							
Instruments aimed at financial Institutions' assets or liabilities (MPIF)					−0.0099 (1.4)	0.0002 (0.1)				
Loan-to-value ratios (LTV)			−0.0054** (2.0)		−0.0019 (0.4)					−0.0023 (0.9)
Levy/tax on financial Institutions (TAX)					−0.0089 (1.2)	0.0001 (0.0)				
Subset of LTV used as strict cap on new loans (LTV_CAP)			−0.0052* (1.9)							

Variable	Japan	Netherlands	Norway	Austria	Portugal	Sweden	Spain	US
All variables aggregated (MPI)		−0.0054** (2.0)	−0.0155*** (3.5)	0.0070 (1.5)	−0.0026 (0.9)	−0.0097* (1.7)		0.0083 (1.5)
Borrower related instruments (MPIB)		−0.0043 (1.1)				−0.0101 (1.7)		
Instruments aimed at financial Institutions' assets or liabilities (MPIF)		−0.0189*** (2.8)	−0.0156*** (3.5)	0.0080* (1.6)	−0.0028 (1.0)			0.0073 (1.3)
Loan-to-value ratios (LTV)		−0.0092 (1.2)				−0.0084 (1.4)		
Levy/tax on financial Institutions (TAX)		−0.0181*** (2.7)		0.0139 (1.4)	−0.0010 (0.2)			
Subset of LTV used as strict cap on new loans (LTV_CAP)		−0.0086 (1.1)				−0.0101 (1.7)		

Notes: Numbers in parentheses are *T*- stats. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * denotes significance at the 10 per cent threshold.

Table 12
Real household credit growth: impact of macroprudential variables, First IMF database, SUR equations.

Variable	Australia	Belgium	Canada	Denmark	Finland	France	Germany	Greece	Ireland	Italy
All variables aggregated (MPI)			0.0022 (1.6)		−0.0125** (2.6)	−0.0141** (2.4)	0.0005 (0.8)			
Borrower related instruments (MPIB)										
Instruments aimed at financial Institutions' assets or liabilities (MPIF)					−0.0122** (2.5)	−0.0138** (2.3)	0.0006 (1.0)			
Loan-to-value ratios (LTV)										
Levy/tax on financial Institutions (TAX)					−0.0135*** (2.6)	−0.0148** (2.3)	0.0004 (0.3)			
Subset of LTV used as strict cap on new loans (LTV_CAP)										

Variable	Japan	Netherlands	Norway	Austria	Portugal	Sweden	Spain	US
All variables aggregated (MPI)		−0.0049 (1.5)	−0.0043* (2.0)	−0.0031* (1.9)	−0.0056** (2.1)	−0.0031 (0.7)		−0.005 (1.2)
Borrower related instruments (MPIB)		−0.0026 (0.4)				−0.0047 (1.0)		
Instruments aimed at financial Institutions' assets or liabilities (MPIF)		−0.0096* (1.7)	−0.0044** (2.1)	−0.0031* (1.9)	−0.0053* (1.9)			−0.006 (1.4)
Loan-to-value ratios (LTV)		−0.0051 (0.4)				−0.0047 (1.0)		
Levy/tax on financial Institutions (TAX)		−0.0088 (1.4)		−0.0077** (2.3)				
Subset of LTV used as strict cap on new loans (LTV_CAP)		−0.0034 (0.3)				−0.0045 (1.0)		

Notes: Numbers in parentheses are *T*- stats. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * denotes significance at the 10 per cent threshold.

in OECD countries, as we do in Table 1 and robustness checks with cointegration detailed above.

From Table 15 it can be seen that with this specification the coefficients on a wide range of macroprudential tools are shown to be significant across these major OECD countries, including all variables aggregated (MPI) and borrower related instruments (MPIB) for both house price growth and household credit growth, and instruments aimed at financial institutions' assets or liabilities (MPIF) for household credit growth. Also, loan-to-value ratios (LTV), debt-to-income ratios (DTI), levy/tax on financial institutions (TAX) and the subset of LTV measures used as a strict cap on new loans (LTV_CAP) are significant for both. Limits on foreign currency loans (FC) and interbank lending limits (INTER) are significant for household credit growth also. Comparison with Table 2 (results also shown in Table 15) shows that there is generally a higher level of significance than for our own results, and also for household credit growth additional variables are suggested to be relevant such as LTV, LTV_CAP, FC and MPIB. We contend that this suggests the importance of using a specification such as ours in Table 1 in obtaining results. A simpler specification such as in Table 14 can result in false inference on the effectiveness of macroprudential tools due to omitted variables bias, they may show more significance for the

Table 13
Robustness check table for sign and significance macroprudential tools (first IMF database).

Specification	Baseline		VECM variant		Lag variant		FMOLS/ lagged dynamics variant		SUR variant	
Variables	PH	CR	PH	CR	PH	CR	PH	CR	PH	CR
All variables aggregated in total (MPI)	−**	−**	−*		−**	−*	−***	−**	CAN (−*) NLD (−**) NOR (−***) SWE (−*)	FIN (−**) FRA (−**) NOR (−*) AUT (−*) POR (−**)
Borrower related instruments (MPIB)	−**		−***		−**	+*	−***	−*	CAN (−*)	
Instruments aimed at financial institutions' assets or liabilities (MPIF)		−***				−***			NLD (−***)	FIN (−**) FRA (−**)
									NOR (−***) AUT (+*)	NLD (−*) NOR (−**) AUT (−*) POR (−**)
Loan-to-Value Ratio (LTV)	−*		−***				−*	−**	CAN (−**)	
Debt-to-Income Ratio (DTI)	−**	+*	−**		−*	+**	−***			
Limits on Foreign Currency Loans (FC)				−**						
Levy/Tax on Financial Institutions (TAX)	−*	−***		−***		−***		−**	NLD (−***)	FIN (−***) FRA (−**) AUT (−**)
Limits on Interbank Exposures (INTER)		−***				−***				
Concentration Limits (CONC)										
Subset of LTV measures used as a strict cap on new loans (LTV_CAP)	−**		−**		−**		−***	−*	CAN (−*)	

Notes: + denotes a positive relationship between the variables of interest, − denotes a negative relationship. Significance at the 1, 5 and 10 per cent thresholds are denoted by ***,** and * respectively. PH: Real house prices, CR: Real household credit, AUT: Austria, CAN: Canada, FRA: France, FIN: Finland, NLD: Netherlands, NOR: Norway, POR: Portugal, SWE: Sweden.

