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Assessing the Cyclical Behaviour of Bank Capital Buffers in a Finance-Augmented Macro-Economy*

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Abstract

This paper empirically analyses how the banks' capital buffers change with the business cycle. We extract the cycle component using univariate and multivariate filters to document how buffers behave. We also account for the impact of financial factors on capital buffers over the business cycle. Using a large panel of banks for the period 2000-2014, we document evidence that once we account for the impact of financial factors on the business cycle, capital buffers behave more pro-cyclically than previously found in the literature. Furthermore, we provide evidence that large commercial banks react differently to business cycle movements compared to small banks. Overall, these results have important implications for the development of macroprudential policy tools for the global financial system.

Keywords: Pro-cyclicality; Capital Buffers; Business Cycle; Financial Cycle; Macroprudential Policy.
JEL classification: E32; GO1; G21; G28;

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1 Introduction

This paper shows that when the estimation of business cycles accounts for movements of financial variables, banks' capital ratios tend to behave more pro-cyclically than previously thought. Following the recent financial crisis, bank capital requirements have become one of the key instruments of modern day banking regulation, providing both a cushion during adverse economic conditions and a mechanism for preventing excessive risk taking ex-ante. Nonetheless, studies have shown that the Basel Accords (Basel I and Basel II) on capital requirements are not sufficient to prevent the pro-cyclical behaviour of capital buffers, especially the decrease in banks' lending activity during the bust phase of the cycle (see for example; Gordy and Howells (2006), Repullo and Suarez (2012), and Behn et al. (2016)).[1]

To be concrete, one of the primary aims of the Basel II accord was to link capital requirements to risks. However, estimates of risks tend to be higher in recession than in expansions. Therefore, under the Basel II accord, capital requirements are expected to increase during a recession, when building reserves becomes difficult while raising new capital is likely to be expensive. In this set up banks would have to squeeze lending, which in turn would exacerbate a recession. This vicious circle ultimately undermines the stability of both the banking and the macroeconomic systems. As a result of this link between capital requirements, risk and business cycle, a widespread concern about Basel II was that it might amplify business cycle fluctuations, forcing banks to reduce credit when the economy enters into a recession. At the same time, there is a major concern that low capital requirements during upturns will generate credit expansion above a sustainable path, which in turn will lead to asset price bubbles sowing the seeds for the next financial crisis. The financial turmoil of 2008 forced the Basel Committee on Banking Supervision to update the regulatory requirements in order to mitigate risks and practices that would exacerbate this cyclical behaviour. To this end, one of the main objectives of the new regulations (Basel III) is to target pro-cyclicality through the building up of buffers in boom phases to be drawn down in bad times.

The main motivation behind the Basel III regulatory framework was driven by the observation that even banks with a good level of capitalisation suffer from systemic risk. This strengthened the call for a macroprudential dimension to augment firm level supervision and more stringent regulation of the banking system. The countercyclical capital buffer (CCCB) of Basel III would seek to build up buffers during booms that could then be used by banks during periods of stress. By increasing the capital buffer when risks are perceived to be low, banks will have an additional cushion of capital with which to absorb potential losses, enhancing their resilience and helping to ensure the stable provision of financial intermediation services. When credit conditions become weak and banks' capital buffers are judged to be more than sufficient,

[1] In our study, we consider as pro-cyclical (countercyclical) a bank capital ratio that is negatively (positively) correlated with the cycle. This means, other things being equal, the ratio tends to decrease (increase) when the economy or financial asset valuation is growing. Along similar lines, Ayuso et al. (2004), Jokipii and Milne (2008) and Jokipii and Milne (2011) associate pro-cyclicality with the negative correlation between capital buffer and economic activity. Alternatively, Brei and Gambacorta (2016) and Adrian and Shin (2010) define pro-cyclicality as the positive interaction between the leverage ratio and business cycle.

the buffer can then be drawn down. This will help to mitigate a contraction in the supply of credit to households and businesses.

The topic of pro-cyclical effects of bank behaviour as a consequence of capital requirements is not new and has been previously analysed in the financial stability literature.[2] Key amongst this literature is Repullo and Suarez (2012) who find that under cyclically-varying risk-based capital requirements, banks hold more buffers in expansions than in recessions. Nevertheless, these buffers are insufficient to prevent a significant contraction in the supply of credit when there is a recession. The literature also provides possible reasons why banks hold these capital buffers (see e.g. Acharya, 1996; Milne and Whalley, 2001). These include, inter alia; reducing the probability of default, adjustment costs, and as precautionary reserves to avoid breaching capital requirements. Note that designing the optimal level of a capital buffer is not an easy task. The theoretical literature is scant. Kashyap et al. (2004) suggest a simple conceptual framework that takes into account the trade-off between the cost and benefit of bank capital regulation.

However, to the best of our knowledge, none of these studies account for the role of the financial cycle when observing the cyclical behaviour of capital. There are two main reasons for this - the first is that for most of the post war period, the financial cycle was considered to be relatively unimportant in mainstream macroeconomics. The second reason is that there is no real consensus about the actual definition of the financial cycle, hence its subsequent measurement and estimation becomes difficult. Regarding the first reason, the view on the business cycle in traditional macroeconomics, which dates back to Okun (1963), defines deviations from potential output with reference to inflation developments. The assertion is, ceteris paribus, inflation tends to rise when output is above potential and vice vera. This conceptual association grew so strong that it was hardly challenged in any regard. As a result, the role of financial factors have been largely ignored. However, the relationship between output and inflation has appeared to have weakened over recent decades, thereby compromising the usefulness of inflation as a sole indicator of potential output. Accordingly, estimates of the output gap that rely on this relationship (the Phillips curve) may prove to be unreliable and inaccurate. Experience has shown that it is quite possible for inflation to remain low and stable and yet see output grow on an unsustainable path when financial imbalances build up (see e.g. Borio and Lowe (2002)).

In particular, the recent financial crisis showed that low and stable inflation could coexist with unsustainable output growth, fuelled by the build up of financial imbalances. Borio et al. (2016) argue that there are four reasons for this; firstly, financial booms could coincide with positive supply shocks. This will lead to higher investment and economic growth and low inflation. The second reason is that economic expansions may weaken supply constraints through higher participation rates. Injection of new capacity will boost economic growth without destabilising inflation. Third, financial booms are often associated with appreciation of the exchange rate, which puts a downward pressure on inflation. A final point is that unsustainability may be

[2]See for example: Jokipii and Milne (2008); Coffinet et al. (2012); Brei and Gambacorta (2016); and García-Suaza et al. (2012).

generated by a sectoral misallocation of resources.

The fundamental implications of Borio et al. (2016) was that cyclical variations in output are influenced by financial developments. Therefore, it is important to account for the extent to which financial conditions have an impact (positive or negative) on the business cycle when a judgement about the sustainability of economic activity is formulated. From this standpoint, Borio et al. (2016) argue, if the ebb and flow of the financial cycle are associated with economic booms and busts, then surely assessments about the sustainability of a given economic trajectory should take financial developments into account. This prompted new research for measuring potential output in which financial factors are allowed to play a pivotal role. Borio et al. (2016) estimate what they refer to as a "finance-neutral" cycle, which is a measure of the business cycle that takes into account private sector credit and property prices.

In light of this, this study examines the cyclical behaviour of banks' capital buffers over both the traditional business cycle and what we will refer to as a finance-augmented business cycle. We contribute to the literature by providing novel estimates on the relationship between banks' capital buffers and the finance-augmented output gap. As previously mentioned, most, if not all of the empirical studies undertaken in this literature, ignore the role of financial sector activities. In addition, a large share of this literature tend to focus on the determinants of bank capitalisation within a single country.[3] This study uses a sample of 33 low, middle, and high income countries to conduct the baseline analysis. However, estimations using the finance-augmented output gap are carried out with a reduced sample of G7 countries, due to data availability.

Our results suggest, on average, banks' capital buffers are negatively related to the business cycle, hence suggesting pro-cyclicality of capital buffers. More importantly, we find that the capital buffer appears to be even more sensitive to the cycle when we incorporate financial variables in our cyclical indicator. Our empirical results also show that the impact of the finance-augmented cycle is greater than that of the business cycle, suggesting some propagation of shocks to the real economy caused by financial sector activities. This result is consistent with the implication of the financial accelerator model where endogenous developments in credit markets can exacerbate and propel shocks to the real economy. In addition to the main findings, we observe that the behaviour of capital buffers across banks is heterogeneous. That is, the negative relationship with the cycle is particularly pronounced for larger banks, consistent with the "*too big to fail*" hypothesis. Due to the perception that the creditors of large banks will be bailed out in case of bank distress, the cost of debt for large banks is lower. This makes larger banks more willing to use leverage and unstable funding, and to engage in risky market-based activities. Finally, we find that only savings and commercial banks display this negative relationship, with the latter being the main driver behind the pro-cyclical impact.

The remainder of the paper is organised as follows. Section 2 describes the statistical methodology used to estimate the cycles. Section 2.1 describes the dataset. Section 3 presents the econometric methodology to estimate the capital buffer. The empirical results are presented in

[3] See e.g. Shim (2013), Coffinet et al. (2012), Tabak et al. (2011), and Stolz and Wedow (2011).

section 4. Section 5 concludes.

2 Business cycles and finance-augmented business cycles

The assessment of how pro- or counter-cyclical capital buffers really are depends on how we measure the output gap. To gauge the impact of the business cycle on capital buffers, our analysis uses both univariate and multivariate statistical models. In particular, we employ three filters: the univariate Hodrick Prescott (HP), the Hamilton (2017) filter and the univariate unobserved component model. We also use the multivariate unobserved component (UC) models to incorporate macroeconomic and financial variables.[4]

We start the empirical exercise by presenting the univariate and multivariate UC model used to compute the business cycle and the financial-augmented cycle.

