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ISSN 1749-8368

SERPS no. 2018003

April 2018

www.sheffield.ac.uk/economics

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

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March 26, 2018

Abstract

This paper empirically analyses how the capital buffer held by banks behave over the business cycle after financial factors have been accounted for. Using a large panel of banks for the period 2000-2014, we document evidence that capital buffers behave more pro-cyclical than previously found in the literature. Furthermore, we also show that this relationship is more pronounced for large commercial banks where access to capital equity markets and external support (bail-out) is likely to constitute a strong incentive to increase credit exposure and lower capital reserves accordingly. 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; .

*This paper benefited from comments from Mustafa Caglayan, Bill Francis, Alex Kontonikas, Georgios Efthyvoulou and Karl Taylor. We thank seminar and conference participants at the University of Sheffield, the International Rome Conference on Money, Banking and Finance, Money, Macro and Finance conference, the Young Finance Scholars' Conference, for helpful suggestions. Any remaining errors are sole responsibility of the authors. † Corresponding author. Email:kpwhyte1@sheffield.ac.uk

1 Introduction

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 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 (2009), and Behn et al. (2016)).[1] [2] The financial turmoil of 2008 has 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 capitalization 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 (CCB) 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, the buffer can then be drawn down. This will help to mitigate a contraction in the supply of credit to households and businesses.

This paper shows that when the estimation of business cycles account for movements of financial variables, banks' capital ratios tend to behave more pro-cyclical than previously thought. The topic of pro-cyclical effects of bank behaviour as a consequence of capital requirements is not new and has also been previously analysed in the financial stability literature.[3] 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 approximation becomes difficult. Regarding the first reason, the view on the business cycle in

[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.

[2] Capital buffer is the difference between the observed capital ratio in bank i in period t and the Basel Accord minimum regulatory capital. Pro-cyclicality in the financial system refers to the mutually reinforcing interactions between the real and financial sectors of the economy that tend to amplify business cycle fluctuations and that are often the cause of financial instability.

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

traditional macroeconomics, which dates back to Okun (1963), define 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 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. This was quite evident during the global financial crisis of 2008.

The experience of the global crisis suggests that financial sector activities should be taken into account when estimating the level of potential output. In fact, the crisis came as a reminder that the financial and real sectors of the economy are inextricably linked. It is from this standpoint that Borio et al. (2016) argue that 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.[4] 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 where components in the equity, housing and credit markets have been accounted for.[5]

In light of this, we examine the cyclical behaviour of banks’ capital buffer 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 buffer 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 capitalization within a single country (see for e.g. Shim (2013), Coffinet et al. (2012), Tabak et al. (2011), and Stolz and Wedow (2011)). This paper uses a sample of 33 low, middle, and high income countries to conduct the 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 buffer. More importantly, we find that the capital buffer is even more sensitive to the cycle when we incorporate financial variables (residential property prices, credit to the private, non-financial sector, and stock prices) in our cyclical indicator. The magnitude of the coefficient on our finance-augmented cycle is markedly

[4] Borio et al. (2016) further lament it is simply impossible to understand business fluctuations and their policy challenges without understanding the financial cycle.

[5] Borio et al. (2016) show that the behaviour of these factors (particularly housing and credit) explains a substantial portion of the cyclical movements in output, thereby contributes to the identification of the unobservable potential output. The "finance-neutral" output gap, which accounts for the relationship between financial developments and real sector activities, indicated that output was well above potential before major financial booms, irrespective of what happens to inflation.

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 cycles 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 organized as follows. Section 2 gives an extensive overview of the literature and the hypotheses. It also discusses the theoretical underpinnings of our empirical framework. Section 3 describes the statistical methodology used to estimate the cycles. Section 4 presents the econometric methodology to estimate the capital buffer and describes the dataset . The empirical results are presented in section 5. Section 6 concludes.

2 Theoretical Underpinnings

This section aims to clarify issues concerning the theoretical underpinnings of our empirical framework. In particular, we focus on explaining the concept of pro-cyclicality, why banks hold excess capital, known as capital buffer, and what are the determinants of capital buffer.

The recent financial crisis has brought to the forefront of banking regulation discussion the potential pro-cyclical effects of risk sensitive regulation. One of the primary aims of the Basel II accord was to link capital requirement to risks. However, estimates of risks tend to be higher in recession than in expansions. Therefore, under 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 recession. This vicious circle ultimately would undermine both the stability of banking and macroeconomic system. As a result of this link between capital requirements, risk and business cycle, a widespread concern about Basel II is that it might amplify business cycle fluctuation, forcing banks to reduce credit when the economy enters into a recession.[6] 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 sewing the seeds for the next financial crisis.

Although the Basel II accord has mainly focused on quantifying the likely variation of capital requirement implied by the pillar 1, well functioning banks hold capital well above the minimum requirement on loan portfolios.[7] This implies that the management of capital buffers across

[6]This is why capital requirements are said to be pro-cyclical despite actually increasing (decreasing) during a downturn (upturn).

[7]Note that under pillar 2 regulators are allowed to demand a buffer of additional capital during economic

the business cycle will be as important, or even more important than the management of capital requirement implied by pillar 1. In 2010, the Basel Committee on Banking Supervision introduced the new Basel III capital requirements. The introduction of this new framework was driven by the need to address the issue of pro-cyclicality. In our study, we consider pro-cyclicality the negative interaction between business cycle and capital buffer, which tend to amplify the former.[8] There is an extensive body of literature that investigates what is viewed as the pro-cyclical impact of the Basel II accord. For example, Repullo and Suarez (2009) investigate the pro-cyclical effects of bank capital regulation. They find that under cyclically-varying risk-based capital requirements, banks hold more buffers in expansions than in a recessions. Nonetheless, these buffers are insufficient to prevent a significant contraction in the supply of credit when there is a recession. Their empirical results show that with cyclical adjustments to the Basel II requirements, this pro-cyclical effect on the supply of credit can be reduced without compromising banks' future solvency targets. The macroprudential framework of this newly implemented accord targets the building up of buffers during booms which could, in turn, be released during periods of stress.

There are three main reasons why banks hold capital buffer. Firstly, holding capital reduces the probability of default, which involves the loss of charter values, reputation costs and legal cost of bankruptcy (see for e.g. Acharya (1996)).[9] The second reason is associated with adjustment cost that entails the changing of capital level. In particular, in addition to transactions cost, there are costs associated with informational asymmetries on capital markets. Third, Milne and Whalley (2001) highlight that though equity capital is expensive relative to debt, the potential costs of a breach of the capital requirement is more detrimental. Coffinet et al. (2012) refer to these as "precautionary" reserves that serve to avoid adjustment costs that are associated with raising equity on short notice or supervisory penalties if they approach the regulatory minimum.[10]

Note that designing the optimal level of capital buffer is not an easy task. Nonetheless, 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. In particular, they argue that if the shadow value of bank capital is low in recession and high in expansion, then optimal capital charges should account for the state of the business cycle. One of the issues that have not been addressed by Kashyap et al. (2004) was whether in the presence of risk-sensitive capital regulation banks have an incentive to build up capital buffer in expansion that can be used to neutralize the effect of recession on capital requirements. To address this

expansion.