Table 14
Simpler specification typical in the literature (2000Q1-2015Q4).

Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
C	0.008*** (2.7)	0. 006** (2.1)
DLGDP(-1)	0.121*** (2.7)	0.108** (2.2)
DLGDP(-2)	0.045 (1.0)	0.139*** (2.9)
LVIX	−0.0024** (2.5)	−0.0005 (0.5)
DR3 M (-1)	−0.0006 (0.6)	−0.0015 (1.5)
DEPENDENT (-1)	0.562*** (22.4)	0.392*** (14.6)
R^2	0.454	0.353
SE	0.016	0.015
Observations	1145	1135
Countries	18	18

Notes: DLGDP is the first difference of the log of real GDP, LVIX is the log of the VIX index, DR3M is the difference of the three month interbank rate. Estimation is by EGLS (estimated generalised least squares). *T*-stats are reported in parentheses. Equations include country fixed effects and cross section weights.

Table 15
Results comparing the baseline with simpler specification: First IMF dataset.

Specification	Baseline (Table 2)		Simpler specification	
Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
All variables aggregated in total (MPI)	−0.002** (2.4)	−0.0016** (2.3)	−0.0019*** (2.9)	−0.0023*** (3.7)
Borrower related instruments (MPIB)	−0.0023** (2.3)	0.0018 (1.5)	−0.002*** (2.9)	−0.002** (2.1)
Instruments aimed at financial institutions' assets or liabilities (MPIF)	−0.0013 (0.9)	−0.0031*** (3.8)	−0.0018 (1.5)	−0.0027*** (3.2)
Loan-to-Value Ratio (LTV)	−0.0023* (1.7)	−0.0023 (1.3)	−0.0049*** (4.2)	−0.0058*** (3.9)
Debt-to-Income Ratio (DTI)	−0.004** (2.0)	0.0043* (1.8)	−0.0037** (2.3)	−0.0037* (1.9)
Limits on Foreign Currency Loans (FC)	0.007 (0.7)	−0.0036 (1.0)	0.0022 (0.2)	−0.0063* (1.8)
Levy/Tax on Financial Institutions (TAX)	−0.0039* (1.7)	−0.0074*** (4.7)	−0.0042** (2.2)	−0.0048*** (3.2)
Limits on Interbank Exposures (INTER)	0.0006 (0.2)	−0.0045*** (2.7)	−0.0004 (0.2)	−0.0035** (2.0)
Concentration Limits (CONC)	−0.004 (0.6)	0.0026 (0.6)	−0.0044 (0.7)	−0.0034 (0.7)
Subset of LTV measures used as a strict cap on new loans (LTV_CAP)	−0.0047** (2.4)	0.0024 (1.1)	−0.0039*** (2.7)	−0.004** (2.2)

Notes: *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

macroprudential tools, and more tools being effective, than is warranted. We note also that as is typical of the existing literature, there is no long run effect in the specification, since it is in first difference form. Hence the long run effects shown in Table 5 could not be calculated.

Our second comparison is between the VECM results shown above (Tables 6–7) and a simple Vector-Autoregression (VAR). The latter simply omits the long run cointegrating relationship on the VECM and is hence set purely in differences with the same variables and lag specification (for reasons of space, we omit details of the VAR results). The comparison with the VECM provides a test of the effect of the exclusion of long run effects feeding through the error correction term on the outcomes for the tools, with other included variables being the same. In this case (as shown in Table 16) here are again more significant variables for the VAR than the VECM in the case of credit with MPIF as well as FC and TAX being significant.

Table 16
Results comparing VECM with a VAR: First IMF database.

Specification	VECM (Table 7)		VAR	
Variable	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)	Real house price growth (DLRPH)	Real household credit growth (DLRLIABS)
All variables aggregated in total (MPI)	−0.00076* (1.8)	−0.00038 (1.1)	0.00003 (0.1)	−0.0005 (1.4)
Borrower related instruments (MPIB)	−0.0032*** (2.6)	−0.0001 (0.1)	−0.002* (1.7)	−0.0002 (0.2)
Instruments aimed at financial institutions' assets or liabilities (MPIF)	−0.0005 (1.0)	−0.0005 (1.3)	0.00032 (0.7)	−0.0006* (1.6)
Loan-to-Value Ratio (LTV)	−0.0034*** (2.7)	−0.0006 (0.6)	−0.0016 (1.2)	−0.0009 (0.9)
Debt-to-Income Ratio (DTI)	−0.0068** (2.2)	−0.0024 (0.9)	−0.007** (2.2)	−0.0024 (0.9)
Limits on Foreign Currency Loans (FC)	0.0058 (1.5)	−0.0078** (2.3)	0.0046 (1.1)	−0.0075** (2.2)
Levy/Tax on Financial Institutions (TAX)	−0.0002 (0.1)	−0.0055*** (4.0)	−0.0002 (0.1)	−0.0056*** (4.0)
Limits on Interbank Exposures (INTER)	0.0003 (0.2)	−0.0007 (0.7)	0.007 (0.6)	−0.0008 (0.8)
Concentration Limits (CONC)	−0.0011 (1.0)	0.0005 (0.5)	0.0014 (1.3)	−0.00004 (0.1)
Subset of LTV measures used as a strict cap on new loans (LTV_CAP)	−0.0039** (2.3)	0.0007 (0.5)	−0.0018 (1.0)	0.00026 (0.2)

Notes: *T*-stats are reported in parentheses. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * at the 10 per cent threshold.

Table 17
Comparison table for sign and significance of macroprudential tools (first IMF database).

