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Policy Implications for the Application of Countercyclical Capital Buffers When the Government Borrowing Crowds Out Private Sector Credit: The Case of Jamaica

Abstract

This paper investigates the use of conditioning variables in guiding the accumulation and release phases of a capital buffer requirement for Jamaican banks. An important innovation of this study is the inclusion of public sector conditioning variables to explore the role of sovereign risk build-up in designing countercyclical buffers.

Keywords: Countercyclical capital buffers, financial stability, procyclicality, early warning indicators, sovereign risk.

JEL classification: E44, E61, G21.

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1. INTRODUCTION

One of the issues that took center stage in the international debate on the lessons of the global financial crisis of 2008-2009 is that of managing procyclicality of the financial system. Procyclicality of the financial system is defined as the amplification of the cyclical fluctuations of the economy by financial sector activities, most notably bank lending (see, for example, Bernanke et al., 1995; Borio at al., 2001; Geršl and Jakubik, 2006). This behavior can have particularly serious implications in an economic downturn as it can considerably prolong and deepen the recession via a feedback effect on the economy.

Countercyclical policy tools have recently been utilized by central banks to mitigate the negative effects of procyclicality of the banking sector. The proximate objective of a countercyclical capital requirement is to encourage banks to build up buffers in good times that can be drawn down in bad times. Buffers in this context comprise Tier 1 capital in excess of the prudential minimum, so that additional capital is available to absorb losses in the event of a boom-and-bust financial cycle. One of the main issues involved in the policy design process is the choice of conditioning variables that can guide the buildup of the buffer during the periods of expansion. Of equal significance is the identification of variables which point to releasing the capital buffer at the beginning of the bust stage.

This paper examines a range of potential early warning indicators or conditioning variables which may be used by policymakers for setting appropriate time-varying capital requirements to address banking sector procyclicality. Specifically, one aim of this study is to assess the ability of specific macroeconomic and commercial bank-level (conditioning) variables, similar to those explored in Drehman et al. (2011), in reflecting risk buildup in the banking system in Jamaica. The key finding from Drehman et al. (2011) is that the ratio of credit-to-GDP and its long-term trend (the credit-to-GDP gap) performs best as an indicator for the build-up phase of a financial boom-and-bust cycle. The authors exclude public sector debt as its tendency to be counter-cyclical reduced the performance of credit related variables in their sample.

In Jamaica's case, the fact that its banking sector has historically operated within an environment of strong fiscal dominance, which led to public sector crowding out of private sector credit, the role of sovereign risk build-up could be important in designing domestic countercyclical buffers. That is, public sector credit and public sector debt holdings could rise in booms and slowdown in the downswing. Fiscal dominance has been manifested in sustained high interest rates in the context of persistent budget deficits. For last two decades, Jamaica has been caught in a vicious cycle of very low private sector credit and unsustainable public sector debt dynamics. Consistent with the running of persistent budget deficits, along with the price incentive of a high sovereign risk premium, the growing stock of public sector debt has been supported by the oversupply of financing by the banking sector. Over this period, the stock of public sector debt (private sector credit) has remained high (low) by international standards at above 100% of GDP (at around 20% to 30% of GDP). Hence, an important innovation of this study is to include indicators capturing the level of public sector credit and investments in public sector bonds by commercial banks as candidate conditioning variables to explore the role of sovereign risk build-up in designing countercyclical buffers.

Similar to the cyclical experience with private sector credit, sovereign risk is likely underestimated by the banking sector in credit cycle upturns and overestimated in downturns. In an upturn, normally associated with higher public revenues, banks would rapidly expand holdings of public sector credit and bonds, contributing to overpriced public sector bonds and lending spreads along with inadequate bank capital buffers. In the downswing, when sovereign risk increases as public revenues decline, the opposite would tend to occur as banks become overly risk averse. In the context of this paper, the positive correlation between the financial cycle upturn and the accumulation of public sector credit and debt holdings is expected to be stronger in countries such as Jamaica which has historically exhibited high sovereign risk premium relative to the private sector interest rates (that is, *crowding out*).

Against this backdrop, the set of conditioning variables considered in the paper have been tailored to the Jamaican historical environment of strong fiscal dominance and high levels of sovereign debt, in addition to the typical private sector credit variables. These variables are evaluated using both signal extraction and receiver operating characteristics (ROC) methods to determine how effective their deviations from long-term trends (gaps) were in signaling buffer accumulation and release phases around financial crisis episodes. The main conclusion derived from the analysis is that the credit (public and private)-to real GDP gap, investment (in public sector bonds)-to-real GDP gap, private sector credit-to-real GDP gap and public sector credit-to-real GDP gap, all indicate significant signaling value for the accumulation phase. In addition, non-performing loan growth gap and provision for loan loss growth gap reveal significant predictive power for the release phase. However, similar to the finding of Drehman et al. (2011), the overall results of this study do not support the use of any fail-safe conditioning variables to guide policy. Rather, the combination of a set of conditioning variables and judgment is advisable in designing a policy framework for dampening procyclicality.

The paper is organized as follows. In the next section, the data used in the analysis is defined. Sections 3 and 4 compares the performance of different conditioning variables around crisis episodes by using the signals approach and describes the evaluation of these variables using ROC curve analysis, respectively. Section 5 presents the empirical results from the signal extraction method and the ROC curve analysis. The final section concludes and provides some policy implications.