The univariate UC model follows Clark (1987). In order to distinguish between the cycle and the stochastic trend of real output, we consider the following unobserved component model:

$$y_t = n_t + x_t \tag{1}$$

$$n_t = g_{t-1} + n_{t-1} + v_t \tag{2}$$
$$v_t \sim i.i.d\ N(0, \sigma_v^2) \tag{3}$$

$$g_t = g_{t-1} + w_t \tag{4}$$
$$w_t \sim i.i.d\ N(0, \sigma_w^2) \tag{5}$$

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t \tag{6}$$
$$e_t \sim i.i.d\ N(0, \sigma_e^2) \tag{7}$$

where y_t is the log of real GDP, n_t is the stochastic trend, x_t is the stationary cyclical component, and v_t, e_t and w_t are shocks that follow a white noise process. The drift term (g_t) in the stochastic trend component is modelled as a random walk. Equations (2) to (6) can be written in state-space form to estimate a univariate UC model.

It is expected, but not necessarily true, that we can obtain better assessments of the business cycle when we add economic information to a univariate filter. To fully be able to make any inference regarding the cyclicality of the capital buffers once we account for financial variables in our estimates of the output gap, we need to make a fair comparison. Therefore, we compare output gaps calculated using the same methodology. This implies utilizing a multivariate UC

[4]In the empirical analysis we also compute the band-pass filter suggested by Christiano and Fitzgerald (2003). However, since results are consistent with those obtained from the HP and UC model, they are not presented here, but are available upon request.

model with one specification including financial factors and one that has been augmented by standard macroeconomic variables such as inflation and unemployment.[5]

When we compute the multivariate UC model we assume that the financial and macroeconomic variables follow a unit root process, so we can decompose both sets of variables into trend and cyclical components:

$$z_{it} = L_{it} + C_{it} \tag{8}$$

$$L_{it} = L_{it-1} + v_{lit} \tag{9}$$
$$v_{lit} \sim i.i.d\ N(0, \sigma^2_{vli}) \tag{10}$$

$$C_{it} = \alpha_{0i}x_t + \alpha_{1i}x_{t-1} + \alpha_{2i}x_{t-2} + e_{cit} \tag{11}$$
$$e_{cit} \sim i.i.d\ N(0, \sigma^2_{ci}) \tag{12}$$

where i indicates either the financial or real variables that we will use to capture developments in the financial and macroeconomic environment. L_{it} and C_{it} represent the permanent and cyclical component of the ith financial and/or real variable, respectively. In equation (11), we allow for lags in the cyclical component to account for phase shifts.[6] Note that equations (6) and (11) assume that z_{it} contains information only about the cyclical component while it does not have any impact on the potential output.[7]

We can write equations (1) to (11) in compact form as follows:

$$\begin{aligned} \mathbf{y}_t =& \mathbf{H}\xi_t + \mathbf{w}_t \\ & \mathbf{w}_t \sim N(\mathbf{0}, \mathbf{R}_t) \end{aligned} \tag{13}$$

$$\begin{aligned} \xi_t =& \mathbf{F}\xi_{t-1} + v_t \\ & v_t \sim N(\mathbf{0}, \mathbf{Q}_t) \end{aligned} \tag{14}$$

where $\mathbf{y_t} = \begin{bmatrix} y_t & z_{it} \end{bmatrix}'$ and $i = 1, 2$. $\xi_\mathbf{t} = \begin{bmatrix} n_t & x_t & x_{t-1} & x_{t-2} & g_t & L_{1t} & L_{2t} \end{bmatrix}'$ (13) and (14) are

[5]For example, Kuttner (1994) studies a bivariate unobserved component model including output and inflation, while Sinclair (2009) considers output and unemployment. To account for model uncertainty, using a Bayesian framework, Chan et al. (2017) show that unemployment is useful in estimating the output-gap, while inflation, conditional on the unemployment gap, no longer has a significant effect on the output gap. This is consistent with Morley et al. (2015) who show, using data of G7 countries that the unemployment gap explains a large fraction of the inflation variation.

[6]This is consistent with the argument of Harvey and Koopman (1997) who show that a multivariate stochastic cycle allows one to model the lead and lags among variables in a symmetrical way. This permits the definition of phase shifts from cross-covariance functions.

[7]With respect to financial variables, such direct impact is possible. For example, Borio et al. (2016) argue that there is evidence suggesting that banking crises following a credit boom have a lasting effect on output.

the observation and measurement equations of the state-space model.[8]

We estimate equations (13) and (14) using maximum likelihood. However, estimates of the standard deviation of v_t, w_t, v_{lit} and e_{cit} might be biased toward zero due to the pile up problem discussed by Stock (1994).[9] To get around the pile up problem, we follow Laubach and Williams (2003) and use a two step approach. In the first step, we use the median unbiased estimator of Stock and Watson (1998) to obtain estimates of the ratios $\lambda_y = \sigma_v^2/\sigma_e^2$ and $\lambda_{zi} = \sigma_{vli}^2/\sigma_{ci}^2$.[10] In the second step, we impose the ratios obtained from the first step and estimate the remaining model parameters.[11]

The next section presents the data used to estimates the cycles and the estimations of the cycles.

2.1 Data and model selection

This section provides details of the estimation of the multivariate models. The computation of the univariate models require little explanation since they are standard in the literature.

Concerning the estimate of the multivariate UC models, the variables included are selected based on three criteria. First, we implement an out-of-sample forecasting exercise where indicators are selected based on their forecasting power of output growth. Although indicators might help to forecast output growth, at times they might fail to signal an imminent recession. Hence, in the second stage we select variables that have both a significant forecasting power in forecasting output growth and the subsequent measure of the output gap is able to capture major recessions in our sample. For example, if we select three financial variables (i.e. credit to GDP ratio, house prices and stock prices) on the basis of their forecasting performance, but measures of output gap fail to capture the recession of 2008, we drop this model. Finally, we provide further validation of output gaps obtained from the UC filter by comparing them to standard gaps estimated by big institutions such as the OECD. In particular, we calculate the correlation coefficient of the output gap obtained by the multivariate and univariate filter with the output gaps published by the OECD. It is worth noting that there might be a large number of models that satisfy the first two criteria. However, we select only the models which have reasonable correlation with the output gap produced by the OECD.

Following Borio (2014), Stremmel (2015) and Drehmann et al. (2012), we compute a finance-augmented cycle by considering, along with the GDP, three additional financial variables. These

[8]When we compute the finance-augmented cycle, L_{1t} and L_{2t} indicate credit to GDP ratio and house prices, while they represent unemployment and inflation when we compute the macro-augmented cycle.

[9]Sargan and Bhargava (1983) show within an MA(1) model that maximum likelihood estimates of the moving average parameter are equal to 1 even if the true value is less than one. This is known as a pile up problem. Moreover, Stock (1994) show that a MA(1) model can be written in a state space form and when the noise to signal ratio is close to zero then the model is subject to the pile up problem. More formally, Stock (1994) show that when the "noise to signal ratio" σ_v^2/σ_e^2 is zero or T^{-2} neighborhood of zero, then estimation of σ_v^2 is zero with finite probability.

[10]Stock and Watson (1998) show that estimation of parameter λ_y is T times the ratio of the long-run standard deviation of Δn_t to the long-run standard deviation of e_t

[11]It is worth clarifying that we initially estimate univariate state space models. In particular, we estimate (1) to (6) assuming that $g_t = g$ and we compute $\lambda_y = \sigma_v^2/\sigma_e^2$. We then estimate the full model by imposing $\lambda_y = \sigma_w^2/\sigma_y^2$ and $\lambda_{zi} = \sigma_{vli}^2/\sigma_{ci}^2$.

are; (i) residential property prices; (ii) credit to the private, non-financial sector; and (iii) credit–to–GDP ratio. These variables are considered to be the most parsimonious way of capturing the financial cycle.[12] Alternatively, we compute a measure of output gap accounting for macro-variables by considering inflation and unemployment. It is worth stressing here that we consider all bivariate and trivariate unobserved component models and we select as optimal the model that satisfied all three criteria.[13]

More formally, we employ a procedure which creates a number of possible regression-based models:

$$\Delta y_t = c + \sum_{i=0}^{p}\sum_{j=1}^{k}\beta_j g_{t-i,j} + u_t \tag{15}$$

For k indicators and p lags the procedure generates $M^j = \sum_{i=1}^{s} \frac{q!}{(q-i)!i!}$ models, where s is the maximum number of indicators chosen to enter a particular model j. More specifically, from a set of $q = k(p+1)$ indicators, we compute all possible models up to s indicators. Thus, in our case for $s = 3$ and $p = 4$, we have 575 models. At each point in time, we estimate recursively all possible models and the preferred model is then selected using the Bayesian Information Criterion (BIC). Our results show that when we select an optimal model with three indicators, they all have a significant impact, but the optimal model changes at each point in time. Alternatively, when a single variable is chosen results vary across countries. Note that the forecast performance of an optimal model including three variables is not significantly better than a model including a single variable.[14] For example, Figure A1 shows that for the US and the UK, credit-to-GDP ratio is selected for more than 80 % of the out-of sample period, while for the rest of the countries in our sample stock prices and house prices are selected for most of the out-of sample period. However, Figure A2 shows that when macro indicators such as unemployment and inflation are used to forecast output growth, unemployment is selected for most of the out-of-sample period.[15] Evidence that the optimal model changes across time makes it challenging to compute the output-gap using different indicators at each point in time. Therefore, we compute both trivarite and bivariate models and focus both on their ability to capture key recessions in our sample and on their correlations with the output-gap published by OECD.

Although estimates from the trivariate model are consistent with empirical evidence con-

[12] All the series used to capture both cycles are in real terms (deflated by CPI) and in logs, with exception of the credit-to-GDP ratio. Further, we normalise the series to their respective values in 1985 to ensure comparability of the units.