Specification	Baseline		Simple variant		VECM variant		VAR Variant	
Variable	PH	CR	PH	CR	PH	CR	PH	CR
All variables aggregated in total (MPI)	−**	−**	−***	−***	−*			
Borrower related instruments (MPIB)	−**		−***	−**	−***		−*	
Instruments aimed at financial institutions' assets or liabilities (MPIF)		−***		−***				−*
Loan-to-Value Ratio (LTV)	−*		−***	−***	−***			
Debt-to-Income Ratio (DTI)	−**	+*	−**	−*	−**		−**	
Limits on Foreign Currency Loans (FC)				−*		−**		−**
Levy/Tax on Financial Institutions (TAX)	−*	−***	−**	−***		−***		−***
Limits on Interbank Exposures (INTER)		−***		−**				
Concentration Limits (CONC)								
Subset of LTV measures used as a strict cap on new loans (LTV_CAP)	−**		−***	−**	−**			

Notes: + denotes a positive relationship between the variables of interest, − denotes a negative relationship. Significance at the 1, 5 and 10 per cent thresholds are denoted by ***,** and * respectively. PH: Real house prices, CR: Real household credit.

For house prices we have only MPIB and DTI significant in the VAR with MPI, LTV and LTV_CAP insignificant, which are significant in the VECM. However, since these variables are significant in virtually all the other estimates (Table 13), this suggests again a form of bias when long run effects are omitted.

Table 17 provides a summary of results from the comparison section as compared to the baseline. As can be seen, the baseline estimates (with cointegration and a wider range of appropriate independent variables) show less favourable results for macroprudential policies than the simple estimates more typical of the literature, which may exaggerate the effects. Omission of cointegration in a VAR gives more nuanced results but it can again be suggested that such omission may induce bias.

6. Conclusions

We have suggested that extant empirical evidence on macroprudential tools is often unsatisfactory in the sense of omission of effects relating to long run cointegration as well as omitting important control variables, and in some cases omitting a crisis dummy, leading to a risk of bias in results for the impact of macroprudential policies. Following this suggestion, we have presented results for the significance of macroprudential tools in equations for house prices and household credit with cointegration estimation on a dataset of up to 19 OECD countries, using data periods from three available global databases (from the IMF and the BIS). We have included extensive robustness tests within a cointegration framework which underpin the main results, including tests that have not to our knowledge been undertaken in this literature to date (Vector-Error-Correction (VECM), Fully-Modified OLS (FMOLS) and Seemingly-Unrelated (SUR) estimation). We also provide a comparison of results from cointegration with non-cointegrating specifications, where there are major differences in significance with the cointegration approach, in line with the underlying hypothesis that existing work on effectiveness of macroprudential policy may be vulnerable to bias.

We contend that our results provide a more rigorous check on the effectiveness of macroprudential tools than the existing literature and can accordingly provide a fresh baseline for work in this area. Nevertheless, the results suggest that even in a cointegrating framework, some policies are shown as more effective than others in the up to 19 countries we study, which is information of key relevance to regulators. These include, in particular, taxes on financial institutions, general capital requirements, strict loan-to-value ratios and debt-to-income ratio limits. Limits on foreign currency lending, limits on interbank exposures and concentration limits are also shown to be effective in some estimates. We have shown the estimated cumulative impacts over time on house prices and household credit of significant macroprudential tools, a useful "ready reckoner" for policy makers that shows both typical short and long term effects, within the limitations of the categorical variables used in macroprudential datasets. We have also shown which policies are more effective for house prices vis a vis household credit, thus allowing consideration of appropriate targeting in the light of macroeconomic and macroprudential conditions. For example, policies such as limits on debt-to-income ratios appear relatively more effective for house prices, while tools such as limits on interbank exposures impact comparatively more on household credit.

We suggest that the way forward for reduced form modelling focusing on OECD countries is the panel error correction approach using cointegration such as we include here. Such an approach could have been employed in much of the existing literature even with the limited data available on global samples, given variables such as GDP, house prices and household credit are generally non-stationary and likely to cointegrate. Lags for the macroprudential variables may be considered in line with the estimates in Table 8 and potential issues of reverse causality. We suggest the VECM, FMOLS and SUR approaches are also worthy of further consideration for research and policy purposes; given that VECM addresses the issue of interaction of policy, real and financial sectors; FMOLS corrects for potential endogeneity; and SUR may be of considerable assistance to regulators for appropriately assessing the impact of policies in their own country while allowing for cross-country correlations.

Meanwhile, we cannot exclude that the use of these policies being quite limited in OECD countries and also affected by the financial crisis, further significant effects could emerge in the future, and it will be important for the databases and empirical studies to be regularly updated to allow for this possibility, employing a cointegration approach. Furthermore, implementation of macroprudential policies in national and global macroeconomic models would further underpin macroprudential policy and its relation to monetary and fiscal policy. Our estimates can be used to calibrate such effects in macroeconomic models, which in the future will be important tools for forecasting and policy analysis, not just for monetary and fiscal policymakers, but also for macroprudential policymakers and they consider impacts of their own policies as well as the appropriate overall policy mix (see Carreras et al. (2018), for example).

Going beyond the focus of the current work on housing and credit, avenues for further research could include an assessment of the impact of macroprudential tools on a wider range of variables using cointegration approaches such as construction activity and commercial property prices and an inclusion of additional control variables for financial structure and the nature of financial supervision. Equally, more work could be undertaken on the impact of disintermediation on macroprudential policies and its determinants (our results here show the average effect of policies including such disintermediation). Finally, for regulators, it would also be useful to have more precisely defined datasets for macroprudential tools in numerical rather than categorical form, with for example time series of actual percentage loan-to-value limits, which would, inter alia, enable more precise sets of ready reckoner tables to be constructed. However, we have also highlighted the difficulties in such an exercise in references from the existing literature.

Funding

This work was supported by the European Commission under the FIRSTRUN project of Horizon-2020, Project id: 649261, website www.firstrun.eu.

Acknowledgements

We thank an anonymous referee, an Associate Editor, Iftekhar Hasan (the Editor), Mauro Costantini, Monique Ebell, Simon Kirby, Dennison Noel and participants in seminars at NIESR, CASE Warsaw and Brunel University as well as Eugenio Cerutti for help, advice and suggestions.

Appendix A.

Table A1
Recent empirical studies using reduced form regressions.