[8]Along similar line 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.

[9]Lindquist (2004), argues that poorly capitalised bank are at a risk of losing market confidence and damaging their reputation. Simillarly Estrella (2004), claims that excess capital capital acts as an insurance against costs that may occur due to unexpected loan losses and difficulties in raising new capital.

[10]Coffinet et al. (2012) also argue that if regulatory capital is only an imperfect reflection of the risk of losing charter value, then capital buffers act as a cushion that protects its going concern value.

issue, Repullo and Suarez (2009) construct a model which shows that under risk-based capital requirements, banks hold larger buffers in expansion than in recession but these buffers were insufficient to prevent contraction in the supply of credit during recessions.

Although Kashyap et al. (2004) and Repullo and Suarez (2009) provide a theoretical framework to analyze the interaction between capital buffers and the phases of business cycles, a consistent estimate of such interaction has to take into account the impact of other determinants of capital buffer. Following the partial adjustment model with quadratic cost of the adjusting capital suggested by Ayuso et al. (2004) and Estrella (2004), the literature on banks' capital buffer, though diversified, tends to maintain a common set of explanatory variables. Banks return on equity (ROE) - a proxy for the cost of capital, bank size - often measured by banks' total asset, a risk variable - commonly proxied by some ratio of non-performing loans, and loan growth, are all utilized by, amongst others Brei and Gambacorta (2016), Coffinet et al. (2012), and Tabak et al. (2011).[11]

Holding excess capital involves a direct cost that has to be remunerated. This cost is approximated by institutions' ROE and is expected to have a negative sign.[12] The relationship between the risk profile of an institution and capital buffer is less clear. Salas and Saurina (2003) argue that for risk averse institution there is a negative relationship between risk and capital buffer, while for low risk averse bank this relationship can be positive.[13] Jokipii and Milne (2008) argue that for an ex-post measure of risk such as non-performing loans to total loans ratio, a positive relationship is expected to be seen between risk and capital buffer.[14] Ayuso et al. (2004) lament that an increase in loans imply an increase in capital requirements, and in a context where the cost of adjusting capital is very high, is likely to transitorily reduce capital buffers. Therefore, there is a much anticipated negative relationship between the growth of loans and banks' capital reserve.[15] Inter alia, Ayuso et al. (2004) highlight that big banks tend to hold relatively lower capital buffers, consistent with the the well-known too big-to-fail hypothesis.[16]

2.1 The Link between Financial and Business Cycle

To gauge the cyclicality of capital buffer, a proxy reflecting the phase of the business cycle has to be constructed. A fundamental concept in both understanding and estimating a proxy of a

[11] See also Ayuso et al. (2004), Boucinha et al. (2008).

[12] Milne (2004) argues that for financially strong banks, there will be a negative relationship between ROE and capital buffers, pointing to the fact that a high level of earnings acts as a substitute for capital buffer against unexpected shocks. see also (Ayuso et al. (2004), Jokipii and Milne (2008), and Tabak et al. (2011).

[13] Salas and Saurina (2003) highlight the relationship between risk and capital buffer from a franchise value perspective. They argue that a decrease in franchise value of banks brings about an increase in the proportion of riskier loans. In this context, banks with a very low risk aversion may have an incentive to maintain a level of buffer capital that is closer to the regulatory minimum compare to more conservative banks.

[14] In particular Jokipii and Milne (2008) argue that for ex-post measure of risk if banks might set their capital in line with the true riskiness of their portfolio, then a positive relationship is expected to be seen with capital buffer.

[15] Note also that earlier studies such as Sharpe et al. (1995) and Jackson et al. (1999) conclude that, at least in the short-run, adverse shocks to capital causes low-capitalized banks to cut back on new lending during recessions.

[16] In particular, these studies predict bank's size and capital buffer move in opposite direction. See Jokipii and Milne (2008), Coffinet et al. (2012) and Hancock and Wilcox (1998)

business cycle is the potential output, defined as the level of output produced when available resources are fully and sustainably utilized. Potential output is unobserved and econometric estimation traditionally rely heavily on inflation (i.e. the so-called Taylor rule). The conceptual association between output-gap and inflation was so strong that the literature has ignored the impact of financial variables on business cycle fluctuation. The basic idea was that deviation of actual output from the potential level will drive inflation. Therefore, inflation is the symptom of unsustainability. However, while variation of inflation might signal output deviation from potential level, the pre-crisis experience suggests that this view is too narrow.

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.[17] Borio et al. (2016) argue that there are four reasons for this. First, financial booms could coincide with positive supply shocks. This will lead to lower inflation and higher asset prices that weakens credit constraints. The ultimate results will be higher investment and economic growth and low inflation. The second reason is that economic expansions may weaken supply constraints either through higher participation rates or immigration. Injection of new capacity will boost economic growth without destabilizing inflation. Third, financial booms are often associated with appreciation of exchange rate, which put a downward pressure on inflation. A final and frequently neglected point is that unsustainability may be generated by a sectoral misallocation of resources (see Borio et al. (2016)). Therefore, financial and real development might provide a wrong signal concerning the robustness of economic activity.[18]

The fundamental implications of Borio et al. (2016) analysis was that cyclical variation of 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 business cycle when a judgement about the sustainability of economic activity is formulated. From a measurement perspective, Borio et al. (2016) show that ignoring financial developments which may contain valuable information about the cyclical component of output, may produce a less reliable estimate of potential output. They argue that the crisis revealed that problems that originate in the financial sector can spill over and quickly permeate through sectors of the real economy and therefore further amplify initial economic shocks. It also revealed that there is insufficient literature on the identification of the financial cycle and its possible effects on the real economy. Borio et al. (2016) suggest a framework for measuring potential output that can be seen as an extension of a growing literature that seeks to investigate the link between, financial cycles, business cycle and banking crisis (see Claessens et al. (2012); Aikman et al. (2015)). Based on the finding of Borio and Drehmann (2009) and Drehmann et al. (2012), Borio et al. (2016) extend a conventional standard HP-filter in a multivariate framework accounting for the impact of credit and property prices. In so doing, they compute the so-called "finance-neutral" potential

[17] Even though inflation was low, credit and property prices grew at high levels, sewing the seeds for the last financial crisis.