[13] We use the Gross Domestic Product (GDP) obtained from the World Bank's World Development Indicators (WDI) database. Data on property prices, credit to non-financial sector, and credit-to-GDP ratio are retrieved from the BIS database. Data on the consumer price indices (CPI) was also retrieved to deflate the series. Data on CPI and unemployment are from the OECD. All macroeconomic data spans the period 1975-2014. A typical issue with the use of any filter is that they have an end-of sample problem. As such, we try to alleviate the end-point problem by following Watson (2007). We have used VAR(p) and AR(p) models to forecast three year quarterly data of GDP. The filters then have been applied to the extended series.

[14] The Diebold and Mariano (2002) test for equal forecast accuracy accepts the null that the three-indicator model is not statically different from single-indicator model.

[15] Exception to this is the case of Japan where the optimal model frequently includes only inflation.

cerning the recession of 2008, their correlation with the OECD output-gap is very low compared to those computed by bivariate UC models. Therefore, we estimate two bivariate finance-augmented cycles: one including real GDP and credit-to-GDP, while the second model includes real GDP and house prices. Estimates from the latter model encounter two main problems. First, in some countries we could not get around the pile-up problem while in other estimates the model fails to capture the global recession of 2008. Second, the correlation coefficient of the subsequent measure of the output-gap with the OECD series was low and in some countries even negative. Alternatively, the finance-augmented cycle computed by real GDP and credit-to-GDP appears to both capture the main recession in our sample and have high correlation with the OECD series. We also employ two bivariate models to compute macro-augmented cycles (i.e., the first model comprises real GDP and unemployment while the second model includes real GDP and inflation). The macro-augmented cycle computed by real GDP and unemployment gap seems to satisfy both criteria: consistency with empirical recession and the high correlation with officially published output-gap series by OECD. On the other hand, estimates of output gap using inflation and real GDP not only fail to capture the recession of 2008 but also had very low correlation with the series of the OECD.

Finally, we estimate a model that comprises both macro and financial indicators: credit to real GDP ratio, house prices, stock prices, unemployment and inflation. However, unlike the sub-models that include either macro or financial variables, q does not include lagged values of indicators (i.e., $q = k$).[16] We also observe that the optimal model change both across time and country. For example, for the US the optimal model consists of credit to real GDP ratio, house prices and unemployment, while for the UK the optimal model includes credit to real GDP ratio, unemployment and inflation.[17] In Italy and France the optimal model varies across time and indicators. An ideal approach would be to apply the Dynamic Model Average (DMA) procedure suggested by Koop and Korobilis (2012) in the forecasting literature. However, such a procedure is computationally demanding in our context. Alternatively, we can employ all five indicators in a six dimensional filter. However, a possible drawback of this route is that it becomes hard to extract sensible estimates out of the filter due to the many noise to signal ratios that need to be estimated. Therefore, we consider only sub-sets of variables to construct a measure of output-gap. More formally, we focus on two bivariate models (i.e. the finance-augmented and Macro-augmented cycle) and a trivariate model which includes real GDP, the credit to real GDP ratio and unemployment.

Figure 1 shows the output gap estimates derived by the univariate unobserved component model and the finance-augmented cycle. We can observe the difference in amplitude between the finance-augmented cycle and the univariate business cycle. This is consistent with Borio et al. (2016) who show that the finance-neutral cycle was above the potential level before the financial crisis, while other measures of the output gap were below or close to the potential level; however, this might not necessarily be driven by the information extracted from the financial

[16]For $q = k$ and $s = 3$, the total number of models generated by our procedure is 25.

[17]Results are available upon request.

variables.[18] In Figure 2 we show the macro-augmented cycle and the finance-augmented cycle. We can clearly see that for many periods in our sample, the bivariate macro-augmented cycle lies above the finance-augmented cycles. This suggests that the argument that financial variables help to extract a more accurate measure of the output gap might not be correct in the sense that other variables can also help to extract a better signal of potential output. In Table A1 we show the correlation coefficient of output gaps across the univariate and multivariate filters with the output gap published by the OECD. We do observe that, with few exceptions, the correlation of finance-augmented and macro-augmented cycles with the OECD series is above 0.6. In particular, only in the cases of Japan and the US are the correlation of the finance-augmented cycles lower than the correlation of macro-augmented cycle. Finally, there is evidence that the correlation of the cycles generated by the trivariate filter is almost as high as the correlation of the finance-augmented cycle. Here it is worth stressing that in the case of the UK where the correlation of finance-augmented cycle is rather low, the correlation of the cycle produced by the mixed filter is much higher. Therefore, the use of both macro and finance variables can help to produce more accurate estimates of the cycles.

3 Capital buffer: econometric methodology and data

Having extracted the business cycles using different statistical methodologies, this section moves to estimate how changes in economic conditions affect banks' capital buffer. Following the partial adjustment model with quadratic cost of adjusting capital suggested by Ayuso et al. (2004) and Estrella (2004), we employ the following empirical model:

$$\begin{aligned} BUFF_{i,j,t} = \mu + \theta CYCLE_{j,t} + \alpha BUFF_{i,j,t-1} + \beta ROE_{i,j,t} + \gamma RISK_{i,j,t} + \delta SIZE_{i,j,t} + \\ + \varphi \Delta LOAN_{i,j,t} + \phi_i + \lambda_t + \epsilon_{i,j,t} \end{aligned} \tag{16}$$

where $BUFF_{i,j,t}$ indicates the capital buffer for bank i in country j in year t, ROE denotes return on equity, while $SIZE$ and $CYCLE$ are variables reflecting the size of the bank and the proxy of business cycle, respectively. The lag of the dependent variable is used to capture adjustment cost and the sign of this coefficient is expected to be positive. ROE reflects the greater cost of capital funding relative to deposit or debt. The $SIZE$ variable is included to detect differences in the buffer according to the size of each bank. The ratio of non-performing loans to total loans ($RISK$), is included since a bank's probability of failure is partially dependent on its risk profile. $\Delta LOAN$ denotes credit growth, while $CYCLE$ represents the business cycles estimated in the previous section. This is the key variable of interest and is used to address our main question concerning the pro-cyclicality of capital buffers. Finally, ϕ_i is a bank fixed effect, λ_t is a time fixed effect and ϵ_{ijt} represents the error term.

The empirical analysis of equation (16) is based on an unbalanced panel, drawn from an international sample of 578 banks from 33 countries for the period 2000 to 2014. Table 1

[18] In particular, Borio et al. (2016) show that the output gaps produced by OECD, IMF as well as those based on a simple HP filter indicate that the output gap was below the potential in the US.

provides details on the number of banks per country in the sample. The bank-level data are extracted from Bureau van Dijk's Bankscope which provides information on consolidated and aggregated statements of banks and their specialisation.[19] A key variable of interest is the capital buffer, which is the difference between the observed capital ratio of bank i in country j, in period t, and the Basel III minimum regulatory capital. Table 2 provides definitions of the variables used in our estimation.

[Table 2 ABOUT HERE]

It is worth noting, in (16) when the time dimension of the panel T is fixed, the fixed effect and random effect estimators are biased. Ample literature of consistent instrumental variable (IV) and Generalised Method of Moments (GMM) estimators have been proposed as an alternative for the fixed effect estimator. Arellano and Bond (1991) argue that additional moments can be obtained by exploiting the orthogonality conditions that exist between the lagged values of the dependent variable and the disturbances.

However, Blundell and Bond (1998) and Binder et al. (2005) show that the IV and the one-step and two-step GMM estimators are subject to weak instrument problem as the variance of the individual effects ϕ_i increases relative to the variance of the error term $\epsilon_{i,t}$, or as the lag coefficient α approaches 1. Blundell and Bond (1998) and Arellano and Bover (1995) get around the weak instrument problem by including in the set of instrumental variables not only the lagged levels but also the lagged differences of the dependent variable.[20] Pesaran (2015) points out the number of orthogonality conditions tend to infinity as $T \to \infty$. Here, we circumvent the proliferation of instruments generated by the difference and system GMM by using as instruments only certain lags, instead of all available lags. Another important point to note is that the consistency of the GMM estimator depends on the errors being serially uncorrelated i.e., $E(\Delta\epsilon_{i,j,t}, \Delta\epsilon_{i,j,t-2} = 0)$. Hence, Arellano and Bond (1991) suggest to test that the second-order auto-covariances for all periods in the sample are zero.

The instruments chosen include the full complement of lags of the dependent variable ($BUFF$) and two to four lags of $RISK$ and ROE variables. These lags have been chosen to avoid correlation with the error term $\epsilon_{i,j,t}$ (which now appears in first differences) while simultaneously minimising the number of lost observations. We report two main post-estimation tests to validate the appropriateness of our dynamic GMM estimations. The first is the Hansen (1982) J-test statistic for over-identifying restrictions. The J-test is related to the order condition of identification and test the null that instruments being uncorrelated with the error term.[21] The other test is the Arellano-Bond test for autocorrelation of errors, as described above.

[19]Consolidated data is used for most banks. The scope of information provided by consolidated balance sheets is wider and information about banking subsidiaries operating outside of the home country is also included. In addition, consolidated data captures interdependence between macro factors and therefore make prudential data more consistent with real outcomes. Where consolidated data is not available, the aggregated data is used. The study focuses on three specific bank specialisations, namely; commercial, savings and co-operative banks.

[20]The original Arellano and Bond (1991) method is known as "difference GMM" while the expanded estimators are known as "system GMM".

[21]Failure to reject the null hypothesis indicates that our instruments are exogenous.

4 Empirical results

We first examine the cyclicality of banks' capital buffers using the full sample of banks. Subsequently, we discuss the impact of the finance-augmented business cycle on the capital buffer. However, because of data availability we focus our analysis on G7 countries.