Study	Dependent	MP variables	Method	Date of sample	Key result
Aiyar et al. (2014)	Individual UK banks	Bank-specific higher capital adequacy requirements	Micro panel regression	1998–2007	Capital requirements dampened lending by individual banks but were ineffective due to increased lending from foreign bank branches.
Akinci and Olmstead-Rumsey (2015)	Bank credit, housing credit and house price growth	Index of domestic MP policies	Dynamic GMM panel, controls include VIX, GDP growth, policy rate	57 countries, 2000-13	MP are effective in curbing asset prices and credit growth, especially targeted policies on housing, and capital inflow limits in EMEs
Bruno et al. (2017)	Banking and bond inflows, bank credit, total credit	Macroprudential measures and capital flow measures	OLS and Dynamic GMM panel	12 Asia-Pacific economies, 2004-13	Capital flow policies slow inflows, MP policies most effective alongside monetary policy
Buchholz (2015)	Domestic credit growth	Leverage ratio	Difference-in-difference	69 economies, 2002-14	Leverage cap prior to the crisis entails more rapid credit growth after it

Table A1 (*Continued*)

Study	Dependent	MP variables	Method	Date of sample	Key result
Cerutti et al. (2015, 2017)	Real credit and house price growth	Indices of MP policy overall, for borrowers and financial firms and for specific instruments	Dynamic GMM panel, controls include GDP growth, policy rate, banking crises and country fixed effects	2000–2013, 119 countries	Policies are effective but especially in the upturn; policies are weaker in more open and financially deeper economies
Claessens et al. (2013)	Individual global banks' balance sheets	Policies aimed at borrowers (DTI, LTV), banks' assets or liabilities (CG, FC, RR,), policies that encourage counter-cyclical buffers (CTC, DP) and profits distribution restrictions (PRD)) and other (miscellaneous) policies	Panel GMM	2000–2010, 48 countries, 25 advanced and 23 EMEs, with 2820 banks and 18000 observations.	Policies aimed at borrowers are effective in (indirectly) reducing the build-up of banking system vulnerabilities. Measures aimed at banks' assets and liabilities are very effective, but counter-cyclical buffers are not. The category "other" is also very effective
Dell'Ariccia et al. (2012)	Credit booms and busts (dummy)	Macroprudential controls	Cross section	175 observations	Reduction in probability of a bad boom and a bust
Gambacorta and Murcia (2017)	Credit growth	Various macroprudential tools.	Meta-analysis of panel regressions using individual loan data from credit registries	Country by country results for 5 Latin American countries and 3 non-Latin countries	Macroprudential policy is effective in stabilising credit cycles and macroprudential tools have a greater effect on credit growth when reinforced by monetary policy.
Kuttner and Shim (2016)	Growth in house prices and housing credit	DTI, LTV, TAX	Panel regression, controls are interest rate and growth in GNI per capita	1980 or later-2012, 57 countries unbalanced panel	DTI and TAX affect housing credit but only TAX affects house price growth
Lim et al. (2011)	Private sector credit and leverage	RR, DP, LTV, DTI, CCG, FC	Panel GMM regression	2000–2010, 49 countries	MP Policies can affect credit growth and leverage, especially LTV, DTI, CCG, RR, DP
Vandenbussche et al. (2015)	House price growth	CR, RR	Panel regression, error correction framework	16 CEE countries, 2002-11	CR and RR help slow house prices
Wong et al. (2011)	Mortgage delinquency ratios	LTV	Panel; controls include property prices, GDP growth, mortgage debt/GDP and interest rates.	1991–2010, 13 countries unbalanced panel	Economies with LTV policy are estimated to have a lower sensitivity of mortgage delinquency ratios to property prices than those without LTV policy
Zhang and Zoli (2014)	House prices, credit, equity prices and bank leverage	Index of MP and CFM measures	Event study, cross country macro panel, bank level micro panel	46 economies, 2000–2013	LTV, TAX and FC are most effective MP tools

Notes: abbreviations used in the table; CCG – ceilings on credit growth, CEE – Central and Eastern Europe, CFM – capital flow measures, CG – limits on domestic currency loans, CR – capital ratio limits, CTC – countercyclical buffers, DP – time varying/dynamic loan-loss provisioning, DTI – debt-to-income limits, EMEs – Emerging Market Economies, FC – limits on foreign currency loans, GMM – Generalised Method of Moments, LTV – loan-to-value limits, MP – macroprudential, OLS – Ordinary Least Squares, PRD – profit distribution restrictions, RR – reserve requirements, TAX – levy/tax on financial institutions, VIX – a measure of the implied volatility of S&P 500 index options.

Table A2
First (2015) IMF dataset.

Variable	Description
CTC	General Countercyclical Capital Buffer/Requirement
LEV	Leverage Ratio for banks
DP	Time-Varying/Dynamic Loan-Loss Provisioning
LTV	Loan-to-Value Ratio
DTI	Debt-to-Income Ratio
CG	Limits on Domestic Currency Loans
FC	Limits on Foreign Currency Loans
RR	Reserve Requirement Ratios
TAX	Levy/Tax on Financial Institutions
SIFI	Capital Surcharges on SIFIs
INTER	Limits on Interbank Exposures
CONC	Concentration Limits
LTV_CAP	Subset of LTV measures used as a strict cap on new loans
RR_REV	Subset of RR measures that impose a specific wedge on foreign currency deposits or are adjusted countercyclically
MPI	All variables aggregated in total and then in two subgroups:
MPIB	Borrower related (LTV_CAP and DTI)
MPIF	Those others which are aimed at financial institutions' assets or liabilities

Source: Cerutti et al. (2015, 2017).
Notes: each individual variable is a dummy that takes on two values: 0 for no policy and 1 for policy in effect. The database covers an annual sample from 2000 to 2013. The data are available in Excel on the IMF website at: www.imf.org/external/pubs/ft/wp/2015/Data/wp1561.zip.

Table A3
Second (2016) IMF database.