[18] A subsequent recession amplified by credit constraints make the recovery of economic growth a difficult task. Campello et al. (2010) and Drehmann et al. (2012) show that during such times the overhang debt makes the task of capital and labour redistribution harder. In so doing, the correction of resource misallocation build-up during the boom is hindered.

output. Borio et al. (2016) highlight that this new "finance-neutral" output gap will: (i) show that output was well above potential before strong financial booms, irrespective of inflation behaviour; (ii) be estimated more precisely; and most importantly, (iii) will be more robust in real time.

3 Cycles

3.1 Business cycle approximation

In our analysis, to gauge the impact of business cycle on capital buffer, we use both univariate and multivariate statistical models. In particular, we have applied the univariate HP and an unobserved component (UC) model to GDP.[19] Despite its popularity, the HP-filter has some important drawbacks that should restrict its application. In particular, Hamilton (2017) argues that the HP-filter involves several levels of differences, so that for a random walk process, subsequent observed patterns are the by-product of having applied the filter rather than reflecting the underlying data generating process (DGP).[20] Hamilton shows that: i) the HP-filter produces spurious dynamics which are disconnected by the true DGP; ii) the HP-filter produces a cyclical component with observations at the end of the sample differing from those in the middle of the sample; iii) estimates of the smoothing parameter of the HP-filter produces values vastly at odds with the common practise.[21]

Hamilton (2017) suggests an alternative proxy for the cyclical component that avoids those problems. In particular, he assumes that the cyclical component of a possible non-stationary series should address the question of how different is the value at time $t + h$ from the value we expect to observe based on its behaviour at time t. Hamilton's proxy does not require knowing the nature of stationarity and to have the correct model to forecast the series. Instead, he establishes that we can run an OLS regression of y_{t+h} on a constant and the 4 most recent values of y_t.[22]

$$y_{t+h} = \beta_0 + \beta_1 y_t + \beta_2 y_{t-1} + \beta_3 y_{t-2} + \beta_4 y_{t-3} + v_{t+h} \tag{1}$$

where the estimated residuals, $\widehat{v}_{t+h}$, offer a reasonable way to construct the transient component for a broad class of underlying processes. The proposed procedure has a number of advantages compared to the HP-filter. First, unlike the cyclical component of the HP-filter, $\widehat{v}_{t+h}$, is un-

[19] 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. Moreover, to correct for the uncertainty about these estimates at the sample end-points we follow Watson (2007) methodology.

[20] Cogley and Nason (1995) show that HP filter can be approximated by taking the fourth-differences of the original data and then take a long, smooth weighted average of past and future values of these differences. See also King and Rebelo (1993).

[21] Hamilton (2017) wrote the HP-filter in a state-space form and estimate the smoothing parameter λ using maximum likelihood. Estimates of λ based on quarterly data were close to 1, therefore far away from the conventional $\lambda = 1600$.

[22] Proposition 4 of Hamilton (2017) provide a general framework of (1).

predictable.[23] Second, the value of $\widehat{v}_{t+h}$ is model-free. In particular, Hamilton (2017) argues that regardless of how the data have been generated, as long as $(1-L)^d y_t \leq 4$, there exist a population projection of y_{t+h} on $(y_t, y_{t-1}, y_{t-2}, y_{t-3}, 1)$', which can be used to construct a cyclical component. Furthermore, for large samples, OLS estimates of (1) converges to $\beta_1 = 1$ and $\beta_j = 0$ for $j = 0, 2, 3$, and 4. Therefore, the resulting filter becomes equal to the difference $\widetilde{v}_{t+h} = y_{t+h} - y_t$. Because $\widetilde{v}_{t+h}$ does not require estimation of any parameter it can be used as a quick check for $\widehat{v}_{t+h}$ being model free. Third, any correlation of $\widehat{v}_{t+h}$ with macro-variable x, reflect the true ability of y to predict rather than being an artefact of the filter. Here, we account for Hamilton's suggestion and we also produce a cyclical component given by $\widehat{v}_{t+h}$.

3.2 Finance-augmented business cycles

Following Borio (2014), Stremmel (2015), and Drehmann et al. (2012), we consider, along with GDP, three additional financial variables to construct our measure of the finance-augmented cycle. These are; (i) residential property prices; (ii) credit to the private, non-financial sector; and (iii) stock prices. These variables are considered to be the most parsimonious way of capturing the financial cycle.[24]

Here, we present the multivariate UC model used to compute the "financial-augmented cycle". In particular, we apply a version of Clark (1987) unobserved component model to quarterly GDP, credit supply, house and stock prices. To distinguish between trend and stochastic trend of real output, Clark (1987) consider the follow unobserved component model:

$$y_t = n_t + x_t \tag{2}$$

$$n_t = g_{t-1} + n_{t-1} + v_t \tag{3}$$

$$g_t = g_{t-1} + w_t \tag{4}$$

$$x_t = \phi_1 x_{t-1} + \phi_2 x_{t-2} + e_t \tag{5}$$

where y_t is the log of real GDP, n_t is the stochastic trend and x_t is the stationary cyclical component; v_t, e_t and w_t are shocks that follow a white noice process. We follow Clark (1987) in modelling the drift term (g_t) in the stochastic trend component as a random walk. Assuming that the financial variables follow a unit root process, we can also decompose the financial variables into trend and cyclical components:

$$z_{it} = L_{it} + C_{it} \tag{6}$$

[23] Hamilton (2017) show that an application of HP filter to consumption and stock prices generates proxies of cyclical component which were extremely predictable from their own lagged values as well as each other. Note under the assumption that both consumption and stock prices follow random walk then the first difference of these series, in line with Hamilton's (2017) approach, should be unpredictable.