4.1 Traditional business cycles

Table 3 presents the results obtained from the estimation of the baseline model described in equation (16). The first two sets of results in Table 3 were carried out using the HP-filter to compute the cycle variable while the remaining two columns present the estimates of the capital buffer model where the Hamilton (2018) methodology was used to construct the proxy of business cycles.

[Table 3 ABOUT HERE]

Table 3 provides evidence that, after controlling for other determinants, there is a negative and statistically significant relationship between the capital buffer and the phase of the business cycle. The estimated coefficients in columns (1) and (2) suggest that capital buffers respond negatively to changes in the output gap. In other words, as real economic activity declines, banks build up their capital buffers. This suggests that banks increase their precautionary reserves in bad or uncertain times.[22]

The bank specific controls also provide some interesting results. First, we focus on the cost of adjustment variable, i.e. the lagged dependent variable, which appears positive and significant in all four specifications. This finding is consistent with the view that the cost of capital adjustment is important in determining how much capital banks hold. The estimated coefficient on ROE in Table 3 appears positive and statistically significant in specifications (2) and (4). The positive impact of ROE on capital buffer indicates the importance that banks place on retained earnings to increase their capital buffer. Furthermore, the positive coefficient on $RISK$ in all four specifications suggests that banks with risky portfolios tend to hold more capital in reserve. Such behaviour would influence increases in total capital buffers and thus have implications for the cyclical behaviour of bank capital. It is worth noting that Jiménez et al. (2014) argue that the non-performing loans is an ex-post measure of risk which understates the risk taking behaviour of banks. Therefore a positive coefficient of non-performing loans on capital buffers might underestimate the procyclical behaviour of banks.

The impact of credit growth in columns (2) and (3) is significant at the 1% level and, as expected, enters with a negative sign. This suggests that a contemporaneous increase in credit growth reduces the capital buffer, in line with the findings of Ayuso et al. (2004). Also, we consider whether our results might be influenced by the fact that $\Delta LOAN$ could be a cyclical variable. If it is, it could influence the sign and significance on the business cycle variable. We

[22] The findings of Coffinet et al. (2012), Jokipii and Milne (2008) and Ayuso et al. (2004) are also consistent with our results.

test this for each approach by excluding the $\Delta LOAN$ variable in columns (1) and (4). Finally, contrary to our expectation, the bank $SIZE$ carries a positive and significant coefficient in column (2). Note that consistent with the "*too big to fail*" hypothesis, we expected this coefficient to be negative, which would indicate that, *ceteris paribus*, larger banks tend to hold less capital in reserve. We will further investigate the impact of bank size on capital buffer when we split the sample, separating big from small banks and carrying out separate estimations.

The regressions pass both the Arellano-Bond test for autocorrelation of order 2 and the Hansen J-test for over-identifying restrictions.

[Table 4 ABOUT HERE]

Next, we consider the possibility that the capital ratios of different types (commercial, savings and co-operative) and sizes of banks may react differently to business cycle conditions. We classify big banks as those that fall in the highest decile of the size distribution of total assets, while small banks are those that fall in the lowest 30 percentile of the size distribution. These classifications are done by country. Table 4 reports estimates accounting for the type and size of banks. Although we continue to find evidence of pro-cyclicality in capital buffers for commercial and savings banks, for co-operative banks the cycle enters with a positive coefficient, albeit statistically insignificant. These results suggest that the pro-cyclicality of capital buffers observed in Table 3 is being driven by commercial and savings banks. We consider the possibility that the results concerning savings banks could be driven by the relatively small number of observations. However, using a sample of nearly 500 German savings banks (4346 observations), Stolz and Wedow (2011) find that the capital buffer of these banks are negatively associated with the cycle. The consistency of our findings with those of Stolz and Wedow (2011) eases this concern regarding our small sample size.

The $\Delta LOAN$ is negative and significant across all bank types, with the sensitivity approximately being the same for all three categories. Therefore, irrespective of product specialisation, credit growth will have a negative impact on capital buffers. The $RISK$ coefficient remains positive for all three categories, but statistically insignificant for savings banks. The impact of bank $SIZE$ on capital buffer is in line with results in Table 3 as it remains insignificant across all types of banks. Next we analyse estimates accounting for the bank size as presented in the last two columns of Table 4. In these two specifications we remove $SIZE$ from the setup. As expected, the $CYCLE$ variable for big banks carry a negative sign, while for small banks it carries a positive but insignificant coefficient. This is consistent with the *too-big-to-fail* hypothesis. This finding is well established in the literature (see for e.g. Jokipii and Milne (2008) and Ayuso et al. (2004)).

To summarise our results using the business cycle as our cyclical indicator, we find evidence of pro-cyclicality in capital buffers. The pro-cyclicality of capital buffers is driven by commercial and savings banks, but the impact is more significant for commercial banks. Big banks display pro-cyclicality in their capital buffers while for smaller banks the evidence suggests that capital buffers are not pro-cyclical.

4.2 Finance-augmented business cycles

In this section we discuss the results of the relationship between banks' capital buffers and output gaps obtained using the multivatiate UC model. Given the limited availability of data to compute the financial-augmented cycles, we restrict our sample to the G7 countries. Though reduced, the sample remains sufficiently large enough to carry out the estimations. To ease comparability, we also present the univariate cycle as estimated by the univariate UC model. These set of estimates using the G7 sample ensure the results are consistent with those presented for the full sample in Table 3.[23]

As previously mentioned in section 2.1, Table 5 uses two bivariate output gaps (labelled as "Bivariate macro" and "Bivariate finance" business cycle) and a trivariate unobserved component model. The "Bivariate macro" includes GDP and unemployment rate, while the "Bivariate finance" comprises of GDP along with the credit-to-GDP ratio. The trivariate UC filter combines information used in the bivariate cycles, which includes real GDP, credit to GDP ratio and unemployment. We maintain all the bank-specific control variables and simply replace the cycle indicator in our model. The findings are presented in Table 5.

[Table 5 ABOUT HERE]

Focusing on columns 2 and 3, where we introduce the new cyclical measures, we observe negative and statistically significant coefficients on these cycle indicators. However, the coefficient on the finance-augmented cycle appears much more sensitive, as reflected by its magnitude. Although the magnitude of the finance-augmented cycle is larger than the coefficient of the macro-augmented cycle, this might be driven by the higher amplitude of the latter.[24] Therefore, this in itself does not suggest that capital buffers become more pro-cyclical when we account for financial variables. To compare the responses of capital buffers to different measures of the business cycle, we use four different evaluation metrics. Firstly, we run a *horse-race* model where both gaps are included in the model. The final column in Table 5 provides results from the horse-race model.

We do observe that while the impact of the finance-augmented cycle is negative and statistically significant at the conventional statistical level, we cannot reject the hypothesis that the macro-augmented cycle does not have a statistically significant effect on the capital buffer. In other words, the results suggest that the credit-to-GDP ratio adds more explanatory power to the output gap than the unemployment rate.

With respect to the other determinants, the signs of the coefficients are predominantly similar to those presented in previous tables and in accordance with previous results. Second, to alleviate the problem of the cycles being at different scale or having different amplitude, we standardise both univariate and bivariate cycles and re-estimate the models of Table 5. Results from the standardised cycle presented in Table A3 are consistent with the *horse-race* exercise.

[23] The results, shown in columns 1 and, are largely consistent with that of the full sample in Table 3.

[24] Note that the magnitude of the coefficient depends on how large the estimated business cycles swings are. For example multiplying the estimated gaps by 2, will reduce the coefficient by half.

In particular, models 2 and 3 provide evidence that the response of capital buffers to the finance-augmented cycle is stronger than the response to the macro-augmented cycle. Though both are statistically significant, given that both cycles are unit-less, the magnitude of their coefficient can be used as a gauge of their impact on capital buffers. Third, we also compare the impact of the two bivariate cycles on capital buffers by computing their elasticities. In doing so, we attenuate the problem of the cycles being in different scales. Results in Table A4 enhance the view emerging from the *horse-race* exercise where only the impact of finance-augmented cycle is significant. Finally, the RMSE of models 2 and 3 in Table A3 shows that the latter model (i.e. the model which includes the finance-augmented cycle) fitted the data better than the former.[25] Next we look at the impact of the trivariate cycle on capital buffer presented in the last column of Table 5. Although the coefficient of the trivariate cycle is out-weighted by the impact of the finance-augmented cycles, we need to make them comparable by using standardised cycles. Table A4 also indicates that the impact of the trivariate standardised cycle is marginally larger than the impact of both bivariate cycles. However, Table A5 provides strong evidence that the marginal effects of the trivariate cycle is more than four times larger than the marginal effects of both bivariate cycles. Our results imply that both real and financial variables provide useful information for the construction of an accurate measure of output-gap.

[Tables 6 and 7 ABOUT HERE]

Table 6 provides a comparable breakdown to Table 4. We examine the cyclical behaviour of banks' capital buffer by size and specialisation using the G7 sample. Similar to results of Table 4, we observe that the capital reserves of big banks are pro-cyclical, whilst there is no evidence to suggest the same for smaller banks. This might be driven by evidence that small banks are more prone than large banks to hold capital buffers (see e.g. Kashyap and Stein (2000)). By doing so, small banks are less affected by changes of the macroeconomic environment. Furthermore, we find evidence that only commercial banks exhibit this pro-cyclical behaviour. In summary, results based on the finance-augmented cycle are broadly consistent with those of the business cycle. Finally, we also experiment with a model where the cycle is computed by a trivariate filter accounting for unemployment and credit to GDP ratio. Results presented in Table 7 are consistent with the implications of Table 6. The pro-cyclicality of capital ratios appears, however, significantly stronger over the finance-augmented cycle.