Variable	Description
Changes in prudential instruments	
sscb_res	Change in sector specific capital buffer: Real estate credit. Requires banks to finance a larger fraction of these exposures with capital
sscb_cons	Change in sector specific capital buffer: Consumer credit Requires banks to finance a larger fraction of these exposures with capital
sscb_oth	Change in sector specific capital buffer: Other sectors. Requires banks to finance a larger fraction of these exposures with capital
cap_req	Change in general capital requirements. Implementation of Basel capital agreements
Concrat	Change in concentration limit. Limits banks' exposures to specific borrowers or sectors
Ibex	Change in interbank exposure limit. Limits banks exposures to other banks
ltv_cap	Change in the loan-to-value ratio cap. Limits on loans to residential borrowers
rr_foreign	Change in reserve requirements on foreign currency-denominated accounts
rr_local	Change in reserve requirements on local currency-denominated accounts
Aggregate indexes	
Sscb	Sum of changes in sector-specific capital buffers across the residential, consumer, and other sectors
PruC	Country index by time t and country c, equal to 1 if the sum of the 9 instruments is >=1 and −1 if the sum of the instruments is <=-1, 0 otherwise
PruC2	Country index by time t and country c, equal to 1 if the sum of the 9 instruments is >=1 and −1 if the sum of the instruments is <=-1, 0 otherwise. In this case, all individual instruments are adjusted to have maximum and minimum changes of 1 and −1
Cumulative indexes (relative to 2000q1)	
cum_sscb_res	Cumulative change in sector specific capital buffer: Real estate credit
cum_sscb_cons	Cumulative change in sector specific capital buffer: Consumer credit
cum_sscb_oth	Cumulative change in sector specific capital buffer: Other sectors
cum_cap_req	Cumulative change in general capital requirements
cum_concrat	Cumulative change in concentration limit
cum_ibex	Cumulative change in interbank exposure limit
cum_ltv_cap	Cumulative change in the loan-to-value cap
cum_rr_foreign	Cumulative change in reserve requirements on foreign currency-denominated accounts
cum_rr_local	Cumulative change in reserve requirements on local currency-denominated accounts
cum_sscb	Cumulative change in the aggregate sector-specific capital buffer instrument
cum_PruC	Sum of the cumulative version of the 9 instruments by country c and time t
cum_PruC2	Sum of the cumulative version of the 9 instruments by country c and time t. In this case, all individual instruments are adjusted to have maximum and minimum changes of 1 and −1

Source: Cerutti et al. (2016).
Note: Database covers a quarterly sample from 2000q1 to 2014q4.The data can be downloaded from https://www.newyorkfed.org/medialibrary/media/ibrn/prudential_ind_3.xlxs.

Table A4
2016 BIS dataset.

Variable	Description
RR	Reserve requirements
CRG	Credit growth limit
LIQ	Liquidity requirement
GENERAL CREDIT	Sum of the three above variables
LTV	Loan-to-value limit
DSTI	Debt service to income limit
EXPO	Exposure limit related to housing
RW	Risk weighting related to housing
PROV	Provisioning related to housing
TAX	Housing related tax

Source: Kuttner and Shim (2016).
The database covers a monthly sample from 1990 to 2012. It is available online as a supplementary data table to the article at https://doi.org/10.1016/j.jfs.2016.07.014.

Table A5
Log real house price and log real household credit, first stage: specification and test for stationarity.

Variable	Log real house prices (LRPH)			Log real household credit (LRLIABS)		
Countries	Controls	Sample period	Stationary residuals?	Controls	Sample period	Stationary residuals?
Australia	LRPDI, LRR, LRIH	1986 onwards	***	LRPDI, U, LRKH, LRPH	1990 onwards	**
Belgium	LRPDI, LRR, LRIH	1991 onwards	**	LRPDI, U, LRKH, LRPH	1980–2005	**
Canada	LRPDI, LRR, LRKH	1970 onwards	***	LRPDI, U, LRKH, LRPH	1990–2008	**
Denmark	LRPDI, LRR, LRIH	1991 onwards	**	LRPDI, LRKH, LRPH	1996–2004	***
Finland	LRPDI, LRR, LRIH	1993 onwards	**	LRPDI, U, LRKH, LRPH	2000 onwards	**
France	LRCW, LRR, LRIH	1971 onwards	*	LRPDI, U, LRKH, LRPH	1970 onwards	***
Germany	LRPDI, LRKH	1985 – 2008	***	LRPDI, U, LRKH, LRPH	2000 onwards	***
Greece	LRPDI, LRR, LRIH	2006 onwards	***	LRPDI, U, LRKH, LRPH	2000 onwards	**
Ireland	LRPDI, LRR, LRIH	1982 onwards	*	LRPDI, U, LRKH, LRPH	1970–2013	**
Italy	LRCW, LRR, LRIH	1986 onwards	***	LRCW, U, LRKH, LRPH	2000 onwards	***
Japan	LRPDI, LRR, LRIH	1966 onwards	*	LRPDI, U, LRKH, LRPH	1980 onwards	**
Netherlands	LRPDI, LRR, LRIH	1986 onwards	**	LRPDI, U, LRKH, LRPH	1970 onwards	***
Norway	LRPDI, LRR, LRKH	2010 onwards	*	LRPDI, LRKH, LRPH	2010 onwards	***
Austria	LRPDI, LRR, LRIH, CRISES	1971 onwards	**	LRPDI, U, LRKH, LRPH	1970 onwards	**
Portugal	LRCW, LRR, LRKH	2005 onwards	***	LRPDI, LRKH, LRPH	1995 onwards	***
Sweden	LRPDI, LRR, LRIH	1970 onwards	***	LRPDI, U, LRKH, LRPH	1975 onwards	**
Spain	LRPDI, LRR, LRIH	1980 onwards	**	LRPDI, U, LRKH, LRPH	1971 onwards	**
UK	LRCW, LRR, LRIH	1993 onwards	***	LRPDI, U, LRKH, LRPH	2010 onwards	**
US	LRCW, LRIH, CRISES	1985 onwards	***	LRPDI, U, LRKH, LRPH	2000 onwards	**

Notes: we have used the Augmented Dickey-Fuller test to test for stationary residuals. *** means that the null hypothesis of non-stationarity is rejected at the 1 per cent significance level, ** means the null is rejected at the 5 per cent level and * at the 10 per cent level. A blank means that we cannot reject the null. LRPDI: Log real personal disposable income, LRPH: Log real house prices, LRLIABS: Log real household credit, LRCW: Log real consumer wage, LRR: long term real interest rate and LRIH: log real housing investment, LRKH: Log real housing stock, U Unemployment rate.

Table A6
Real house price growth, second stage: baseline equation using SUR.