[24] All the series used to capture both cycles are in real terms (deflated by CPI) and in logs. Further, we normalize the series to their respective values in 1985 to ensure comparability of the units.

$$L_{it} = L_{it-1} + v_{lit} \tag{7}$$

$$C_{it} = \alpha_{0i}x_t + \alpha_{1i}x_{t-1} + \alpha_{2i}x_{t-2} + e_{cit} \tag{8}$$

where $i = 1, 2, 3$ indicates credit supply, house prices and stock prices respectively, L_{it} and C_{it} present the permanent and cyclical component of ith financial variable. Note that (8) allows the cyclical component of real GDP to influence the cyclical component of financial variables but not vice versa. Here, we assume that expected output and lagged values of GDP will have an impact on the financial variables.[25] A state-space representation of (2) to (8) is given by:

$$\begin{bmatrix} n_t \\ x_t \\ x_{t-1} \\ x_{t-2} \\ g_t \\ L_{1t} \\ L_{2t} \\ L_{3t} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & \phi_1 & \phi_2 & 0 & 0 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 1 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 1 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} n_{t-1} \\ x_{t-1} \\ x_{t-2} \\ x_{t-3} \\ g_{t-1} \\ L_{1t-1} \\ L_{2t-1} \\ L_{3t-1} \end{bmatrix} + \begin{bmatrix} n_{vt} \\ e_t \\ 0 \\ 0 \\ w_t \\ v_{l1t} \\ v_{l2t} \\ v_{l3t} \end{bmatrix} \tag{9}$$

$$\begin{bmatrix} y_t \\ z_{1t} \\ z_{2t} \\ z_{3t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & \alpha_{01} & \alpha_{11} & \alpha_{21} & 0 & 0 & 0 & 0 \\ 0 & \alpha_{02} & \alpha_{12} & \alpha_{22} & 0 & 0 & 0 & 0 \\ 0 & \alpha_{03} & \alpha_{13} & \alpha_{23} & 0 & 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} n_t \\ x_t \\ x_{t-1} \\ x_{t-2} \\ g_t \\ L_{1t} \\ L_{2t} \\ L_{3t} \end{bmatrix} + \begin{bmatrix} 0 \\ e_{c1t} \\ e_{c2t} \\ e_{c3t} \end{bmatrix} \tag{10}$$

We can write write (9) and (10) in compact form as follows:

$$\begin{aligned} \mathbf{y}_t &= \mathbf{H}\xi_t + \mathbf{w}_t & (11) \\ & \mathbf{w}_t \tilde{} N(\mathbf{0}, \mathbf{R}_t) & (12) \end{aligned}$$

$$\begin{aligned} \xi_t &= \mathbf{F}\xi_{t-1} + v_t & (13) \\ & v_t \tilde{} N(\mathbf{0}, \mathbf{Q}_t) & (14) \end{aligned}$$

where (11) and (13) are the observation and measurement equations of the state-space model.

[25] Note that data on GDP are published with a delay at least one month after the end of the reference quarter. Thus, contemporaneous values of GDP will have an impact on future values of financial variables.

Note that,

$$\mathbf{R}_t = \begin{bmatrix} 0 & 0 & 0 & 0 \\ 0 & \sigma^2_{e1t} & 0 & 0 \\ 0 & 0 & \sigma^2_{e2t} & 0 \\ 0 & 0 & 0 & \sigma^2_{e3t} \end{bmatrix}$$

and

$$\mathbf{Q}_t = \begin{bmatrix} \sigma^2_{vt} & 0 & 0 & 0 & 0 & \sigma_{v1t} & \sigma_{v2t} & \sigma_{v3t} \\ 0 & \sigma^2_{et} & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\ 0 & 0 & 0 & 0 & \sigma^2_{wt} & 0 & 0 & 0 \\ \sigma_{v1t} & 0 & 0 & 0 & 0 & \sigma^2_{v1t} & 0 & 0 \\ \sigma_{v2t} & 0 & 0 & 0 & 0 & 0 & \sigma^2_{v2t} & 0 \\ \sigma_{v3t} & 0 & 0 & 0 & 0 & 0 & 0 & \sigma^2_{v3t} \end{bmatrix}$$

where σ^2_{eit} for $i = 1, 2, 3$ is the observed variance of the financial variables, σ^2_{vt} and σ^2_{et} are the variances of the trend and cyclical component of real GDP, while σ^2_{vit} for $i = 1, 2, 3$ indicates the variance of the trend component of the financial variables. The key extensions of our model are the covariances σ_{v1t}, σ_{v2t} and σ_{v3t} between the shocks affecting the trend component of real GDP and the trend component of the three financial variables included in our model. Unlike Clark (1987), here we allow shocks concerning the trend component of real GDP to be affected by shocks concerning the trend components of the financial variables. This is consistent with Borio et al. (2016), which explain that there is evidence suggesting that banking crises following booms have permanent negative impact on output and hence on potential output. In particular, Borio et al. (2016) argue that the information content that financial variables have for the cyclical component of output will have significant impact on the estimation of potential output.

To capture a proxy for the traditional and the financial-augmented business cycle, we employ the Gross Domestic Product (GDP) obtained from the World Bank's World Development Indicators (WDI) database. We also collect data on property prices, credit to non-financial sector, and stock prices from the BIS database. Data on the consumer price indices (CPI) was also retrieved to deflate the GDP data. All macroeconomic data spans the period 1975 - 2014. This is a deliberate attempt to get the best possible approximation of the cyclical components and to avoid the well documented end-point problem associated with the use of statistical filters that are applied to the data.

Figure 1 depicts the output gap estimates using the approach proposed by Hamilton (2017), while Figure 2 depicts the finance-augmented output gap estimates using the unobserved component model. We observe that both the amplitude and the variance of the business cycles generated by Hamilton's univariate approach is larger than the variance of the finance-augmented cycles generated by the multivariate UC model. This implies that financial variables provide valuable information to reduce the noise around the mean of business cycles. This observation is borne out in Table 1. Specifically, the final column of Table 1 indicates that the signal-to-noise ratio of the finance-augmented cycle, computed by the ratio of mean to standard deviation, is much higher than the ratio for the cycle computed using Hamilton's approach.

[FIGURE 1 AND 2 ABOUT HERE]

4 Capital buffer: econometric methodology and data

Following the partial adjustment model with quadratic cost of adjusting capital suggested by Ayuso et al. (2004) & Estrella (2004), we employ the following empirical model:

$$BUFF_{i,j,t} = \mu + \alpha BUFF_{i,j,t-1} + \beta ROE_{i,j,t} + \gamma RISK_{i,j,t} + \delta SIZE_{i,j,t} + \theta CYCLE + \varphi \Delta LOAN + \phi_i + \theta_t + \epsilon_{i,j,t} \quad (15)$$

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 is included to detect differences in the buffer according to the size of each bank. $RISK$, the ratio of Non-performing loans to total loans, is included since a bank's probability of failure is partially dependent on its risk profile. $\Delta LOAN$ denotes credit growth, $CYCLE$ is a proxy of the business cycle, in the first instance, then as the finance-augmented cycle in the latter estimations. It is used to address our main question concerning the pro-cyclicality of capital buffer. Finally, ϕ_i is a bank fixed effect, θ_t is a time fixed effect and $\epsilon_{i,j\ ,t}$ represents the error term.