4.3 Robustness

In this subsection, we employ robustness checks on our empirical approach to ensure that the key results are consistent. To do this, we replicate estimations from Table 3 and Table 5, using the Arellano and Bover (1995) system GMM estimator. The system GMM estimator tends to perform well in the presence of highly persistent variables. The results are shown in Table A2 of the Appendix. All the main results remain largely consistent with those presented

[25] In particular the RMSE of the latter model was 2.342 while the RMSE of the former model was 3.187

in the previously mentioned tables. Our cyclical indicators remain negative and significant throughout.[26]

Finally, we account for direct and indirect effects of financial crisis on capital buffers. We do so by using the five specifications presented in Table A6. The first two models include proxies of the business cycle along with the crisis dummy while the other two add an interaction dummy between a proxy of the business cycle and the crisis dummy. We also estimate a model including only an interaction dummy between the finance-augmented cycle and the crisis dummy. We notice that the crisis dummy is significant only in two specifications. The first is the model which includes a proxy of the macro-augmented cycle and the interaction dummy between the macro-cycle and the crisis dummy. The second is the model which excludes proxies of the business cycle and includes only an interaction dummy between the finance-augmented cycle and the crisis dummy. Note that in the former case the macro-augmented cycle is not significant which implies that the macro-cycle has an indirect impact on capital buffers through expectations about an imminent crisis driven probably by negative forecasts about future economic growth. Alternatively, the later case show that the crisis dummy has only an indirect impact on banks' behavior through the financial variables. Our results provide further support for the importance of financial variables when we construct a proxy of the output gap.

[Table A6 ABOUT HERE]

5 Conclusion and Policy Implications

This paper examines how the capital buffers of banks behave over the business cycle. The paper uses two cyclical measures to examine this behaviour. It relies on the widely used business cycle measure, proxied by GDP, and also introduces a novel approach in the form of a finance-augmented cycle. We apply the Arellano-Bond GMM difference estimator to control for adjustment costs, unobservable heterogeneity and potential endogeneity of the explanatory variables. Our work is unique in two ways. First, it differs from much of the empirical literature on banks' capital buffer, as most of these studies focus on a single country. Our study is cross-country and provides results for countries across all three income levels. Second, and more importantly, the majority of this literature solely focuses on the business cycle, disregarding the potential impact of financial sector activities. Our analysis uses a proxy of the business cycle which accounts for developments in the financial sector. The inclusion of information about the financial side of the economy can provide more reliable estimates of the output-gap than the conventional filter-based approach used in the literature.

[26] We also consider the fact that expectations might affect how and when banks adjust their capital buffer. To test this, we create dummy variables to represent the announcement dates of the Basel Accords. With our dataset spanning the period 2000 - 2014, we capture the announcement of both Basel II and Basel III capital standards requirement. As such, we use an event study to test whether these announcement dates were significant in determining the timing and nature of adjustment of banks' capital buffers. We find that these announcements are statistically insignificant. Results available upon request.

Our results indicate a negative relationship between the holding of capital buffers and the business cycle. That is, during an economic downturn banks increase their capital buffers, whilst in booms they reduce them. Furthermore, we find that this negative relationship is particularly related to large banks. The reason for this is owing to the fact that big banks hold less capital with the expectation that, in the event of a financial crisis, they will inevitably be bailed out. On the other hand, small banks are more reliant on retained earnings as a protection against insolvency,which explains why they increase capital buffers during booms. Further analysis indicates that this negative relationship is being driven by commercial and savings banks, with the former being more sensitive to the business cycle. Our results also highlights that capital ratios are even more pro-cyclical when using a finance-augmented output gap.

An important implication of the these findings is the key role of monetary authorities in the supervision of risk management practices. Particularly, from a macroprudential policy standpoint, regulators should adopt more flexible instruments to mitigate credit risk in banks globally. This recommendation is motivated by the fact that even with the prudential framework set out in the new Basel accords (Basel III), the pro-cyclical behaviour of banks' capital buffers will still persist.

Our analysis shows that it is not always safe to assume that regulatory or supervisory capital standards automatically constrain banks. Market power, for example, may induce banks to hold capital in excess of the minimum required, thereby reducing the power of capital requirements as instruments of financial stability.

A major step towards mitigating the pro-cyclical impact of capital ratios is the introduction of a capital conservation buffer (countercyclical capital buffer). This particular tool is designed to ensure that banks build-up sufficient capital buffers in the banking system during booms and to encourage their use during stressful periods, thereby easing the strains on credit supply. Our finding of a greater degree of pro-cyclicality of banks' capital ratios would suggest that the approach to setting the countercyclical capital buffer rate for banks might need to be more prescriptive.

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Figure 1: Univariate vs Bivariate Output gap

