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Estimation of effects of recent macroprudential policies in a sample of advanced open economies

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Estimation of effects of recent macroprudential policies in a sample of advanced open economies.

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13 September 2018

Abstract

We analyse a quarterly panel data set consisting of ten advanced open economies that have introduced macroprudential policy measures: caps on loan to value and income (LTV and LTI), and debt service to income (DSTI) requirements in particular, but also risk weights (RW), amortization (Amort) and, less used, countercyclical buffer (CCyB). Estimation of dynamic panel data models, that also include the central bank rate, and controls for common nominal and real trends, gives support to the view that several of the measures may have reduced credit growth when they were introduced. The estimated impact effects are most significant for LTV, LTI and RW. For Amort, the long-run effect on credit growth is significant, and the same is found for RW. The estimation results when house price growth is the dependent variable are in the main consistent with the results for credit growth. The results do not support that CCyB has reduced lending (as a consequence of higher financing costs), and we suggest that the variable is mainly a control in our data set. In that interpretation, it is interesting that the estimated coefficients of the other five instruments are robust with respect to exclusion of CCyB from the empirical models. The results are also robust to controls in the form of impulse indicator saturation (IIS).

Keywords: Macroprudential policy measures, house prices, credit growth, open economies, macro panel, impulse indicator saturation, robust estimation.
JEL classification: C23, C44, C58, G28, G38.

1 Introduction

It is well documented that the usage of macroprudential polices have increased over time, and that the advanced economies have been later in adopting such policies than emerging markets and developing economies have been. Macro prudential policies also represent a varied menu of policy instruments. For example, reserve requirement ratios and limits on foreign currency loans tend to be more used by emerging countries, while caps on loan to value (LTV) have been more used by advanced economies, notably after the financial crisis, see Cerutti et al. (2016).

In this paper we estimate the effects of macroprudential policies on credit growth and housing price changes using a sample of ten advanced and open economies. The objective of our econometric investigation is to aid the assessment of the macroprudential policies that have been implemented in Norway. With this purpose in mind, the data set consists of

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countries that have implemented polices that are similar to the Norwegian measures, that we wish to estimate effects of. This resulted in a data set which has a smaller cross-section dimension than the broad data sets analyzed by Kuttner and Shim (2013, 2016) , Cerutti et al. (2015) and Akinci and Olmstead-Rumsey (2017). Hopefully, the policy measures that we include represent a relatively homogenous set of policy measures in the 10-country sample. As noted this includes caps (ie limits) on loan to value ratios (LTV) and on loan to income ratios (LTI). We also include tools of the type debt service to income, risk weights (ie in capital requirement regulations of credit institutions) and amortization requirements and the level of countercyclical buffer rates.

The evidence in the existing empirical literature that uses broader panels, but shorter time series than we do, indicate that policies in the LTV and debt (service) to income categories have been effective for credit growth, see Kuttner and Shim (2016), and that there has been some impact on housing prices, see Cerutti et al. (2015). Stronger evidence for effects on housing prices is found by Akinci and Olmstead-Rumsey (2017), who focus on the imbalances in the housing sector. However, the literature strongly indicates that the effects of macroprudential policies depend on economy and country specific characteristics. Cerutti et al. (2015), mention the concern that macroprudential polices may be undermined (circumvented) by cross border banking and other forms of external financing. Hence, the degree of openness might be negatively associated with the power of policies that are set into effect to stabilize credit growth and the price formation process in the housing market. Since all the economies in our sample are open, and the period with active policies are longer than in existing studies, the econometric results shed new light on the estimated effect of macroprudential policies in open economies.

The results of the empirical investigation give support to the view that macroproduden-tial policies may have a statistically significant effect on nominal credit growth. The size of the coefficients for (introduction of) LTV and LTI are economically as well as statistically significant, and the same is found for increases in the risk weights on mortgage loans. For risk weights and amortization requirements we also estimate a longer-term effect on credit growth. We find insignificant short-run and long-run coefficients for the debt service to income indicator, and the countercyclical requirements indicator is estimated to have positive coefficients, which are all statistically insignificant, though. The panel data results for housing price change give the same picture, with the loan to value and the risk-weighting variables as the measures with highest statistical significance.

2 Data

Our analysis makes use of data from 10 advanced economies which have implemented macroprudential instruments to counter unsustainable household indebtedness and housing price growth since 1998. The instruments included in the analysis are: i) limits to Loan-to-Value (LTV), ii) limits to Loan-to-Income (LTI), iii) limits to Debt-to-Income (DTI), iv) limits to Debt-Service-to-Income (DSTI), v) Amortization requirements (Amort), vi) tightening of Risk Weights on mortgage loans in the capital adequacy regulation of credit institutions (RW) and vii) level of Countercyclical Buffer rate (CCyB). In order to simplify the smorgasbord of instruments in the analysis, DTI is merged in LTI, since these instruments are very similar.[1] Another simplification lies in the definition of DSTI. Here, DSTI includes both regulation on the share of income spent on debt servicing (*ie* interests paid, instalments and fees), and imposing on the credit institutions an obligation to carry out debt servicing stress tests to assure that the borrowers are capable to service their mortgages also in the case of a certain interest rate increase.