The empirical analysis in equation 15 is based on an unbalanced panel, drawn from an international sample of 578 banks from 33 countries for the period 2000 to 2014.[26] The bank-level data are extracted from Bureau van Dijk's Bankscope which provides information on consolidated and aggregated statements of banks and their specialization. There are two major advantages to using this source. First, the sampled banks account for up to 90 percent of the total assets in each country, hence providing a fairly comprehensive coverage. Second, the bank-level information is reported in standardized formats, after adjusting for country differences.[27] The main 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 4 provides definitions of the variables used in our estimation while Table 5 provides some descriptive statistics for our sample of banks.

[26] See Table 2 for details on the number of banks per country in the sample.

[27] 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 specializations, namely; commercial, savings and co-operative banks. Table 3 provides details on the number of banks per specialization type in the sample.

[TABLE 4 ABOUT HERE]
[TABLE 5 ABOUT HERE]

It is worth noting, in (15) when the time dimension of the panel T is fixed, the Fixed Effect (FE) and Random Effect (RE) estimators are biased. This bias is known as Nickell bias, because it was Nickell (1981) who first showed that the FE estimator of α was biased.[28] Ample literature of consistent instrument variable (IV) and Generalised Method of Moments (GMM) estimators have been proposed as an alternative of FE estimator. Anderson and Hsiao (1981) suggested to remove the individual heterogeneity (i.e. ϕ_i) by taking the first difference and use the second lag of the dependent variable as an instrument for the differenced one-time lagged dependent variable. The IV estimation deliver consistent but not efficient estimates of the parameters in the model because it does not exploit all the available orthogonality conditions. 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. In particular, if $y_{it} = BUFF_{it}$ then we can write (15) as [29]

$$y_{it} = \alpha y_{it-1} + \beta' \mathbf{x}_{it} + v_{it} \tag{16}$$

where $i = 1, .., N, t = 1, ...T$, $\mathbf{x}_{it} = [ROE_{i,t}, RISK_{i,t}, SIZE_{i,t}, CYCLE,\ \Delta LOAN]'$ is a vector of possibly endogenous variables and $v_{it} = \phi_i + \epsilon_{i,t}$. Arelano and Bond (1991) suggest a GMM estimator to the stacked observations of

$$\Delta \mathbf{y}_{i.} = \alpha \Delta \mathbf{y}_{i-1} + \beta' \Delta \mathbf{X}_{i.} + \Delta \epsilon_{it} \tag{17}$$

where $\Delta y_{i.} = [\Delta y_{i2}, \Delta y_{i2}, ...\Delta y_{iT}]'$, $\Delta y_{i-1} = [\Delta y_{i1}, \Delta y_{i2}, ...\Delta y_{iT-1}]'$, $\Delta x_{i.} = [\Delta x_{i2}, \Delta x_{i2}, ...\Delta x_{iT}]'$, $\Delta \epsilon_{it} = [\Delta \epsilon_{i2}, \Delta \epsilon_{i3}, ..., \Delta \epsilon_{iT}]'$ and the number of instruments increases with each additional time period:[30]

$$dg(\mathbf{W}_i) = diag(y_{i1}, y_{i1}y_{i2}, ...y_{i1}y_{i2}...y_{iT-2})$$

$\mathbf{W}_i$ is a diagonal matrix of instruments. The moment conditions can be expressed compactly as $E(W_i^{'} \epsilon_{it}) = 0$.

However, Blundell and Bond (1998) and Binder et al. (2005) show that the IV and the one-step and two-step GMM estimators deteriorates 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. In particular, the covariance of the lagged levels with the first-differenced variables (i.e. $E(\Delta y_{i-t-1}, y_{i,t-s}$) for $s > 1$) is an inverse function of α. Therefore, it is possible to show that

[28] The Nickell bias is of order T and disappears only if $T \to \infty$. It could be large if T is small and α close to unity:

$$bias = -\frac{(1+\alpha)}{T} + O(T^{-2})$$

For further details see chapter 4 of Hsiao (2014) and and chapter 27 of Pesaran (2015).

[29] For easy of exposition we dismiss the country indicator j.

[30] $\Delta = 1 - L$ is the difference operator.

the instruments $y_{i,t-s}$ are weakly correlated with the first differences Δy_{it}.[31] 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 dependent variable. The original Arellano and Bond (1991) method is known as "difference GMM" while the expanded estimators is known as "system GMM". But as Pesaran (2015) points out the number of orthogonality conditions $r = T(T-1)/2$ tends to infinity as $T \to \infty$. In this case, Alvarez and Arellano (2003) show that although the GMM estimators remain asymptotically normal, unless $\lim(T/N) = 0$, they become biased. 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. Furthermore, Monte Carlo studies by Hansen et al. (1996) and Arellano and Bond (1991) show that the estimated asymptotic standard errors of the two-step and iterated GMM estimators may have a severe downward bias in small sample, especially when the number of instruments is equal to or greater than the number of cross-sectional units (Beck and Levine (2004)). Windmeijer (2005) have proposed a finite sample correction for the estimates of the asymptotic variance. As such, we ensure that for each specification, the number of instruments are fewer than the number of banks in the sample and also apply Windmeijer's finite sample correction. 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 minimizing 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.[32] The other test is the Arellano-Bond test for autocorrelation of errors, as described above.

5 Empirical results

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

[31] For example, Pesaran (2015) shows that $E(y_{i,t-2}, \Delta y_{i,t-1}) = -\sigma_u^2(1-\alpha)\left(\frac{1-\alpha^{2(t-1)}}{1-\alpha^2}\right)$. It is clear that $y_{i,t-2}$ as an instrument will be weakly correlated with $\Delta y_{i,t-1}$ as α approaches to 1. Note that the IV/GMM approach breaks down for $\alpha = 1$ For further details see Pesaran (2015)

[32] Acceptance of the null hypothesis indicates that our instruments are exogenous.

5.1 Traditional business cycles

Table 6 presents the results obtained from the estimation of the base line model described in equation 15. The first two sets of results in Table 6 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 (2017) methodology was used to construct the proxy of business cycles.

[TABLE 6 ABOUT HERE]

Table 6 provides evidence that, after controlling for other determinants, there is a negative and significant relationship between the capital buffer and the phase of the business cycle. The estimated coefficient suggests that a 1% increase in the growth rate of GDP is associated with a decrease of approximately 4% in banks' capital buffer. In other words, as the real economic activity decline banks build up their capital buffers. This suggest that banks increase their precautionary reserves in bad or uncertain times.[33] 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. 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 appears positive and statistically significant in two specifications. 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 $RISK$ suggests that banks with risky portfolios tend to hold more capital in reserve. Such a behaviour would influence increases in total capital buffer and thus has implications for the cyclical behaviour of bank capital. The impact of credit growth (i.e. $\Delta LOAN$) variable is significant at the 1% level and, as expected, enters with a negative sign.[34] This suggests that a contemporaneous increase in credit growth reduces the capital buffer (Ayuso et al., 2004). Finally, contrary to our expectation, the bank $SIZE$ carries a positive albeit insignificant coefficient. 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 7 ABOUT HERE]

Next, we consider the possibility that the capital ratios of different types (commercial, savings and co-operative) and size of banks may react differently to business cycle conditions. We classify

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

[34] We test 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 test this for each approach by dropping the $\Delta LOAN$ variable from the setup.