Variable	Australia	Belgium	Canada	Denmark	Finland	France	Germany	Greece	Ireland	Italy
Constant	−0.001	0.009***	−0.002	0.000	0.004*	0.003**	−0.004***	−0.01	0.002	−0.001
	(0.3)	(4.5)	(2.0)	(0.0)	(2.0)	(3.0)	(4.0)	(0.9)	(1.0)	(0.5)
Cointegrating residual	−0.081***	−0.023	−0.050***	−0.029	−0.241***	−0.030***	−0.246***	−0.092	−0.046**	−0.077***
	(2.7)	(1.2)	(3.6)	(1.1)	(5.1)	(3.8)	(3.4)	(0.5)	(2.0)	(3.5)
DLRPH(t-1)	0.573***	−0.062	0.649***	0.521***	0.398***	0.530***	−0.136	0.022	0.288***	0.569***
	(7.3)	(0.7)	(12.0)	(7.8)	(4.9)	(9.5)	(1.4)	(0.1)	(3.8)	(9.0)
DLRR(t-1)	−0.006*	−0.003	−0.002	−0.006*	0.003	−0.001	0.001	0.006	−0.006**	0.002
	(2.0)	(0.8)	(2.0)	(1.5)	(0.8)	(0.5)	(0.3)	(0.7)	(2.0)	(1.0)
DLRPDI	0.039	0.246*	0.228***	0.155**	0.189**	0.087	0.292***	0.271***	0.114	0.379***
	(0.4)	(1.8)	(4.3)	(2.4)	(2.1)	(0.9)	(2.9)	(2.8)	(1.5)	(3.5)
DLRLIABS(t-1)	0.175		−0.164***	0.003	−0.129	0.010	0.069	0.078	0.161***	0.154**
	(1.6)		(6.6)	(0.1)	(1.4)	(0.3)	(0.7)	(0.3)	(2.7)	(2.3)
DLRGW	−0.008	−0.061	0.400***	0.254***	0.138**	0.000	−0.039	−0.036	0.084	0.081*
	(0.1)	(1.0)	(3.2)	(5.4)	(2.6)	(0.1)	(0.8)	(1.2)	(1.3)	(1.9)
DU	−0.004		−0.008***	−0.004	−0.003	−0.009***	0.001	−0.019***	−0.012***	0.002
	(0.7)		(4.0)	(0.8)	(1.6)	(3.0)	(0.3)	(3.2)	(3.0)	(0.5)
Crises	−0.003	−0.009**	−0.012***	−0.006	0.010	−0.001	0.004	0.006	−0.019***	−0.002
	(0.6)	(3.0)	(4.0)	(1.5)	(0.3)	(0.3)	(0.6)	(0.5)	(3.8)	(1.0)
Adj. R2	0.31	0.01	0.69	0.70	0.38	0.46	0.11	0.39	0.57	0.59
D-W	1.96	1.86	1.97	1.96	2.12	2.08	1.94	2.43	2.20	2.01

Variable	Japan	Netherlands	Norway	Austria	Portugal	Sweden	Spain	UK	US
Constant	−0.002**	0.004***	0.004	0.005**	−0.006**	0.001	0.004	0.002	0.003**
	(2.0)	(2.0)	(0.7)	(2.5)	(2.0)	(0.5)	(2.0)	(1.0)	(3.0)
Cointegrating Residual	−0.01**	−0.043**	−0.377**	−0.018	−0.633***	−0.034**	−0.038***	−0.173***	−0.061***
	(2.0)	(2.3)	(2.0)	(0.8)	(4.6)	(2.3)	(2.9)	(5.1)	(3.4)
DLRPH(t-1)	0.782***	0.356***	0.656***	0.003	0.317**	0.402***	0.606***	0.233**	0.354***
	(19.6)	(3.4)	(3.0)	(0.1)	(2.2)	(6.2)	(10.1)	(2.6)	(4.3)
DLRR(t-1)	−0.003**	−0.004	−0.006	0.002	−0.004	−0.006**	0.003	0.004	−0.003
	(3.0)	(1.0)	(0.3)	(0.4)	(0.7)	(2.0)	(1.5)	(0.8)	(1.5)
DLRPDI	0.201***	0.296***	0.807***	0.956***	0.008	0.428***	0.126***	0.396***	0.186*
	(4.0)	(4.1)	(3.2)	(9.4)	(0.1)	(5.6)	(2.6)	(3.0)	(1.8)
DLRLIABS(t-1)	−0.055***	−0.018	−0.663**	−0.032	0.09	−0.042	−0.015	0.275*	0.113
	(2.8)	(0.2)	(2.3)	(0.3)	(0.9)	(0.7)	(0.2)	(1.8)	(1.5)
DLRGW	0.14***	0.013		−0.013	0.137	0.129***	0.081**	0.11*	−0.015
	(6.4)	(1.3)		(0.2)	(0.5)	(4.0)	(2.5)	(1.7)	(0.5)
DU	0.004	−0.017***		−0.029***	0.002	−0.008*	0	−0.022***	0.002
	(1.0)	(2.8)		(3.2)	(0.5)	(0.6)	(0.0)	(2.8)	(0.7)
CRISES	−0.001	−0.006		0	0.005	−0.006	−0.009**	−0.002	−0.011**
	(1.0)	(1.5)		(0.0)	(1.3)	(0.5)	(2.3)	(0.5)	(5.5)
Adj. R2	0.79	0.43	0.36	0.37	0.52	0.54	0.61	0.56	0.56
D-W	2.27	1.93	1.92	1.90	2.28	2.11	2.05	1.92	1.83

Notes: Estimated by SUR (seemingly unrelated regression). Numbers in parentheses are *T*-stats. Cointegrating residual shows the coefficient on the residuals estimated from the first stage (Appendix Table A5), DLRPH is the change in log real house prices, DLRR is the change in the long term real rate, DLRPDI is the change in log real personal disposable income, DLRLIABS is the change in log real household credit, DLRGW is the change in real grossu household financial wealth, DU is the change in unemployment rate and CRISES is a crisis dummy. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and a * denotes significance at the 10 per cent threshold. Adj. R2 denotes the adjusted R-squared statistic and D-W denotes the Durbin-Watson test for serial correlation of the residuals. Note for some countries we use DLRCW (difference of log real consumer wage) instead of DLRPDI, as specified in Appendix Table A5.

Table A7
Real household credit growth, second stage: baseline equation using SUR.