The countercyclical buffer rate (CCyB) is included in the set of instruments, even though it is not targeted to impact mortgage loans specifically. However, some claim that due to

[1] While LTI refers to the ratio between an individual loan to a household's income, DTI refers to the ratio between a household's total debt to income.

Table 1: Use of macroprudetial policies in the estimation sample. The array elements indicate in which periods LTV, LTI, DSTI and Amort have been used, in which periods RW has been elevated, and the current level of CCyB in the various countries. Periods not entered and empty cells represent the numerical value 0.

	LTV	LTI*	DSTI	Amort	RW	CCyB
Australia			2017(2)-17(2)	2017(2)-17(2)	2004(4)-17(2)	
Canada	2008(4)-17(2)		2008(4)-17(2)	2008(4)-17(2)		
Denmark	2015(4)-17(2)		2016(1)-17(2)			
Finland	2016(3)-17(2)					
Ireland	2015(1)-17(2)	2015(1)-17(2)	2012(1)-17(2)		2007(1)-17(2)	
Netherlands	2013(1)-17(2)		2013(1)-17(2)			
New Zealand	2013(4)-17(2)					
Norway	2010(1)-17(2)	2010(1)-11(4) 2017(1)-17(2)	2011(4)-17(2)	2015(3)-17(2)	1998(3)-01(1) 2014(1)-17(2)	2015(3)-16(2), 1% 2016(3)-17(2), 1.5%
Sweden	2010(4)-17(2)			2016(2)-17(2)	2013(2)-17(2)	2015(4)-16(2), 1% 2016(3)-17(1), 1.5% 2017(2)-17(2), 2.0%
UK		2014(4)-17(2)	2014(2)-17(2)			
Note:	*: In Norway, LTI is specifically a DTI-requirement					

increased financing costs, build up of CCyB can dampen credit growth. Applying the same reasoning, all the other capital buffer requirements in the Basel III Accord could be included. Unlike the other buffer requirements, however, CCyB is designed to be adjustable over time in order to counteract pro-cyclicality in the financial system. For this reason CCyB is included, and the other buffer requirements are not. Taxes and fees (*eg* regulations on tax deductible interests paid and stamp fees) is another type of instruments which could be included in the analysis. Whether to reckon taxes and fees among the macroprudential instruments or not, seems to differ quite substantially among the countries included in the sample. Lack of consistent and comprehensive data on taxes and fees necessitates omitting this type of instruments from the analysis. Information about the active use of the different measures in the countries in the panel is found in Table 1.

Each of the indicators representing the application of the macroprudential instruments LTV, LTI, DSTI and Amort has been assigned the numerical value 1 if the instrument has been implemented and activated by the public authorities in the relevant country in the relevant period of time, and zero otherwise. Risk weights on bank's exposures (explicit or implicit) are inherent in any capital adequacy regulation. Applying the same rule for assigning numerical values to the RW indicator therefore seems little fruitful. Instead, the RW indicator is assigned the numerical value 1 if the risk weight on mortgage loans has been increased in the relevant country in the relevant period of time, and 0 if the risk weight has been lowered. In all periods which the risk weight has been kept unchanged, the RW indicator is assigned the same numerical value as in the previous period. Still, the RW indicator is not calibrated to reflect the transition from one generation of Basel Accords to the next. The CCyB indicator is assigned numerical value (in per cent) pursuant to the current regulations in the relevant country.

Two special cases need to be commented. In the Netherlands, the market participants established self-regulation prior to the codification into national law in 2013. In accordance with the rules outlined above, self-regulation does not qualify to be assigned the numerical value 1. Hence, LTV and DSTI are assigned the numerical value 1 for the Netherlands only as of first quarter 2013, when the code of conduct was incorporated into national law. In Canada, macroprudential instruments was implemented and activated well in advance of 2008. The Canadian regulation was in general softened until 2007, and tightened from 2008. This could motivate several different approaches with regard to assigning indicator values. For simplicity, in this analysis, periods in which regulation has been softened are regarded as if there is no instruments activated. Accordingly, LTV, DSTI and Amort are assigned the numerical value 1 for Canada as of fourth quarter 2008.

The data on usage of macroprudential instruments is mostly collected from the International Monetary Fund (IMF), the European Systemic Risk Board (ESRB) and national authorities (financial supervisory authorities and central banks), see C.2 for details. In order to tackle contradictory information provided by the data sources, a set of guiding principles has been employed. Closeness between the institution and the data, and to what extent the institution has utilizing the data, have been emphasized in the assessment.