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. Table 7 reports estimates accounting for the type and size of banks. We first discuss results concerning the type of banks as presented in the last three columns of Table 7. Although we continue to find evidence of pro-cyclicality in capital buffer for commercial and savings banks, for co-operative banks the cycle enters with a positive, albeit statistically insignificant. These results suggest that the pro-cyclicality of capital buffer observed in Table 6 is being driven by commercial and savings banks. 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 specialization, credit growth will have a negative impact on capital buffer. 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 6 as it remains insignificant across all type of banks. Next we analyse estimates accounting for the bank size as presented in the first two columns of Table 7. In this specification 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 coefficient. This is consistent with the *too-big-to-fail* hypothesis.

To summarize our results using the business cycle as our cyclical indicator, we find evidence of pro-cyclicality in capital buffer. The pro-cyclicality of capital buffer is driven by commercial and savings banks, but the impact is more significant for commercial banks. Big banks display pro-cyclicality in capital buffer while for smaller banks, capital buffer is countercyclical.

5.2 Finance-augmented business cycles

In this section we discuss the results of the relationship between bank's capital buffer and the financial-augmented output gap as our cyclical indicator. Given the limited availability of data, we restrict our sample to the G7 countries. Though reduced, the sample remains sufficiently large enough to carry out the estimations. As previously mentioned in section 3, we derive a measure of a finance-augmented cycle using a multivariate unobserved components model. The model composition includes GDP along with three financial sector variables (residential property prices, credit to the private, non-financial sector, and stock prices). We maintain all the bank-specific control variables (with the exception of $\Delta LOAN$, as we believe this is highly correlated with the financial cycle proxies), and simply replace the cycle indicator in our model. The findings are presented in Table 8.

[TABLE 8 ABOUT HERE]

Focusing on the last two columns of results, where we introduce the new cyclical measure, we observe a negative coefficient, but one that is much more sensitive to the cycle, as reflected by its magnitude.[35] Therefore, capital ratios are even more pro-cyclical when we account for

[35] Before doing any estimations with our new cyclical measure, we first run regressions using the business cycle to ensure the results are consistent (with the full sample in Table 6) using the G7 sample. The results, as shown in columns 1 and 2, are largely consistent with that of the full sample in Table 6.

financial sector developments in the business cycle. With respect to the other determinants, the signs of the coefficient are predominantly the same. Table 8 provides further results accounting for the impact of financial crisis on capital buffer. We do so by introducing a crisis dummy which takes the value of 1 in the years 2008-2012 and 0 otherwise. The coefficient on the crisis dummy is positive but statistically insignificant. Note that crisis dummy reflects the impact of a structural break, and as such it is considered exogenous and unpredictable. Therefore, it is not surprising that the crisis dummy does not have a significant impact on capital buffer.

[TABLE 9 ABOUT HERE]

Table 9 provides a comparable breakdown to Table 7. We examine the cyclical behaviour of banks' capital buffer by size and specialization using the G7 sample. Similar to results of Table 7, we observe that the capital reserve of big banks are pro-cyclical, whilst there is no evidence to suggest the same for smaller banks. 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. The pro-cyclicality of capital ratios appear, however, significantly stronger over the finance-augmented cycle.

5.3 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 6 and Table 8, 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 A1 of the Appendix. All the main results remain largely consistent with those presented in the previously mentioned tables. Our cyclical indicators remain negative and significant throughout.

Further, we consider the fact that expectations might affect how and when banks adjust their capital buffer. The question of whether banks react to expected changes in regulation remains largely unexplored. This issue raises concerns about the understanding of banks' behaviour, especially during times of significant regulatory change. For example, expectations of forthcoming policy changes might lead to earlier reactions by banks. To test this, we create dummy variables to represent the announcement dates of the Basel Accords. In June 1999, the Basel Committee issued a proposal for a new capital adequacy framework to replace the 1988 Accord. This led to the release of a revised capital framework (Basel II) in June 2004. The announcement of Basel III was made in 2010, and subsequently its implementation began to phase-in in 2013. 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 buffer. We find that these announcements are statistically insignificant.[36] There are two possible reasons for this.

[36] For brevity, we did not include these insignificant results, but they are available upon request

First, the frequency of our data might not allow for accurately capturing the expectation effects. Banks are likely to make adjustments to their buffer stock over monthly or quarterly intervals, in anticipation of a policy change. The second reason is that the implementation process of Basel capital regulations is not homogeneous across countries. Some countries or regions are much slower in implementing these regulatory changes than others, which makes it difficult for us to capture the effect of expectations or anticipation across our panel data.

6 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 provide results for countries across all three income levels. Second and more importantly, the majority of this literature solely focus 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.[37]

Our results indicate a negative relationship between the capital buffer and the business cycle. That is, during an economic downturn banks increase their capital buffer, whilst in booms they reduce it. Furthermore, we find that this negative relationship is particularly related to large banks. The reason for this is owing to the fact that Global Systemically Important Banks (G-SIBs) or 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, as such, explains why they increase capital buffer during booms. Further analysis indicate 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.[38]

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.

[37]For further details on reliable estimate of output-gap accounting for the information of financial variables see Borio et al. (2016).

[38]While it is understood that the task of disentangling credit cycles from business cycles and measuring both accurately is quite difficult, it is important to capture as much information about the financial sector if we are to realise the true impact of macroprudential regulation.

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 buffer will still persist.

Our analysis shows that 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 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 rigid.

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Figure 1: The output gap estimates for G7 countries using the approach proposed by Hamilton (2017).