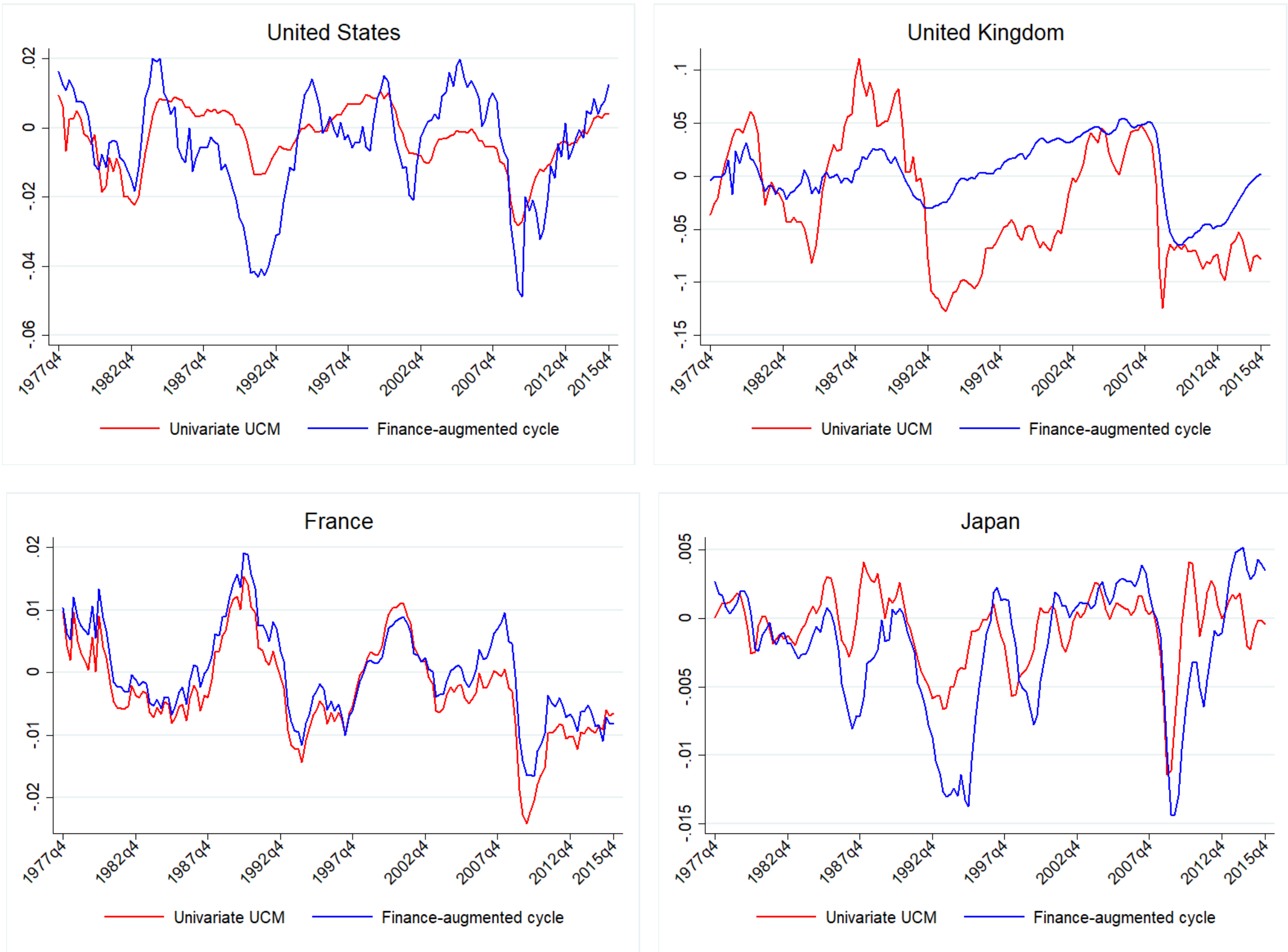


Figure 2: Output gap developments

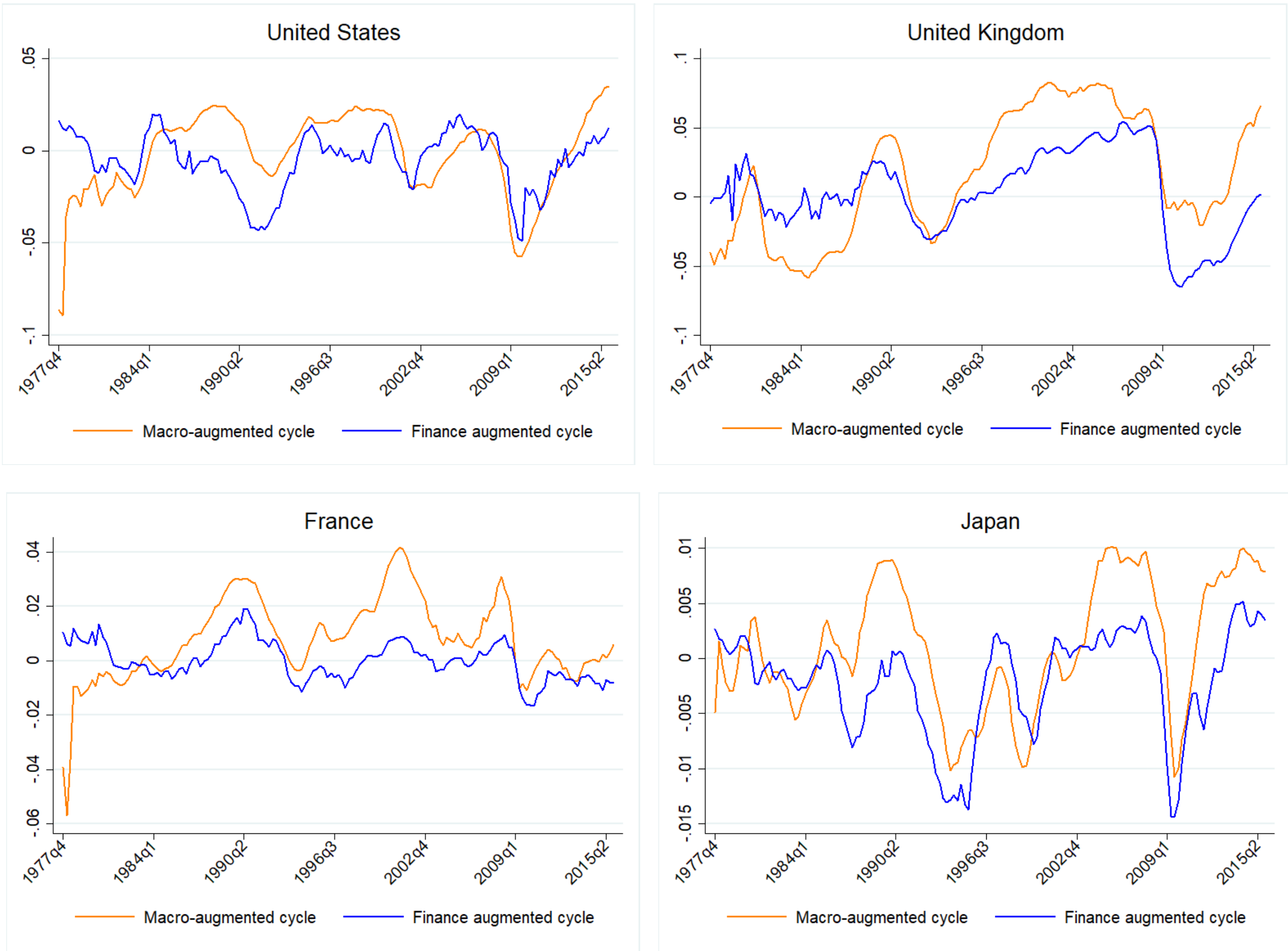


Table 1: Countries and number of banks

Country	Total no. of banks	Commercial bank	Cooperative banks	Savings banks
AUSTRALIA	10	9	1	
AUSTRIA	16	9	5	2
BELGIUM	9	6	1	2
BRAZIL	25	25		
CANADA	6	5	1	
CZECH REPUBLIC	5	5		
DENMARK	16	12		4
ESTONIA	5	5		
FINLAND	5	4	1	
FRANCE	16	13	3	
GERMANY	8	7	1	
GREECE	7	7		
HUNGARY	6	6		
INDIA	12	12		
INDONESIA	14	14		
ISRAEL	10	10		
ITALY	38	17	16	5
JAPAN	116	109	7	
LATVIA	8	8		
LUXEMBOURG	5	5		
MEXICO	15	13	1	1
NETHERLANDS	13	12	1	
NEW ZEALAND	5	5		
NORWAY	26	4		22
POLAND	12	10	1	1
PORTUGAL	7	6		1
SLOVAKIA	5	4		1
SLOVENIA	7	7		
SPAIN	17	9	2	6
SWITZERLAND	5	4	1	
TURKEY	18	18		
U.K	15	15		
U.S.A	71	60	3	8

Table 2: Description of Variables

Variable	Description
BUFF	Total capital ratio minus Basel III regulatory minimum
RISK	Ratio of NPLs to Gross Loans
NET LOANS	Loans over total assets
SIZE	Natural log of total assets
ROE	Return on equity
PROFIT	Profit after tax over total assets
ΔLOAN	Annual loan growth
UNIVARIATE BUSINESS OUTPUT-GAP	Cyclical component of real GDP
BIVARIATE BUSINESS OUTPUT-GAP	Cyclical component of real GDP and unemployment
FINANCE AUGMENTED OUTPUT-GAP	Cyclical component of real GDP and credit-to-GDP

Table 3: Baseline model

	(1) HP-Filter	(2) HP-Filter	(3) Hamilton	(4) Hamilton
Business cycle	-4.235**	-3.994***	-2.251***	-3.449***
	(1.654)	(1.290)	(0.662)	(0.545)
$Buff_{i,j,t-1}$	0.460***	0.530***	0.483***	0.511***
	(0.091)	(0.077)	(0.093)	(0.081)
ROE	0.821	3.320***	1.928	3.545***
	(1.092)	(1.001)	(1.953)	(0.998)
Risk	0.276***	0.118*	0.137*	0.217***
	(0.083)	(0.069)	(0.078)	(0.069)
Size	0.003	0.486**	0.406	0.173
	(0.300)	(0.247)	(0.295)	(0.276)
$\Delta Loan$		-0.033***	-0.032***	
		(0.004)	(0.004)	
$\alpha(1)$	0.00	0.00	0.00	0.00
$\alpha(2)$	0.66	0.40	0.49	0.27
Hansen J	0.06	0.09	0.06	0.26
Observations	4,508	4,468	4,320	4,471
Number of Banks	577	577	577	577

Notes: This table provides results for the baseline specification of our model. The first two columns use a cyclical component of the output gap derived using the HP-filter. The final two columns use estimates of the output gap derived by the approach proposed in Hamilton (2018). The dependent variable (BUFF) is the bank's capital buffer ratio. All estimations are based on the Arellano and Bond (1991) difference GMM estimator. Robust standard errors are reported in parentheses, $\alpha(1)$ and $\alpha(2)$ are first and second order residual autocorrelation tests. The null hypothesis of the AR(2) test is that errors in the first-difference regression exhibit no second-order serial correlation. The null hypothesis of the Hansen test is that the instruments are valid. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Estimation by specialisation and size

	(1) Commercial	(2) Cooperative	(3) Savings	(4) Large	(5) Small
Business cycle	-2.444***	1.237	-4.249*	-5.662**	-0.081
	(0.533)	(0.872)	(2.442)	(2.280)	(1.206)
$Buff_{i,j,t-1}$	0.590***	0.468***	0.619***	0.685***	0.486***
	(0.061)	(0.091)	(0.117)	(0.083)	(0.106)
ROE	2.975**	3.058*	5.130**	0.198	4.402**
	(1.153)	(1.748)	(2.426)	(1.240)	(2.033)
Risk	0.097*	0.129***	0.089	0.289**	0.170
	(0.053)	(0.045)	(0.074)	(0.132)	(0.139)
Size	0.467	-0.173	-0.537		
	(0.285)	(0.791)	(1.121)		
$\Delta Loan$	-0.035***	-0.026**	-0.036***	-0.028**	-0.048***
	(0.005)	(0.010)	(0.011)	(0.012)	(0.012)
$\alpha(1)$	0.00	0.02	0.18	0.00	0.00
$\alpha(2)$	0.28	0.92	0.33	0.33	0.74
Hansen J	0.06	0.98	0.52	0.56	0.37
Observations	2,992	270	318	347	763
Number of banks	433	41	50	52	145

Notes: This table provides results by bank specialisation and size. The first, second and third columns highlight the results for commercial, cooperative and savings banks, respectively. The fourth column provides results using large banks. Large banks are those that fall in the highest decile of the size distribution of total assets within each country. The fifth column provides results for small banks, those that fall in the lowest 30 percentile of the size distribution within each country. The cycle variable used in each specification is derived using the Hamilton (2018) approach. The dependent variable (BUFF) is the bank's capital buffer ratio. All estimations are based on the Arellano and Bond (1991) difference GMM estimator. Robust standard errors are reported in parentheses, $\alpha(1)$ and $\alpha(2)$ are first and second order residual autocorrelation tests. The null hypothesis of the AR(2) test is that errors in the first-difference regression exhibit no second-order serial correlation. The null hypothesis of the Hansen test is that the instruments are valid. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Estimation using G7 countries

	(1) Univariate UCM	(2) Bivariate macro	(3) Bivariate finance	(4) Trivariate UCM	(5) Horse-race
Uni-variate output	-7.301*				
	(4.260)				
Bi-variate macro cycle		-5.123**			4.231
		(2.052)			(3.289)
Finance augmented cycle			-23.482***		-2.180
			(6.462)		(7.232)
Multivariate cycle				-8.033***	-9.414***
				(1.807)	(2.680)
$Buff_{i,j,t-1}$	0.498***	0.534***	0.655***	0.674***	0.700***
	(0.076)	(0.074)	(0.075)	(0.076)	(0.076)
ROE	4.847***	4.921***	4.333***	4.327***	4.977***
	(1.216)	(1.120)	(1.326)	(1.274)	(1.015)
$Risk$	0.242***	0.227***	0.140	0.164	0.157*
	(0.081)	(0.083)	(0.108)	(0.107)	(0.087)
$Size$	0.465	0.247	0.058	-0.002	0.368
	(0.432)	(0.457)	(0.451)	(0.443)	(0.304)
$\Delta Loan$	-0.035***	-0.034***	-0.031***	-0.031***	-0.032***
	(0.009)	(0.009)	(0.006)	(0.006)	(0.006)
$\alpha(1)$	0.00	0.00	0.00	0.00	0.00
$\alpha(2)$	0.39	0.37	0.24	0.27	0.30
Hansen J	0.10	0.14	0.88	0.91	0.73
Observations	2,540	2,389	2,389	2,389	2,389
Number of banks	281	281	281	281	281