There is little doubt that the complete discretization ("on"/"off") is an oversimplification, and that it is credible that there have been examples of gradualism (tightening and loosening of measures) in macroprudential policies. However, to ensure correct judgements about stricter and less strict policies requires expert knowledge of individual countries that we cannot claim to have. Moreover, it seems plausible that statistically and economically significant response to a change in an indicator variable is a clear sign that also a more refined operational measure of macroprudential policy change will be significant. In any case we refer to the studies with larger cross-section dimension, a broader definition of non-interest rate policies, but also a shorter sample, for estimated effects of thightening/loosening of policies, *eg* Akinci and Olmstead-Rumsey (2017).

The house price and credit data are retrieved from the Bank of International Settlements (BIS) Statistical Warehouse, see C.1 for details. All data are seasonally unadjusted and are measured on a quarterly basis.

3 Method

As noted above there is a new literature on the econometric assessments of the effects of macroprudential policy instruments by the use of aggregate panel data sets. There are several and notable differences between the studies, including the operationalization of the policy variables, the number of time periods and countries included in the sample and preference for estimation method.

However, there is also considerable common ground. All existing studies attempt to estimate the effects on at least two variables, credit growth and housing price change, and by the use of separately estimated equations. The explanatory variables usually belongs to three categories: (i) One or more lags of the dependent variable, (ii) economic control variables (*eg* GDP and GNI growth) and (iii) a battery of policy variables. It is custom to include the monetary policy interest rate (ie central bank rate) as one of the control variables. This makes sense since it is easy to imagine that the monetary transmission mechanism creates a dependency between the central bank rate and the interest rate that affects housing demand, and hence the evolution of housing price and credit growth.

3.1 A stylized model equation

A model that includes the mentioned elements, with a single macro prudential instrument for notational convenience, is:

$$y_t = \varphi_{10} + \varphi_{11} y_{t-1} + \varphi_{12} r_{t-1} + \beta_{10} pol_t + \beta_{11} pol_{t-1} + \gamma_{10} z_t + \varepsilon_{yt} \quad (1)$$

$$r_t = \varphi_{20} + \varphi_{21} y_{t-1} + \varphi_{22} r_{t-1} + \beta_{20} pol_t + \beta_{21} pol_{t-1} + \gamma_{20} z_t + \varepsilon_{rt} \quad (2)$$

where y_t symbolizes either credit growth or housing price change in period t (measured as a growth rate or percent change), r_t denotes the central bank rate, pol_t denotes the macro prudential policy indicator and z_t represents the mentioned control variable. In this formulation, we assume that z_t is a valid conditioning variable (to save space there is no lags in this variable).

(1) represents a simplified but typical model equation in the literature. (2) is consistent with the universal treatment of the policy interest rate as an endogenous variable, though no studies actually estimate that equation.

Appendix A contains a derivation of (1) and (2) which commences from a simultaneous equation model (SEM), where not only y_t and r_t, but also pol_t are endogenous variables. The aim of the derivation is to clarify whether the endogeneity of pol_t in the system (*ie*

SEM or VAR), transfers to the partial model of the system represented by (1)-(2). The answer is "no", because (1)-(2) can be valid conditional models, which implies that *pol* is instantaneously uncorrelated with the disturbance in for example (1). Hence, while pol_t is endogenous in the system, it can be a predetermined variable in the two derived conditional model equations, in (1) specifically which is our main model equation of interest.

3.2 Parameters of interest

The model equations that we estimate below are empirical versions of (1). In the literature, there is some disagreement about parameters of interest. Kuttner and Shim (2016) state that the individual coefficients in the distributed lag on the policy variables are "of little intrinsic interest", it is the sum of the coefficients that is of interest. In the notation above, this corresponds to having $(\beta_{10} + \beta_{11})$ as the parameter of interest. However, other studies focus on a single coefficient in the estimated models, cf Akinci and Olmstead-Rumsey (2017) who estimate models with a single lag in each policy variable (corresponding to setting β_{11} as the parameter of interest).

Below we report baseline model equations for credit growth and house prices which show point estimates of β_{10} and β_{11} individually. In the tables that summarize the results, we show β_{10}, the *Impact* coefficient, together with *Long-run* coefficient, which in the case of (1) is defined as:

$$\text{Long-run} = \frac{(\beta_{10} + \beta_{11})}{1 - \varphi_{11}}$$

noting however that since the interest rate r_t is endogenous in general, the reported Long-run coefficients are only suggestive of the longer-term effects of a policy. Even in our simplified formulation, in order to represent the full effect, it is required that $\beta_{20} = \beta_{21} = \varphi_{21} = 0$. To assess these conditions requires a more system oriented approach than is usual in the literature, and which goes beyond the scope of the paper.

3.3 Estimation methodology

As noted above, the policy variable can be regarded as pre-determined in the conditional model, also when we start from the premise that it is endogenous in the system. Hence, both least squares and method-of-moments estimators may give consistent estimation if the model equation is econometrically well specified (the residuals are approximately Gaussian). As noted in the appendix, there are good reasons for choosing least squares for estimation of dynamic panel data models when the time series dimension is long, which it is in our case. In the context of panel data, and assuming a fixed effects model for the unobserved individual effects, the direct parallel to OLS estimation of (1) is estimation by Least squares dummy variable estimation, LSDV (also called the Within estimator).