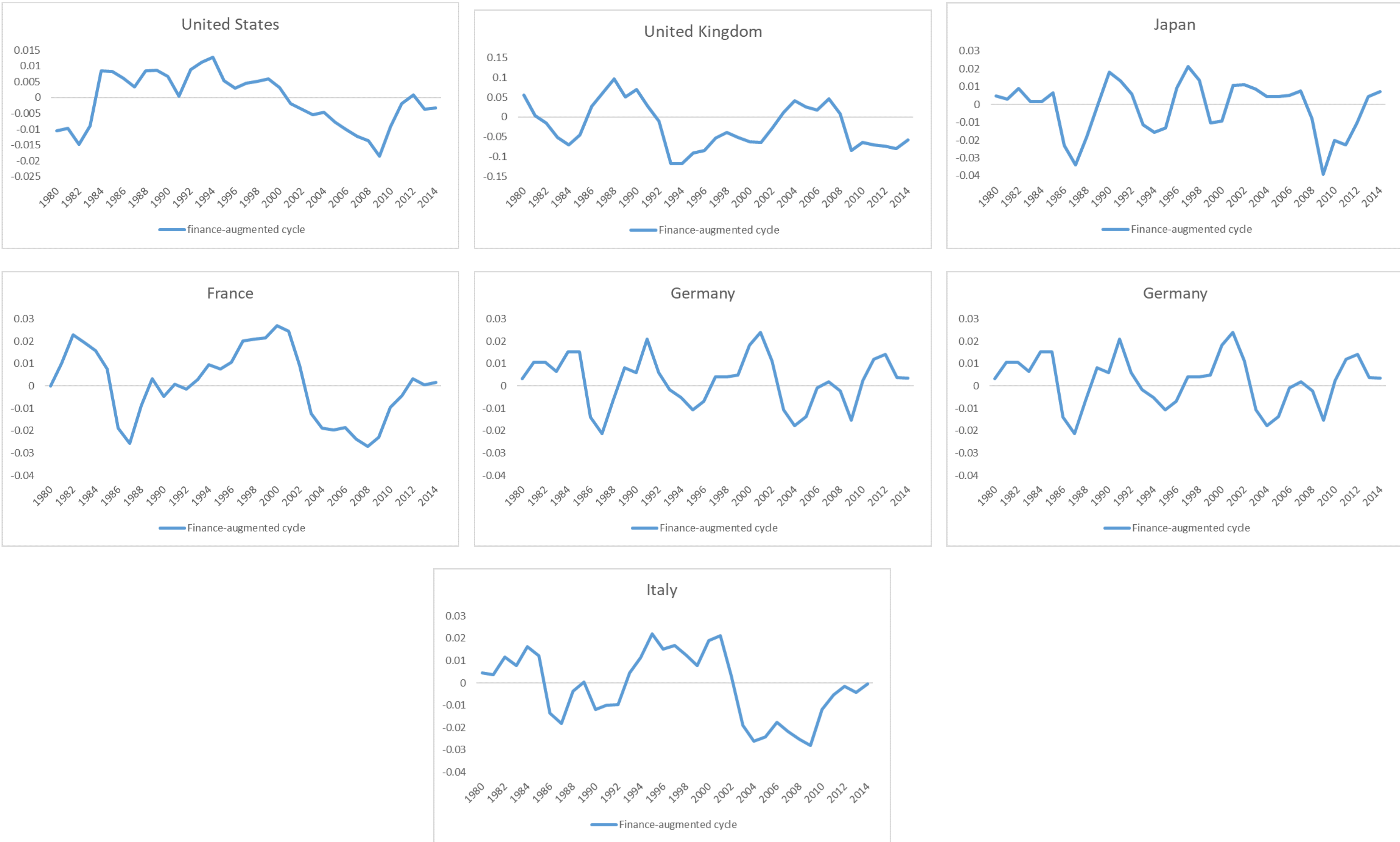

Figure 2: The finance-augmented output gap for G7 countries estimates using the unobserved component model.

Table 1: Summary statistics of cycles by country

Cycle	Country	Mean	St. Dev	SNR
Hamilton	Canada	0.0147	0.0455	0.3238
UC Model		*-0.0068*	*0.0168*	*0.4059*
Hamilton	Germany	-0.0030	0.0514	0.0590
UC Model		*0.0021*	*0.0123*	*0.1735*
Hamilton	France	0.0023	0.0384	0.0611
UC Model		*-0.0059*	*0.0165*	*0.3574*
Hamilton	UK	0.0014	0.0553	0.0250
UC Model		*-0.0279*	*0.0466*	*0.5981*
Hamilton	Italy	-0.0018	0.0502	0.0355
UC Model		*-0.0093*	*0.0153*	*0.6085*
Hamilton	Japan	-0.0034	0.0394	0.0864
UC Model		*-0.0034*	*0.0144*	*0.2342*
Hamilton	USA	-0.0046	0.0495	0.0931
UC Model		*-0.0061*	*0.0056*	*1.0980*

Notes: This table provides some basic statistics for the cycles computed using both the unobserved component model and Hamilton (2017) approach, for the G7 countries. It gives information on the mean, noise and other interferences (St. Dev), and the signal to noise ratio (SNR) - measured as the ratio of the mean to standard deviation, expressed in absolute terms.

Table 2: **Countries and number of banks**

Country		Country		Country	
AUSTRALIA	10	GREECE	7	NEW ZEALAND	5
AUSTRIA	16	HUNGARY	7	NORWAY	26
BELGIUM	9	INDIA	12	POLAND	12
BRAZIL	28	INDONESIA	17	PORTUGAL	7
CANADA	6	ISRAEL	10	SLOVAKIA	5
CZECH REPUBLIC	6	ITALY	38	SLOVENIA	7
DENMARK	16	JAPAN	122	SPAIN	17
ESTONIA	5	LATVIA	10	SWITZERLAND	5
FINLAND	5	LUXEMBOURG	5	TURKEY	18
FRANCE	16	MEXICO	18	U.K	15
GERMANY	8	NETHERLANDS	13	U.S.A	77

Table 3: Distribution of the sample

Specialization	Number of banks
Commercial banks	477
Cooperative banks	45
Savings banks	56

Table 4: 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
$\Delta LOAN$	Annual loan growth
BUSINESS CYCLE	Growth rate of real GDP

Table 5: Descriptive statistics for regression variables

	Obs.	Mean	St. Dev.	Min	Max
Bank variables					
Buffer	6,363	6.021	5.316	-1.200	41.640
Return on equity	6,620	0.069	0.108	-0.606	0.317
Risk	5,989	4.699	5.398	0.000	89.980
Loan growth	6,333	9.536	17.698	-36.710	108.630
Macroeconomic variables					
Output gap (HP-filter)	8,220	0.0005	0.0292	-0.1456	0.1265
Output gap (Hamilton)	8,220	0.0013	0.0702	-0.5842	0.3968
Output gap (UC model)	4,029	-0.0063	0.0174	-0.0844	0.0459