Notes: Column (1) provides results for G7 countries using the cycles extracted using the unobserved component model. In Column (2) *Bivariate macro*: components (GDP and unempoyment rate); in column (3) we use the *Bivariate Finance* components (GDP and credit-to-GDP ratio). The dependent variable (BUFF) is the bank's capital buffer ratio. All estimations are based on the Arellano and Bond (1991) difference GMM estimator. Robust standard errors are reported in parentheses, $\alpha(1)$ and $\alpha(2)$ are first and second order residual autocorrelation tests. The null hypothesis of the AR(2) test is that errors in the first-difference regression exhibit no second-order serial correlation. The null hypothesis of the Hansen test is that the instruments are valid. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 6: Estimation by specialisation and size using G7 Countries

	(1) Commercial	(2) Cooperative	(3) Savings	(4) Large	(5) Small
Finance augmented cycle	-19.088***	-3.634	16.337	-26.042**	-10.419
	(6.721)	(14.973)	(33.477)	(11.112)	(8.591)
$Buff_{i,j,t-1}$	0.670***	0.385**	0.766**	0.685***	0.707***
	(0.093)	(0.146)	(0.323)	(0.067)	(0.099)
ROE	4.044***	6.794**	9.878	1.306	3.845*
	(0.988)	(3.103)	(7.888)	(1.122)	(2.177)
$Risk$	0.035	0.162**	0.125	0.095*	-0.046
	(0.072)	(0.067)	(0.134)	(0.054)	(0.110)
$Size$	0.806**	-0.125	0.853		
	(0.377)	(0.812)	(2.280)		
$\Delta Loan$	-0.044***	-0.019	-0.070	-0.014	-0.084***
	(0.013)	(0.018)	(0.050)	(0.011)	(0.022)
$\alpha(1)$	0.00	0.06	0.08	0.00	0.00
$\alpha(2)$	0.48	0.86	0.22	0.23	0.88
Hansen J	0.41	0.99	0.42	0.89	0.90
Observations	2,013	212	126	436	636
Number of banks	228	30	14	54	82

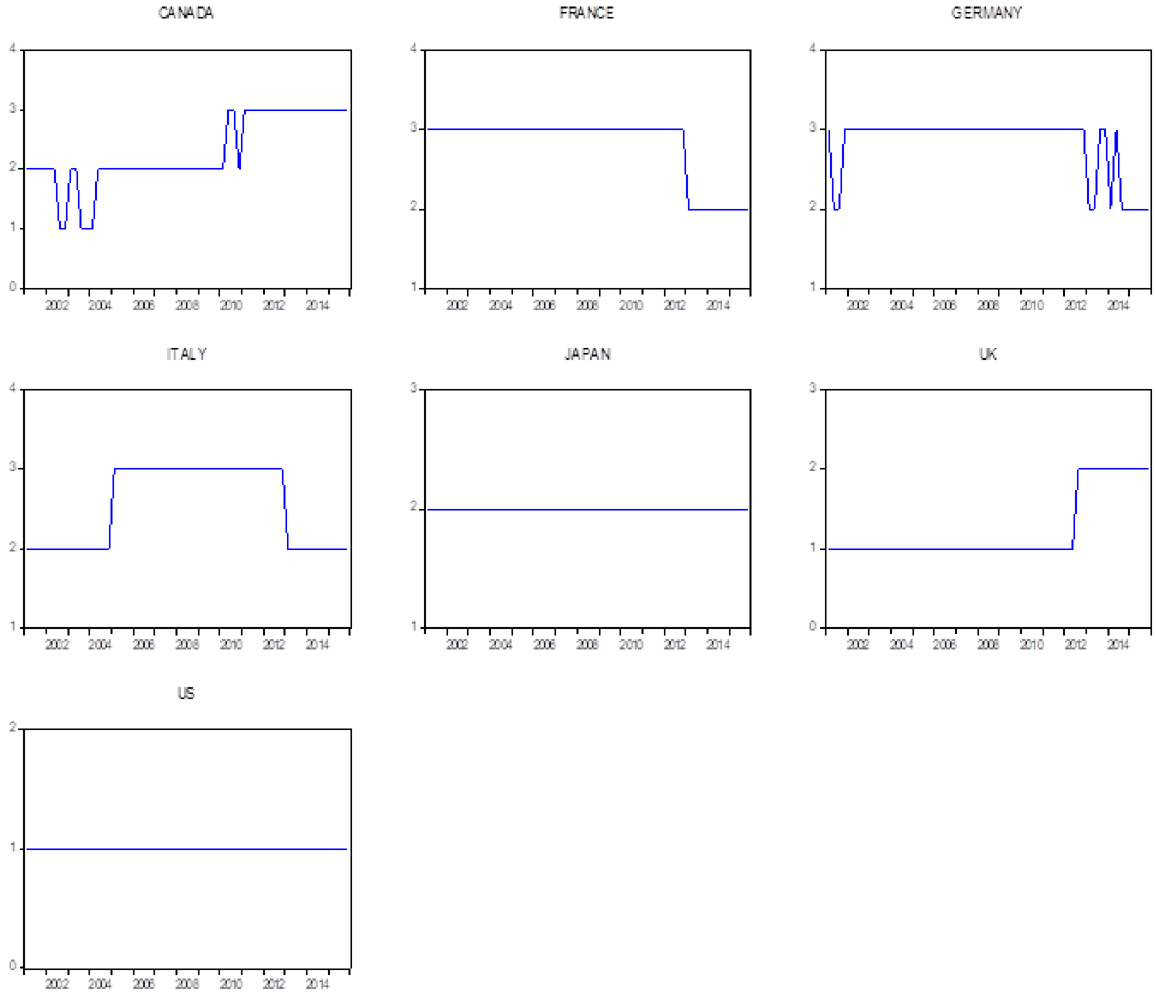
Notes: This table provides results by bank specialisation and size. The first three columns highlight the results for commercial, cooperative and savings banks, respectively. The fourth column provides results using large banks. Large banks are those that fall in the highest decile of the size distribution of total assets within each country. The fifth column provides results for small banks, those that fall in the lowest 30 percentile of the size distribution. The cycle variable used in each specification is derived using the unobserved component model. The dependent variable (BUFF) is the bank's capital buffer ratio. *Finance augmented cycle*: components (GDP and credit-to-GDP ratio). All estimations are based on the Arellano and Bond (1991) difference GMM estimator. Robust standard errors are reported in parentheses, $\alpha(1)$ and $\alpha(2)$ are first and second order residual autocorrelation tests. The null hypothesis of the AR(2) test is that errors in the first-difference regression exhibit no second-order serial correlation. The null hypothesis of the Hansen test is that the instruments are valid. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Estimation by specialisation and size using G7 Countries

	(1) Commercial	(2) Cooperative	(3) Savings	(4) Large	(5) Small
Trivariate cycle	-6.323***	-2.708	6.711	-12.387***	-5.173
	(1.422)	(4.121)	(16.188)	(4.606)	(5.341)
$Buff_{i,j,t-1}$	0.678***	0.383**	0.656**	0.649***	0.837***
	(0.084)	(0.149)	(0.270)	(0.074)	(0.098)
ROE	3.908***	6.569*	8.591**	2.147	4.854*
	(1.078)	(3.241)	(3.015)	(1.292)	(2.486)
Risk	0.064	0.153**	0.062	0.219*	0.093
	(0.071)	(0.058)	(0.126)	(0.120)	(0.173)
Size	0.591	-0.041	2.335		
	(0.460)	(0.796)	(2.562)		
$\Delta Loan$	-0.045***	-0.022	-0.069*	-0.016*	-0.091***
	(0.013)	(0.018)	(0.034)	(0.009)	(0.029)
$\alpha(1)$	0.00	0.06	0.00	0.00	0.00
$\alpha(2)$	0.48	0.94	0.31	0.07	0.56
Hansen J	0.37	0.99	0.73	0.79	0.39
Observations	2,013	212	126	436	636
Number of banks	228	30	14	54	82

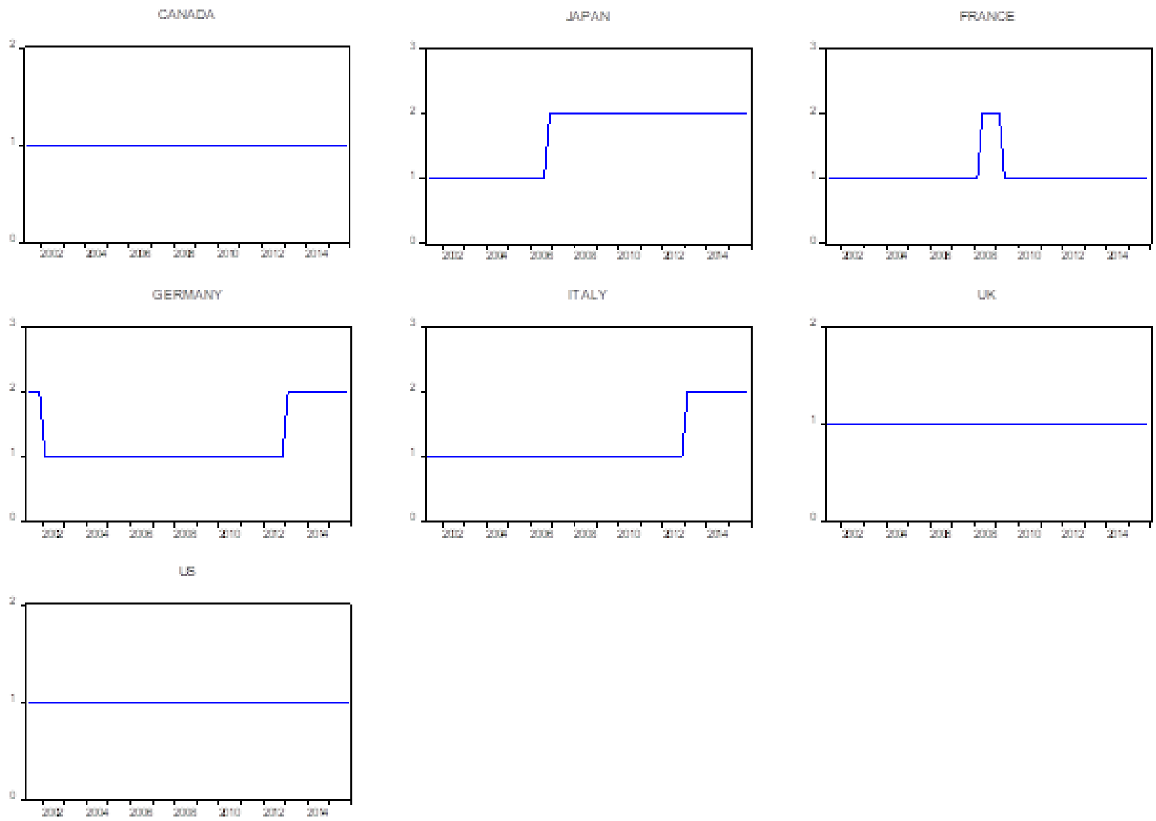
Notes: This table provides results by bank specialisation and size. The first three columns highlight the results for commercial, cooperative and savings banks, respectively. The fourth column provides results using large banks. Large banks are those that fall in the highest decile of the size distribution of total assets within each country. The fifth column provides results for small banks, those that fall in the lowest 30 percentile of the size distribution. The cycle variable used in each specification is derived using the unobserved component model. The dependent variable (BUFF) is the bank's capital buffer ratio. *Trivariate cycle*: components (GDP, unemployment, and credit-to-GDP ratio). All estimations are based on the Arellano and Bond (1991) difference GMM estimator. Robust standard errors are reported in parentheses, $\alpha(1)$ and $\alpha(2)$ are first and second order residual autocorrelation tests. The null hypothesis of the AR(2) test is that errors in the first-difference regression exhibit no second-order serial correlation. The null hypothesis of the Hansen test is that the instruments are valid. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Figure A1: **Optimally Selected Financial Indicator of Output Growth**