It is a strong assumption to maintain, as the random effects model does, that unobserved individual effects are uncorrelated with the interest rate and all other observable explanatory variables of the model. The fixed effects model is more attractive in our case. Another reason is that the data set contains a large number of time series observations, while there are only ten cross section units, and in such sample situations there are few (new) problems raised by estimating model equations of the type in (1) by LSDV, Biorn (2017, Ch. 8.3). Finally, as we note below, the LSDV estimator can be robustified against the influence of sample variation that the model equation has little to say about, notably structural breaks.

In the random effects model, the inherent equi-correlation damages the pre-determinedness of y_{t-1}. In principle that problem is fixed by the Arellano and Bond GMM estimation method for dynamic macro models, Arellano and Bond (1991). In practice, the availability of valid and relevant instrumental variables determines what is gained by panel GMM, if the VAR is relatively well specified in the first place, Bun and Windmeijer (2010). It may happen that the fix for a relatively small estimation issue (lack of consistency in the cross-section direction) creates a relatively large cost of inference due to *eg* an increase in estimated coefficient variance.

In addition to estimating the effect (β_{10}) from the introduction of the policy, and the requisite ($\beta_{10} + \beta_{11}$) for long-term effect of unchanged policy, we might be interested in estimating dynamic effects, *eg* four quarters after the introduction, 2 years after, and so on. These parameters, though well defined in the VAR, cannot in general be efficiently estimated from (1) alone. The required condition is $\varphi_{21} = 0$ in (2), ie that the system is characterized by one-way Granger causality.

In practice the order of dynamics of the VAR must be specified empirically. Underspecification of lag order can imply residual mis-specification, ie the assumption about approximate Gaussian VAR disturbances may become untenable, and the statistical inference can become unreliable.

In addition to dynamic specification, the controls are important for securing near white-noise residuals. In this study the controls take two forms: First, we include economic variables that are likely to be correlated with credit growth and house price changes in open economies: world stock price change, oil price change and growth in international trade. The second class of controls consists of country and period specific indicator variables for breaks in the intercept of the relationship, ie location shifts or breaks. Because such location breaks often will be correlated with one or more of the regressors, the estimation of the parameters of interest will in general be robustified by the inclusion of significant indicators for breaks, see Hendry and Johansen (2015), Hendry (2018), Castle et al. (2013).

The determination of indicators for location shifts is done objectively with the aid of the computer implemented algorithm *Impulse Indicator Saturation (IIS)* in Autometrics, Hendry et al. (2008), Hendry and Doornik (2014), using relatively strict significance levels for one country data set at a time. The significant indicators is then added to the panel data set and the empirical model equations of (1) is estimated, augmented by the complete set of indicators. The resulting estimates are labelled LSDV-Robust, following the theoretical developments in Johansen and Nielsen (2009) and the panel data application in Nymoen and Sparrman (2015).

3.4 Nominal or real house price and credit growth?

Another important decision is the measurement of the dependent variable, y_t above. In the existing literature, the custom has become to model changes in real housing prices and in real credit. However, from a regulator's point of view, the aim is certainly to affect the increase in nominal credit and in nominal house price growth. Using the nominal relative changes avoids that and autocorrelated measurement errors (ie the inflation rate) may lead to residual autocorrelation in the model equations.

4 Results

As noted above, the number of time periods in our sample is relatively long and covers the 1980s for most countries. This is helpful for the empirical specification of the autoregressive lag structure, which is likely to be of a relatively high order in any historical period. At the same time, it is clear that the information about macroprudential policies comes from the last part of the sample period. This raises the issue about possible sample dependency in the estimated effects of the new policies. However, comparison of the results reported by Kuttner and Shim (2016) (long time series), with the findings in Cerutti et al. (2015) and Akinci and Olmstead-Rumsey (2017) (data start in 2000) does not suggest that sample dependency is a main problem. Another indication of the same is that the authors of the existing papers do not discuss sample selection as a source of over/under estimation of effects.

Table 2: Credit growth. Estimated (LSDV) effects for LTV, LTI, DSTI, RW, Amort and CCyB . Results for the central bank rate shown in the Memo part of the table. t-values are shown below the estimated impact and long-run effects. Statistical significance (two sided test) is indicated by $**$ (5 % level) and $*$ (10 % level).