Notes: ***Buffer*** **is the difference between the observed capital ratio of bank i in country j, in period t, and the Basel III minimum regulatory capital.** ***Return on equity*** **is the ratio of net income to equity.** ***Risk*** **is the ratio of non-performing loans to total loans.** ***Loan growth*** **is the growth rate of total loans.** ***Output gap*** **is the cyclical component of GDP derived from the HP-filter, Hamilton approach, and unobserved component model, respectively.**

Table 6: Baseline model

	(1) HP-Filter	(2) HP-Filter	(3) Hamilton	(4) Hamilton
$Buff_{i,j,t-1}$	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)	
Business cycle	-4.235**	-3.994***	-2.251***	-3.449***
	(1.654)	(1.290)	(0.662)	(0.545)
$\alpha(1)$	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 (2017). 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 7: Estimation by specialization and size

	(1) Large	(2) Small	(3) Commercial	(4) Cooperative	(5) Savings
$Buff_{i,j,t-1}$	0.628***	0.487***	0.590***	0.468***	0.619***
	(0.068)	(0.088)	(0.061)	(0.091)	(0.117)
ROE	0.138	4.032*	2.975**	3.058*	5.130**
	(1.627)	(2.231)	(1.153)	(1.748)	(2.426)
Risk	0.293***	-0.064	0.097*	0.129***	0.089
	(0.109)	(0.147)	(0.053)	(0.045)	(0.074)
Size			0.467	-0.173	-0.537
			(0.285)	(0.791)	(1.121)
$\Delta Loan$	-0.017*	-0.088**	-0.035***	-0.026**	-0.036***
	(0.010)	(0.042)	(0.005)	(0.010)	(0.011)
Business cycle	-4.675**	0.771	-2.444***	1.237	-4.249*
	(2.030)	(1.828)	(0.533)	(0.872)	(2.442)
$\alpha(1)$	0.00	0.00	0.00	0.02	0.18
$\alpha(2)$	0.43	0.40	0.28	0.92	0.33
Hansen J	0.75	0.73	0.06	0.98	0.52
Observations	401	1,119	2,992	270	318
Number of banks	65	203	433	41	50

Notes: This table provides results by bank size and specialization. The first column provides results using large banks. Large banks are those that fall in the highest decile of the size distribution of total assets. The second column provides results for small banks, those that fall in the lowest 30 percentile of the size distribution. The third, fourth and fifth columns higlight the results for commercial, cooperative and savings banks, respectively. The cycle variable used in each specification is derived using the Hamilton (2017) 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 8: Estimation using G7 countries

	(1) HP-Filter	(2) Hamilton	(3) UC Model	(4) UC Model
$Buff_{i,j,t-1}$	0.635***	0.643***	0.703***	0.698***
	(0.060)	(0.062)	(0.082)	(0.085)
ROE	4.230***	4.435***	2.892*	3.188*
	(1.078)	(1.062)	(1.607)	(1.734)
Risk	0.221**	0.221**	0.165*	0.165*
	(0.097)	(0.097)	(0.092)	(0.090)
Size	0.479	0.341	0.073	0.057
	(0.371)	(0.354)	(0.464)	(0.483)
$\Delta Loan$	-0.033***	-0.033***	-0.039***	-0.039***
	(0.006)	(0.006)	(0.009)	(0.009)
Crisis				0.044
				(0.218)
Business cycle	-5.829***	-2.677***		
	(1.650)	(0.797)		
Finance_augmented cycle			-11.230***	-9.634**
			(3.314)	(4.696)
$\alpha(1)$	0.00	0.00	0.00	0.00
$\alpha(2)$	0.67	0.59	0.44	0.45
Hansen J	0.94	0.98	0.96	0.96
Observations	2,540	2,540	2,324	2,324
Number of banks	281	281	281	281

Notes: This table provides results for G7 countries using cyclical appraoches from the HP-filter, Hamilton (2017), and the unobserved component model. The dependent variable(BUFF) is the bank's capital buffer ratio. In the last, column we introduce a crisis dummy which takes the value 1 in years 2008 - 2012. 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 9: Estimation by specialization and size using G7 Countries

	(1) Large	(2) Small	(3) Commercial	(4) Cooperative	(5) Savings
$Buff_{i,j,t-1}$	0.676***	0.808***	0.715***	0.358**	0.628**
	(0.085)	(0.099)	(0.092)	(0.135)	(0.254)
ROE	2.788*	4.205*	4.309***	6.090*	1.691
	(1.659)	(2.357)	(0.976)	(3.397)	(10.25)
Risk	0.319**	0.143	0.114*	0.119**	-0.0237
	(0.120)	(0.178)	(0.068)	(0.052)	(0.242)
Size			0.486	-0.023	2.527
			(0.505)	(0.956)	(2.690)
$\Delta Loan$	-0.011*	-0.094***	-0.051***	-0.015	-0.078*
	(0.006)	(0.028)	(0.014)	(0.018)	(0.043)
Finance_augmented cycle	-30.840***	3.201	-10.610***	17.210	35.110
	(8.370)	(12.500)	(3.721)	(16.420)	(91.170)
$\alpha(1)$	0.00	0.00	0.00	0.07	0.04
$\alpha(2)$	0.06	0.53	0.51	0.78	0.23
Hansen J	0.77	0.29	0.3	0.99	0.54
Observations	322	527	2,013	212	126
Number of banks	56	78	228	30	14

Notes: This table provides results by bank size and specialization. The first column provides results using large banks. Large banks are those that fall in the highest decile of the size distribution of total assets. The second column provides results for small banks, those that fall in the lowest 30 percentile of the size distribution. The third, fourth and fifth columns higlight the results for commercial, cooperative and savings banks, respectively. 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. C is a crisis dummy that takes the value of 1 in the years 2008-12 and 0 otherwise. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Appendix

Table A1: Robustness checks using system GMM estimator

	(1) Hamilton	(2) Hamilton (G7)	(3) UC Model
$Buff_{i,j,t-1}$	0.738***	0.933***	0.914***
	(0.055)	(0.044)	(0.040)
ROE	5.594***	4.016**	4.635***
	(1.991)	(1.566)	(1.637)
Risk	0.092**	0.106***	0.078**
	(0.037)	(0.039)	(0.032)
Size	-0.056*	-0.026	-0.029
	(0.032)	(0.024)	(0.029)
$\Delta Loan$	-0.031***	-0.034***	-0.060***
	(0.004)	(0.006)	(0.013)
Business cycle	-3.202***	-4.567***	
	(0.486)	(0.776)	
Finance_augmented cycle			-12.320***
			(2.087)
Constant	1.562***	0.290	0.502
	(0.568)	(0.352)	(0.394)
$\alpha(1)$	0.00	0.00	0.00
$\alpha(2)$	0.20	0.59	0.43
Hansen J	0.06	0.07	0.82
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. 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. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$