Variable	Australia	Belgium	Canada	Denmark	Finland	France	Germany	Greece	Ireland	Italy
Constant	0.012***	0.005***	0.003	0.011***	0.005**	0.009***	−0.001**	0.041***	−0.003	−0.007**
	(6.0)	(2.5)	(1.5)	(2.8)	(2.5)	(4.5)	(1.0)	(5.9)	(0.8)	(2.3)
Cointegrating residual	−0.101***	−0.156*	−0.256***	−0.4**	−0.028	−0.024	−0.209***	0.045	−0.323**	−1.08***
	(2.7)	(1.7)	(3.5)	(2.0)	(0.8)	(1.1)	(3.2)	(0.6)	(2.2)	(4.9)
DLRLIABS (t-1)	0.223***	−0.284***	0.302***	−0.111	0.513***	−0.004	0.368***	−0.072	0.791***	−0.073
	(2.6)	(3.0)	(3.4)	(0.7)	(6.0)	(1.3)	(3.3)	(0.5)	(7.3)	(0.6)
DLRR(t-1)	0.002	−0.007*	−0.004*	0.005	0	0.208	0.002	−0.01	−0.002	−0.016**
	(1.0)	(1.8)	(2.0)	(0.6)	(0.0)	(1.1)	(0.7)	(1.7)	(0.4)	(2.0)
DLRPDI	0.018	0.368**	0.124*	0.365**	0.287***	0.049	0.034	0.33***	0.217***	0.391***
	(0.3)	(2.4)	(1.8)	(2.3)	(2.9)	(0.9)	(0.5)	(3.1)	(3.9)	(2.8)
DLRGW	0.136***	0.071*	0.508***	0.32***	0.091**	−0.004	−0.02	−0.043	0.274***	0.007
	(3.2)	(1.9)	(3.2)	(3.2)	(2.1)	(0.8)	(0.4)	(1.6)	(2.9)	(0.1)
CRISES	−0.007*	−0.421	11.272***	1.763	21.76	0.009	−0.001	−0.027***	0.001	0.009**
	(1.8)	(0.4)	(2.3)	(1.5)	(0.9)	(4.5)	(1.0)	(3.0)	(0.2)	(3.0)
Adj. R2	0.18	0.21	0.22	0.36	0.34	0.0	0.07	0.50	0.75	0.49
D-W	2.06	1.80	1.78	1.86	2.21	2.04	2.06	1.87	1.71	1.47

Variable	Japan	Netherlands	Norway	Austria	Portugal	Sweden	Spain	UK	US
Constant	0.017***	0.007***	0.009***	0.003***	0.001	0.005***	0.007***	0	0.004**
	(8.5)	(3.5)	(3.0)	(3.0)	(0.5)	(2.5)	(3.5)	(0.0)	(4.0)
Cointegrating residual	−0.209***	−0.021	−0.892***	−0.035	−0.015	−0.073***	−0.034*	0.165	−0.092*
	(3.6)	(1.2)	(4.7)	(1.5)	(0.6)	(2.9)	(1.9)	(1.0)	(1.9)
DLRLIABS (t-1)	0.11	0.034	0.084	−0.055	0.643***	−0.027	0.224***	−0.007	0.627***
	(1.4)	(0.5)	(0.7)	(1.1)	(10.5)	(0.5)	(3.2)	(0.1)	(8.4)
DLRR(t-1)	0	−0.006**	0.005	0.004	0.004	−0.002	0	0.013	0.001
	(0.0)	(2.0)	(0.5)	(1.3)	(1.3)	(0.7)	(0.0)	(1.4)	(0.3)
DLRPDI	0.202**	0.48***	0.514***	0.605***	0.46***	0.364***	0.055	0.121*	0.01
	(2.2)	(8.1)	(4.0)	(11.2)	(3.5)	(4.1)	(1.3)	(1.8)	(0.1)
DLRGW	0.058	−0.006		0.125***	0.462***	0.261***	0.132***	0.244***	0.046
	(1.1)	(0.5)		(2.8)	(3.6)	(7.1)	(4.6)	(6.1)	(1.4)
CRISES	−0.017***	0.005		0.002	−0.005*	−0.005	−0.007**	−0.012***	−0.005**
	(5.7)	(1.0)		(0.7)	(1.7)	(1.3)	(2.3)	(4.0)	(2.5)
Adj. R2	0.34	0.25	0.56	0.49	0.84	0.32	0.30	0.70	0.62
D-W	2.06	1.62	1.55	2.13	1.78	1.86	2.01	1.76	2.31

Notes: Estimated by SUR (seemingly unrelated regression). Numbers in parentheses are *T*- stats. Cointegrating residual shows the coefficient on the residuals estimated from the first stage (Appendix Table A5), DLRLIABS is the change in log real household credit, DLRR is the change in the long term real rate, DLRPDI is the change in log real personal disposable income, DLRGW is the change in log real gross financial wealth and CRISES is a crisis dummy. *** denotes that the coefficient is significant at the 1 per cent significance threshold, ** denotes significance at the 5 per cent threshold and * denotes significance at the 10 per cent threshold. Adj. R2 denotes the adjusted R-squared statistic and D-W denotes the Durbin-Watson test for serial correlation of the residuals. Note for some countries we use DLRCW (difference of log real consumer wage) instead of DLRPDI, as specified in Appendix Table A5.

References

Adams, Z., Füss, R., 2012. Disentangling the short and long-run effects of occupied stock in the rental adjustment process. J. Real Estate Finance Econ. 44 (4), 570–590.

Afonso, A., Jalles, J.T., 2012. Revisiting Fiscal Sustainability, Panel Cointegration and Structural Breaks in OECD Countries, ECB Working Paper 1465.

Aiyar, S., Calomiris, C.W., Wieladek, T., 2014. Does macro-prudential regulation leak? Evidence from a UK policy experiment. J. Money Credit Bank. 46 (1), 181–214.

Akinci, O., Olmstead-Rumsey, J., 2015. How Effective are Macroprudential Policies? An Empirical Investigation, International Finance Discussion Papers 1136.

Antipa, P., Mengus, E., Mojon, B., 2010. Would Macroprudential Policy Have Prevented the Great Recession?, Manuscript, Banque de France.

Armstrong, A., Davis, E.P., 2014. Comparing housing booms and mortgage supply in the major OECD countries. Nat. Inst. Econ. Rev., R3–R15.

Banerjee, A., Dolado, J.J., Galbraith, J.W., Hendry, D.F., 1993. Co-integration, Error Correction, and the Econometric,Analysis of Non-Stationary Data. Oxford University Press, Oxford.