1 indicates that lagged or current value of GDP was selected ; 2 indicates current or lagged House Prices was selected; 3 indicates that current or lagged stock prices was selected

Figure A2: Optimally Selected Macro-Indicator of Output Growth



1 indicates that current or lagged value of Unemployment was selected; 2 indicates that current or lagged value of Inflation was selected.

Table A1: Correlation matrix by country

	HP	Hamilton	Univarite UCM	Bivariate output-gap	Finance augmented	Trivariate	
OECD	0.48	0.58	0.95	0.96	0.95	0.88	Canada
	0.43	0.81	0.26	0.83	0.92	0.93	France
	0.95	0.95	0.97	0.23	0.90	0.86	Germany
	0.35	0.85	0.59	0.45	0.86	0.53	Italy
	0.73	0.72	0.40	0.81	0.71	0.80	Japan
	0.71	0.67	0.35	0.82	0.49	0.69	U.K.
	0.63	0.60	0.63	0.87	0.80	0.77	U.S.

Table A2: Robustness checks using system GMM estimator

	(1) Hamilton	(2) Hamilton (G7)	(3) UC Model
$Univariate\ output-gap$	-3.202***	-4.567***	
	(0.486)	(0.776)	
Finance augmented cycle			-19.113***
			(5.911)
$Buff_{i,j,t-1}$	0.738***	0.933***	0.914***
	(0.055)	(0.044)	(0.040)
ROE	5.594***	4.016**	5.781***
	(1.991)	(1.566)	(1.662)
Risk	0.092**	0.106***	0.063*
	(0.037)	(0.039)	(0.033)
Size	-0.056*	-0.026	-0.017
	(0.032)	(0.024)	(0.029)
$\Delta Loan$	-0.031***	-0.034***	-0.058***
	(0.004)	(0.006)	(0.013)
Constant	1.562***	0.290	0.464
	(0.568)	(0.352)	(0.419)
$\alpha(1)$	0.00	0.00	0.00
$\alpha(2)$	0.20	0.59	0.37
Hansen J	0.06	0.07	0.56
Observations	5,001	2,925	2,631
Number of banks	577	281	281

Notes: The dependent variable (BUFF) is the bank's capital buffer ratio. *Finance augmented cycle*: components (GDP, credit-to-GDP ratio). All estimations are based on the Arellano and Bover (1995) system GMM estimator. Robust standard errors are reported in parentheses, $\alpha(1)$ and $\alpha(2)$ are first and second order residual autocorrelation tests. The null hypothesis of the AR(2) test is that errors in the first-difference regression exhibit no second-order serial correlation. The null hypothesis of the Hansen test is that the instruments are valid. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A3: Estimation using G7 countries with standardised cycle variables

	(1) Univariate UCM	(2) Bivariate macro	(3) Bivariate finance	(4) Trivariate UCM	(5) Horse-race
Uni-variate output gap	-0.050**				
	(0.022)				
Bivariate macro output gap		-0.145**			-0.017
		(0.061)			(0.101)
Finance augmented cycle			-0.198***		0.049
			(0.052)		(0.111)
Multivariate augmented cycle				-0.201***	-0.198**
				(0.052)	(0.094)
$Buff_{i,j,t-1}$	0.501***	0.530***	0.676***	0.688***	0.723***
	(0.079)	(0.075)	(0.079)	(0.076)	(0.078)
ROE	4.875***	4.904***	4.883***	4.336***	4.257***
	(1.230)	(1.133)	(1.266)	(1.256)	(1.276)
$Risk$	0.242***	0.223***	0.175*	0.176*	0.104
	(0.084)	(0.080)	(0.104)	(0.106)	(0.086)
$Size$	0.436	0.286	-0.053	0.100	0.477
	(0.434)	(0.465)	(0.460)	(0.439)	(0.352)
$\Delta Loan$	-0.034***	-0.034***	-0.030***	-0.030***	-0.033***
	(0.009)	(0.009)	(0.006)	(0.006)	(0.007)
$\alpha(1)$	0.00	0.00	0.00	0.00	0.00
$\alpha(2)$	0.36	0.38	0.30	0.32	0.45
Hansen J	0.12	0.17	0.92	0.92	0.72
Observations	2540	2389	2,389	2,389	2,389
Number of banks	281	281	281	281	281

Notes: Column (1) provides results for G7 countries using the cycles extracted using the unobserved component model. In Column (2) *Bivariate macro*: components (GDP and unempoyment rate); in column (3) we use the *Bivariate finance* components (GDP and credit-to-GDP ratio). The dependent variable (BUFF) is the bank's capital buffer ratio. All estimations are based on the Arellano and Bond (1991) difference GMM estimator. Robust standard errors are reported in parentheses, $\alpha(1)$ and $\alpha(2)$ are first and second order residual autocorrelation tests. The null hypothesis of the AR(2) test is that errors in the first-difference regression exhibit no second-order serial correlation. The null hypothesis of the Hansen test is that the instruments are valid. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A4: Average marginal effects

	ey/ex	Delta-method Std. Error	Z	P>|Z|
$Bivariate\ output-gap$	0.003	0.006	0.52	0.605
$Finance\ augmented\ cycle$	0.003	0.001	2.48	0.013
$Trivariate\ cycle$	0.014	0.007	2.13	0.033
$Buff_{i,j,t-1}$	0.318	0.115	2.77	0.006
ROE	0.023	0.010	2.40	0.016
$Risk$	0.039	0.040	0.97	0.332
$Size$	0.636	0.137	4.63	0.000
$\Delta Loan$	-0.022	0.010	-2.06	0.039

Notes: This table presents the average marginal effects of the independent variables from column 5 in Table 5.

Table A5: Structural break dummies

	(1) Bivariate UCM	(2) Bivariate UCM	(3) Bivariate UCM	(4) Bivariate UCM	(5) Bivariate UCM
Finance augmented cycle	-18.706**	-44.324**			
	(7.216)	(19.974)			
Bivariate output gap			7.123		
			(4.375)		
Crisis	0.148	0.192	-0.088		
	(0.163)	(0.159)	(0.228)		
*Crisis*Finance augmented cycle*		35.122		-21.637**	
		(26.183)		(9.588)	
*Crisis*Bivariate output gap*			-11.605**		-7.132***
			(4.505)		(1.781)
$Buff_{i,j,t-1}$	0.666***	0.640***	0.605***	0.672***	0.662***
	(0.081)	(0.080)	(0.082)	(0.079)	(0.079)
ROE	4.844***	5.093***	5.019***	4.213***	4.774***
	(1.373)	(1.346)	(1.427)	(1.336)	(1.269)
Risk	0.142	0.115	0.294**	0.171	0.183*
	(0.108)	(0.109)	(0.122)	(0.107)	(0.099)
Size	0.057	0.109	-0.415	0.170	-0.166
	(0.487)	(0.493)	(0.523)	(0.450)	(0.470)
$\Delta Loan$	-0.029***	-0.030***	-0.031***	-0.030***	-0.031***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
$\alpha(1)$	0.00	0.00	0.00	0.00	0.00
$\alpha(2)$	0.32	0.37	0.27	0.28	0.37
Hansen J	0.92	0.94	0.71	0.91	0.81
Observations	2,389	2,389	2,389	2,389	2,389
Number of banks	281	281	281	281	281

Notes: This table presents a series of specifications containing a dummy variable that captures the crisis period. The dummy takes the value of 1 in the years 2008-2012 and 0 otherwise. Each estimation is carried using the same G7 sample as before. All estimations are based on the Arellano and Bond (1991) difference GMM estimator. Robust standard errors are reported in parentheses, $\alpha(1)$ and $\alpha(2)$ are first and second order residual autocorrelation tests. The null hypothesis of the AR(2) test is that errors in the first-difference regression exhibit no second-order serial correlation. The null hypothesis of the Hansen test is that the instruments are valid. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$