	LSDV		LSDV-Robust	
	Impact	Long-run	Impact	Long-run
LTV	-0.46 -3.18^{**}	0.05 0.06	-0.42 -3.56^{**}	0.30 0.52
LTI	-0.23 -1.77^{*}	1.31 1.32	-0.16 -1.12	2.11 1.98^{**}
DSTI	-0.01 -0.04	-0.95 -1.56	0.14 1.06	0.98 1.02
RW	-0.72 -3.19^{**}	-3.47 -1.67^{*}	-0.62 -3.72^{**}	-2.36 -2.27^{**}
Amort	0.07 0.033	-2.43 -2.14^{**}	-0.02 -0.14	-3.21 -2.63^{**}
CCyB	0.23 2.62^{**}	3.09 1.85^{**}	0.23 2.31^{**}	3.20 3.00^{**}
Memo:				
Interest rate (1 pp increase)	$-\ 0.07$ -2.34^{**}	-0.35 -2.52^{**}	$-\ 0.05$ -2.14^{**}	-0.11 -1.01

4.1 Credit growth

Equation (3) shows a baseline empirical model for nominal credit growth, (Δc_t) estimated by LSDV (dummies for countries), and with robust standard errors. We show the results for the autoregressive part, for the interest rate and for the six variables for macroprudential policies. Note that we model total credit to households, and not only housing credit. To save space, the economic control variables and dummies have been omitted from (3), see Table 4 in an appendix for more detailed estimation results.

$$\begin{aligned}
\Delta c_t \;=\;& \underset{(0.055)}{0.234}\ \Delta c_{t-1} + \underset{(0.031)}{0.205}\ \Delta c_{t-2} + \underset{(0.077)}{0.121}\ \Delta c_{t-3} + \underset{(0.068)}{0.354}\ \Delta c_{t-4} \\
& - \underset{(0.029)}{0.069}\ r_{t-1} + \underset{(0.028)}{0.039}\ r_{t-2} - \underset{(0.146)}{0.464}\ \mathrm{LTV}_t + \underset{(0.162)}{0.468}\ \mathrm{LTV}_{t-1} \\
& - \underset{(0.131)}{0.232}\ \mathrm{LTI}_t + \underset{(0.198)}{0.3454}\ \mathrm{LTI}_{t-1} - \underset{(0.163)}{0.007}\ \mathrm{DSTI}_t - \underset{(0.149)}{0.089}\ \mathrm{DSTI}_{t-1} \\
& - \underset{(0.226)}{0.722}\ \mathrm{RW}_t + \underset{(0.14)}{0.422}\ \mathrm{RW}_{t-1} + \underset{(0.209)}{0.070}\ \mathrm{Amort}_t - \underset{(0.202)}{0.280}\ \mathrm{Amort}_{t-1} \\
& + \underset{(0.088)}{0.231}\ \mathrm{CCyB}_t + \underset{(0.112)}{0.036}\ \mathrm{CCyB}_{t-1}
\end{aligned} \tag{3}$$

In the second line in equation (3), we include the estimation results for the two lags of the central bank rate, r_{t-1} and r_{t-2}. The coefficients give estimated percentage points effects of a unit change in the interest rate. Hence, if the interest rate is increased from 2 to 3 percent in period t, (3) implies that nominal credit growth is expected to be reduced by 0.07 percentage point in the following quarter (ie the point estimate of r_{t-1} in the second line of (3) with two decimals). This estimate is also found in the "Memo" part of Table 2, in the column labelled Impact effect in the part of the table with LSDV estimation results.

While the estimated coefficient of r_{t-1} is negative, the coefficient of r_{t-2} is positive. An estimated sign-change of the interest rate effect is not uncommon in the existing studies, *eg*, Kuttner and Shim (2016), Akinci and Olmstead-Rumsey (2017). As noted above, despite the sign change it is not a given thing that the estimated long-run effect is smaller in magnitude than the impact effect. It can go both ways, depending on estimated sum of the autoregressive coefficients. In Table 2, we see that the long-run effect of a permanent increase in the interest rate on nominal credit growth is estimated to be -0.35 with t-value of -2.52 which is significant at the 1 % level.

Turning to the macroprudential policy indicators, equation (3) and Table 2 shows several interesting results. Both LTV and LTI are estimated to have reduced nominal credit growth when they were introduced. The effects are numerically significant: reducing the quarterly growth rate by 0.46 (LTV) and 0.23 (LTI) respectively. These effects are also statistically significant, though strongly so only for LTV. For both indicators the coefficient of the lagged indicator is estimated to be positive. In Table 2, the consequence is that the two Long-run effects are estimated to be positive, but statistically insignificant.

Equation (3) shows that debt service to income (DSTI) is estimated to have a weak effect on credit growth on impact. Although Table 2, shows that the estimated long-run effect is numerically quite large (-0.95), it is not statistically significant. The results for the two coefficients for the RW policy indicator are quite different, suggesting both a significant impact effect (-0.72 with t-value -3.19), as well as a numerically sizeable long-run effect, estimated to be -3.47 in Table 2.

The estimated impact effect of the Amort policy indicator is statistically insignificant. The long- term of effect of Amort is however estimated to be negative, sizeable (-2.43) and statistically significant.