Barrell, R., Kirby, S., Riley, R., 2004. The current position of UK house prices. Nat. Inst. Econ. Rev. 189, 57–60.

Barrell, R., Kirby, S., Whitworth, R., 2011. Real house prices in the UK. Nat. Inst. Econ. Rev. 216 (1), F62–F68.

Basel Committee, 2010. Countercyclical Capital Buffer Proposal ? Consultative Document, July 2010. BIS, Basel.

Bennani, T., Després, M., Dujardin, M., Duprey, T., Kelber, A., 2014. Macroprudential Framework: Key Questions Applied to the French Case, Banque de France Occasional papers, No. 9.

Borio, C., Shim, I., 2007. What can (macro-)prudential Policy Do to Support Monetary Policy?, BIS Working Paper No. 242.

Bruno, V., Shim, I., Shin, H.S., 2017. Comparative assessment of macroprudential policies. J. Financ. Stab. 28, 183–202.

Buchholz, M., 2015. How Effective Is Macroprudential Policy During Financial Downturns? Evidence from Caps on Banks' Leverage, Eesti Bank Working Paper 7/2015.

Capozza, D.R., Hendershott, P.H., Mack, C., Mayer, C.J., 2002. Determinants of Real House Price Dynamics, NBER Working Paper, 9262.

Carreras, O., Davis, E.P., Piggott, R., 2016. Macroprudential Tools, Transmission and Modelling, Firstrun Deliverable 4.7, Horizon 2020.

Carreras, O., Davis, E., P, Hurst, I., Liadze, I., Piggott, R., Warren, O., 2018. Implementing Macroprudential Policy in NiGEM, NIESR Discussion Paper Number: 490.

Cerutti, E., Claessens, S., Laeven, L., 2015. The Use and Effectiveness of Macroprudential Policies: New Evidence, IMF Working Paper 15/61.

Cerutti, E., Correa, R., Fiorentino, E., Segalla, E., 2016. Changes in Prudential Policy Instruments, a New Cross Country Database, IMF Working Paper 16/110.

Cerutti, E., Claessens, S., Laeven, L., 2017. The use and effectiveness of macroprudential policies: new evidence. J. Financ. Stab. 28, 203–224.

Cho, H.C., Ramirez, M.D., 2016. Foreign direct investment and income inequality in Southeast Asia: a panel unit root and panel cointegration analysis. Atlantic Econ. J. 44, 411–424.

Claessens, S., Ghosh, S.R., Mihet, R., 2013. Macroprudential policies to mitigate financial system vulnerabilities. J. Int. Money Finance 39, 153–185.

Crockett, A., 2000. Marrying the Micro- and Macro-prudential Dimensions of Financial Stability. Remarks Before the Eleventh International Conference of Banking Supervisors. Bank for International Settlements, Basel, 20–21 September, 2000.

Crowe, C.W., Dell'Ariccia, G., Igan, D., Rabanal, P., 2011. How to Deal with Real Estate Booms: Lessons from Country Experiences, IMF Working Paper No. 11/91.

Davis, E.P., Fic, T.M., Karim, D., 2011. Housing Market Dynamics and Macroprudential Tools. In RUTH, the Riksbank's Inquiry into the Risks in the Swedish Housing Market., pp. 219–298, also Brunel Economics and Finance Working Paper 11–07.

De Nicolò, G., Favara, G., Ratnovski, L., 2012. Externalities and Macroprudential Policy, IMF Staff Discussion Note 12/05.

Dell'Ariccia, G., Igan, D., Laeven, L., Tong, H., 2012. Policies for Macrofinancial Stability: Options to Deal with Credit Booms, IMF Staff Discussion Note 12/06.

Drehmann, M., 2009. Macroeconomic stress testing banks: a survey of methodologies. In: Quagliariello, M. (Ed.), Stress Testing the Banking System: Methodologies and Applications. Cambridge University Press, Cambridge.
Engle, R.F., Granger, C.W., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica J. Econ. Soc. 55, 251–276.
Galati, G., Moessner, R., 2014. What Do We Know About the Effects of Macroprudential Policy?, De Nederlandsche Bank Working Paper No. 440.
Gambacorta, L., Murcia, A., 2017. The Impact of Macroprudential Policies and Their Interaction with Monetary Policy, an Empirical Analysis Using Credit Registry Data, BIS Working Paper 636.
Igan, D., Loungini, P., 2012. Global House Price Cycles, IMF Working Paper WP/12/217.
Izquerido, A., Loo-Kung, R., Rojas-Suarez, L., 2013. Macroprudential Regulations in Central America, Center for Global Development, Working Paper No 318.
Kao, C., 1999. Spurious regression and residual-based tests for cointegration in panel data. J. Econometrics 90, 1–44.
Kuttner, K.N., Shim, I., 2016. Can non-interest rate policies stabilise housing markets? Evidence from a panel of 57 economies. J. Financ. Stab. 26, 31–44.
Lim, C.H., Columba, F., Costa, A., Kongsamut, P., Otani, A., Saiyid, M., Wezel, T., Wu, X., 2011. Macroprudential Policy: What Instruments and How to Use Them? Lessons from Country Experiences, IMF Working Paper 11/238.
Meen, G., 2002. The time-series behavior of house prices: a transatlantic divide? J. Hous. Econ. 11 (1), 1–23.
Muellbauer, J., Murphy, A., 2008. Housing markets and the economy: the assessment. Oxf. Rev. Econ. Policy 24 (1), 1–33.
Pesaran, M.H., 2007. A simple panel unit root test in the presence of cross-section dependence. J. Appl. Econ. 22 (2), 265–312.
Vandenbussche, J., Vogel, U., Detragiache, E., 2015. Macroprudential policies and housing prices—a new database and empirical evidence for Central, Eastern and Southeastern Europe. J. Money Credit Bank. 47 (S1), 343–377.
Wong, E., Fong, T., Li, K., Choi, H., 2011. Loan-to-value Ratio as a Macro-prudential Tool – Hong Kong's Experience and Cross-country Evidence, Hong Kong Monetary Authority Working Paper No. 1.
Zhang, L., Zoli, E., 2014. Leaning Against the Wind: Macroprudential Policy in Asia, IMF Working Paper 14/22.