Finally, the countercyclical buffer variable, CCyB, is associated with positive coefficients in this estimation. Hence, there is no support for the view that due to *eg* increased financing costs, build up of CCyB have dampened credit growth. However, we also remember that the sample information about CCyB comes from only two countries, Sweden and Norway, and one possibility is that CCyB picks up a close correlation between credit growth and introduction of Basel III capital buffer requirements. In that interpretation, where CCyB is a control variable rather than an instrument, it is interesting to note that the results for the remaining five policy indicators are in all important respects unchanged when CCyB is dropped from the empirical model.

We next turn to the results of the robust estimation, using LSDV augmented by indicators for structural breaks as explained above. The results are summarized in the columns of the Table 2 labelled LSDV-Robust. The automatic IIS method found 96 indicator variables which were added to the model equation used for the LSDV estimation.

Looking at the Impact-column first, we see that many of the LSDV estimated coefficients are robust. Although there is a tendency towards smaller magnitudes, the impression that LTV, maybe LTI, and definitively RW may have had negative effects when introduced, remains. The columns with the Long-run effects show larger differences between LSDV estimation and LSDV-Robust estimation. Interestingly, the robust estimation results show much larger numerical effects for both RW and Amort. These coefficients are also statistically significant.

4.2 Housing price growth

The estimated model equation (4) shows a similar specification for nominal house price change, (Δp_t), as we had for credit growth. The only difference, in terms of specification, is that there is an extra, fifth, autoregressive term in the house price model (it has t-value of -4.8). In the same way as above, the economic control variables and dummies are not

Table 3: House price change. Estimated (LSDV) effects for LTV, LTI, DSTI, RW, Amort and CCyB . Results for the central bank rate shown in the Memo part of the table. t-values are shown below the estimated impact and long-run effects. Statistical significance (two sided test) is indicated by ∗∗ (5 % level) and ∗ (10 % level).

	LSDV		LSDV-Robust	
	Impact	Long-run	Impact	Long-run
LTV	−1.04	−0.16	−0.98	−0.28
	−3.22**	−0.48	−2.88**	−0.70
LTI	−0.30	−0.79	−0.18	−0.72
	−0.64	−1.25	−0.39	−1.22
DSTI	−0.03	0.74	0.08	0.97
	−0.06	0.51	0.19	0.63
RW	−0.811	−1.05	−0.79	−0.81
	−2.04**	−0.84	−2.30**	−0.74
Amort	−0.90	−0.21	−0.99	−0.78
	−1.25	−0.19	−1.37	−0.64
CCyB	0.38	0.34	0.46	0.54
	1..00	0.28	1.09	0.43
Memo:				
Interest rate (1 pp increase)	− 0.18	−0.09	−0.18	−0.07
	−2.43**	−2.10**	−2.73**	−1.71*

shown in (4), and more detail about their significance is found in Table 4 in the Appendix.

$$\begin{aligned}
\Delta p_t \quad = \quad & \underset{(0.064)}{0.360}\ \Delta p_{t-1} + \underset{(0.028)}{0.012}\ \Delta p_{t-2} + \underset{(0.018)}{0.117}\ \Delta p_{t-3} + \underset{(0.053)}{0.368}\ \Delta p_{t-4} \\
& - \underset{(0.038)}{0.1837}\ \Delta p_{t-5} - \underset{(0.073)}{0.177}\ r_{t-1} + \underset{(0.070)}{0.147}\ r_{t-2} \\
& - \underset{(0.324}{1.04}\ \mathrm{LTV}_t + \underset{(0.316}{0.990}\ \mathrm{LTV}_{t-1} - \underset{(0.472)}{0.300}\ \mathrm{LTI}_t - \underset{(0.316)}{0.04}\ \mathrm{LTI}_{t-1} \\
& - \underset{(0.431)}{0.027}\ \mathrm{DSTI}_t + \underset{(0.562)}{0.268}\ \mathrm{DSTI}_{t-1} - \underset{(0.397)}{0.811}\ \mathrm{RW}_t + \underset{(0.494)}{0.469}\ \mathrm{RW}_{t-1} \\
& - \underset{(0.724)}{0.902}\ \mathrm{Amort}_t + \underset{(0.826)}{0.833}\ \mathrm{Amort}_{t-1} + \underset{(0.386)}{0.384}\ \mathrm{CCyB}_t - \underset{(0.326)}{0.270}\ \mathrm{CCyB}_{t-1}
\end{aligned} \tag{4}$$

Also in the house price change equation the coefficient of the lagged central bank rate is estimated to be negative, and with a numerically larger coefficient than in the credit growth equation (−0.18). In the same way as for credit, there is a sign change for r_{t-2}, which is positive and with almost the same magnitude as the coefficient for r_{t-1}. Hence, the estimated magnitude of the long-run effect is smaller than the short-run effect (−0.18 and −0.09) in the last row of Table 3.

Also for the macroprudential policy indicators, equation (4) and Table 3 show results that are broadly consistent with what we obtained for the credit growth model. In the LSDV estimation, all measures except CCyB get negative impact coefficients, and for LTV and RW the coefficients are sizeable (-0.9 is the average) and statistically significant. The strong results for those two measures also carry over to the LSDV-Robust estimation.

5 Conclusions

We have analyzed a quarterly panel data set consisting of ten advanced open economies, eight European and Australia and New Zealand, where macroprudential policy measures have been used since the end of the last millennium. The policy instruments include caps on loan to value and income (LTV and LTI), and debt service to income (DSTI) requirements in particular, but also risk weights (RW), amortization (Amort) and, less used, countercyclical buffer (CCyB). We estimated dynamic panel data models, which are in line with the pre-existing literature in this field, and which include the central bank rate, and controls for common nominal and real trends.

A clear impression from the estimated model is that they give support to the view that several of the measures may have reduced credit growth when they were introduced. The estimated impact effects are most significant for LTV, LTI and RW. For Amort, the long-run effect on credit growth is significant, and the same is found for RW. The estimation results when house price growth is the dependent variable are in the main consistent with the results for credit growth. Countercyclical buffer is the only measure where there is no trace of negative effect on nominal credit or house price changes. Hence, any credit dampening effects resulting from the increased financing cost due to capital buffer requirements were not found in our data set.

Our findings are not in contradiction with existing econometric panel data studies that used a broader set of countries, but which also have fewer periods with (for example) active LTV-cap and LTI-cap policies. In one regard our results are stronger about "net effects" than in earlier studies, since we estimated models where all policy variables were included simultaneously from the outset, instead of being added sequentially (estimating the gross effect of one variable a time).

Methodologically we show that the "estimating equation" used in existing studies can be derived as a conditional model form a multi-equation model where the policy variable is endogenous. Econometrically, there is no requisite to lag the policy variables, in order to mitigate endogeneity problems, and this practice can instead have made it difficult to retrieve relevant policy variables. We also demonstrate the usefulness of the methodology developed in time series econometrics, which makes use of automatically selected impulse indicators (IIS) to form a robust OLS estimator. Since the panel data LKDV estimator is a weighted sum of OLS estimators for each country, using LKDV with indicators included, is a robust panel data estimator. Empirically, we conclude that the estimation results for the house price and credit models are robust.

A Endogeniety of macroprudential policy instruments: consequenses for choice of estimation methodology.

Several of the papers cited in the main text mention the endogeneity of for example LTV as a reason for choosing to estimate by GMM (and instrumental variables estimator). However, neither the term endogenous variable, nor its counterpart exogenous variable, refer to precise concepts. Depending on that clarification, the need to consider GMM estimation methodology may or may not follow.

In order to clarify, consider the simultaneous equation model (SEM) with three endogenous variables y_t, r_t and pol_t and one observable non-modelled exogenous variable z_t:

$$\underbrace{\begin{pmatrix} 1 & a_{11} & a_{13} \\ a_{21} & 1 & a_{23} \\ 0 & 0 & 1 \end{pmatrix}}_{\boldsymbol{A}} \begin{pmatrix} y_t \\ r_t \\ pol_t \end{pmatrix} = \underbrace{\begin{pmatrix} b_{11} & b_{12} & b_{13} \\ b_{21} & b_{22} & b_{23} \\ b_{31} & b_{32} & b_{33} \end{pmatrix}}_{\boldsymbol{B}} \begin{pmatrix} y_{t-1} \\ r_{t-1} \\ pol_{t-1} \end{pmatrix} + \boldsymbol{\Gamma} z_t + \boldsymbol{\epsilon}_t \tag{5}$$

For simplicity, we now regard pol_t as a continuous variable, along with y_t and r_t, in which case the linear in parameters formulation is more relevant. Without loss of generality, the vector with SEM disturbances is Gaussian with zero expectation (vector) and diagonal instantaneous covariance matrix.

pol_t is an endogenous variable in (5), since the B matrix captures that pol_t is Granger caused by y_t and/or r_t. The two zeros in the third row of the $\boldsymbol{A}$ matrix captures the idea that endogenous changes in *pol* in any given quarter is likely to be motivated by past values of credit growth and house price changes (and associated indicators of financial stability), and not by the changes in *eg* credit growth in the same quarter (decision and implementation lags are usually large enough to make this a reasonable assumption).

The reduced form of (5) is:

$$\begin{pmatrix} y_t \\ r_t \\ pol_t \end{pmatrix} = \boldsymbol{A}^{-1}\boldsymbol{B} \begin{pmatrix} y_{t-1} \\ r_{t-1} \\ pol_{t-1} \end{pmatrix} + \boldsymbol{A}^{-1}\boldsymbol{\Gamma} z_t + \boldsymbol{A}^{-1}\boldsymbol{\epsilon}_t \tag{6}$$

assuming that the inverse matrix $\boldsymbol{A}^{-1}$ exists. The reduced form residual vector $\boldsymbol{v}_t = \boldsymbol{A}^{-1}\boldsymbol{\epsilon}_t$ is Gaussian with an invertible covariance matrix (not diagonal). (6) is of course a VAR, and by conditioning on pol_t, we can re-write the VAR as a model consisting of two conditional model equations and one marginal model equation, ie:

$$\begin{aligned} y_t &= \varphi_{11} y_{t-1} + \varphi_{12} r_{t-1} + \beta_{10} pol_t + \beta_{11} pol_{t-1} + \gamma_{10} z_t + \varepsilon_{yt} && (7) \\ r_t &= \varphi_{21} y_{t-1} + \varphi_{22} r_{t-1} + \beta_{20} pol_t + \beta_{21} pol_{t-1} + \gamma_{20} z_t + \varepsilon_{rt} && (8) \\ pol_t &= \phi_{21} y_{t-1} + \phi_{22} r_{t-1} + \phi_{33} pol_{t-1} + \alpha_{20} z_t + v_{polt} && (9) \end{aligned}$$

where (7) and (8) are the conditional model equations and (9) is the marginal model equation (ie identical to the third row in (6)). Apart from absence of the lagged variable z_{t-1} (which is omitted as a simplification), we see that (7) and (8) are identical to (1) and (2) in the main text. They also have the same interpretation, implying that $Cov(\varepsilon_{yt}, v_{polt}) = Cov(\varepsilon_{rt}, v_{polt}) = 0$ as well as $Cov(pol_t, \varepsilon_{yt}) = Cov(pol_t, \varepsilon_{rt}) = 0$. Hence there is no endogeneity problem due to correlation between pol_t and the disturbance in model equation (1). It follows that IV (or GMM) estimation of (1) should be motivated by other arguments, *eg* the idea that the finite sample bias of OLS estimators for the coefficients in (1) might be alleviated by GMM, which was the original motivation of Arellano and Bond (1991). This estimator addresses the second order issue of finite sample bias of dynamic panel models, see Arellano (2003, Ch. 6.3) and Baltagi (2010, Ch. 8). However, as mentioned in the main text, empirical models of credit growth and house price changes are likely to include several lags of y from the outset. For model equations of this type, it is unclear how even longer lags of y (than already included) will function as GMM instrumental variables.

B Data sources

B.1 Housing prices and credit

All data are seasonally unadjusted and are measured on a quarterly basis. The data source is the Bank for International Settlements (BIS) Statistical Warehouse.

Housing price indexes for all countries are retrived from the BIS Residential Property Price database which are based on National sources. Further information on the housing prices series are found in `https://www.bis.org/statistics/pp_long_documentation.pdf`.

Household credit data for all countries are retrived from the BIS Long Series on Total Credit. The series are based on national sources, and are compiled by data from financial accounts and the balance sheet of domestic banks. Further information in `https://www.bis.org/statistics/totcredit/credpriv_doc.pdf`.

B.2 Macroprudential policies in the sample

The main sources of the dataset is the European Systemic Risk Board (ESRB), Overview of national macroprudential measures (which can be downloaded from: `https://www.esrb.europa.eu/national_policy/html/index.en.html`), various reports and publications from the International Monetary Fund (IMF) and national authorities (financial supervisory authorities and central banks). A more detailed note (in Norwegian only) outlining the groundwork for the dataset can be provided on request.

C Additional econometric results

Table 2 contains more details about the estimated models for credit growth and house price change, including, sample size and number of parameters estimated, the multiple correlation coefficient and two standard test of residual autocorrelation ($AR(1)$ and $AR(2)$). There is indication of significant first order residual autocorrelation in Table 3 (house prices), but not in the robust estimation (moreover the autocorrelation is negative, implying that the "t-values" of the LSDV estimation is underestimated).

The table also contains several tests of joint statistical significance of groups of variables. We see that the dynamic augmentations of the models ("Autoregressive terms") are highly significant, and so are the included controls, the policy interest rate, and indeed also the macroprudential policy indicators.

Table 4: Summary statistics and tests of joint significance

		Table 2		Table 3	
		LSDV	LSDV-Robust	LSDV	LSDV-Robust
Number of observations		1264	1264	1589	1589
Number of parameters:		34	130	35	119
R^2		0.68	0.82	0.39	0.58
$AR(1)$-test		1.34	1.15	-2.15^{**}	-0.15
$AR(2)$-test		0.04	-0.22	0.97	0.78
Tests of joint significance:					
Autoregressive terms	$\chi^2(4)$	8221^{***}	3380^{***}		
	$\chi^2(5)$			4362^{***}	789^{***}
Controls	$\chi^2(6)$	90.3^{***}	82.1^{***}	125.4^{***}	171^{***}
Interest rate	$\chi^2(2)$	10.3^{***}	4.75^{**}	8.25^{***}	9.62^{***}
Macroprudentials					
-All	$\chi^2(12)$	992^{***}	307^{***}	145.5^{***}	664.1^{***}
-Impact:	$\chi^2(6)$	20.3^{***}	44.3^{***}	62.5^{***}	109.7^{***}
-lags:	$\chi^2(6)$	86.2^{***}	303.7^{***}	16.0^{***}	14.9^{***}

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