2. DATA DESCRIPTION, INDICATOR MEASUREMENT AND THRESHOLD CHOICE

The period for assessment of the historical performance of conditioning (indicator) variables for application of a countercyclical capital buffer to Jamaica's commercial banking sector covers 1990 to 2012. The data set, which was provided by the Central Bank, was unavailable prior to 1990. In the context of this paper, a crisis episode is defined as the occurrence of a threat to overall stability of banking system characterized by: *1)* significant NPLs, consistent with the effects of procyclicality in the down cycle; and *2)* illiquidity, requiring emergency lending assistance (ELA) by the Central Bank, consistent with financial instability. The data set is suitably long as it covers periods of extensive bank vulnerability as well as credit upswing periods[1]. There are two banking crisis episodes identified within the sample period. Accordingly, the conditioning variables are juxtaposed against a banking crisis indicator variable to assess their signaling ability.

The first crisis episode spans the six-quarter period September 1997 to December 1998, which began with successive runs on two commercial banks affiliated with life insurance companies in December 1996 and February 1997. Due to the close relationship between insurance companies and commercial banks, liquidity and insolvency problems that originated in the insurance sector spread to the banking sector. Severe liquidity shortfalls resulted in the Central Bank providing ELA to four commercial banks. In addition, the Government of Jamaica (GOJ) established the Financial Sector Adjustment Company (Finsac) in January 1997 to resolve the serious problems faced by the financial sector. During 1997, the nonperforming loan (NPL) ratio for the commercial bank sector doubled to 28.9%

[1] Similar studies in the literature, which involve the ranking of indicators, have also been constrained in coverage of banking crises. For example, Giese et al. (2012) assess indicators in the UK context using data covering three past episodes of banking system distress. The authors aptly note, however, that their rankings should be treated with appropriate caution.

by the end of the year. The increase in the NPL ratio followed on above-normal expansion in private sector credit growth of 68.9% in 1993 which subsequently slowed to 25.3% by 1996 and –33.5 in 1997. By end-1998, Finsac had intervened in the operations of most of the domestic commercial banks, over half of the life insurance companies as well as a few merchant banks and building societies.

The second crisis episode began in the September 2008 quarter and also spans six quarters. In October 2008, as a direct consequence a slowdown in lending as well as economic activity triggered by the global financial turmoil and to preserve overall financial stability, the Central Bank offered an emergency temporary lending facility in United States dollars to domestic financial institutions. This facility was primarily intended to provide liquidity to these institutions due to contagion which resulted in a dysfunctional interbank money market as well as large margin calls and cancelled repurchase agreements on GOJ global bonds held with overseas institutions. The stated objectives of the temporary lending facility were to *a)* alleviate significant short-term US dollar liquidity needs of domestic financial institutions, *b)* stabilize GOJ global bond prices which had sharply declined, and *c)* minimize volatility pressures in the domestic foreign exchange market. In addition, the Central bank established a special intermediation facility in the final quarter of 2008 to facilitate the flow of credit among local financial institutions. This facility gave extraordinary access to domestic liquidity to deposit-taking institutions (DTIs) with the appropriate collateral, using funds placed at the Central Bank by DTIs with surplus liquidity for on-lending to the borrowing institutions.

During this period of system-wide stress, Jamaica's economy was severely impacted by the global financial turmoil. Real GDP declined by 1.6% for FY2008/2009, with economic conditions deteriorating sharply in the second half of the year. Bauxite and alumina production and exports fell by about 60%, while remittances –a traditional source of balance of payments support– declined by 33%. The value of the Jamaica dollar vis-à-vis the US dollar depreciated by 10% in the December 2008 quarter compared to 1% average depreciation for the first three quarters of 2008. In addition, similar to other developing countries, the external credit market was closed to Jamaica. This damaged investor confidence, especially with regard to the fiscal and debt dynamics and their sustainability. Notably, growth in NPLs for DTIs was also adversely impacted by the international economic slowdown, rising by over 40% over the crisis period. During the first quarter of 2010, the domestic financial environment returned to relative stability, which was underpinned by the signing of a 27-month stand-by arrangement with the IMF in that quarter.

Regarding the construction of the conditional variables, similar to Borio and Lowe (2002) and Drehmann et al. (2011), this paper is concerned with cumulative processes in contrast to levels or growth rates. Specifically, the focus is on the deviation of variables from their respective long-term trends, above explicit thresholds. Trends are determined using only ex ante information and are measured as deviations from one-sided Hodrick-Prescott filters, calculated recursively up to time t. The respective gaps are computed as the difference between the values of the variable and its trend at t. Consistent with Hodrick and Prescott (1991), to capture the cumulative buildup of imbalances, the smoothing parameter lamda (λ) is set to 1,600 for each of the quarterly data series used. However, this choice of λ is notable different from previous advanced economy studies which find that setting λ equal to 400,000 (which is associated with less frequent crisis episodes compared to business cycles) yields better results in picking up the time trends of conditioning variables.

For robustness, multiple horizons are considered for the accumulation phase. Specifically, crisis signals from indicators are judged to be correct if a crisis occurs *at the end* of one-year-ahead and three-month-ahead horizons. Signals from indicators of the release phase can only occur within a shorter horizon as release of the capital buffer should occur contemporaneously with the period of distress.

A range of thresholds are considered for each indicator. The choice of the ideal threshold involves a trade-off between the cost of missing a crisis (type 1 error) and the cost of calling a crisis which turns out to be false (type 2 error). Minimizing the noise-to-signal threshold has been the popular method of finding optimal thresholds in past studies (pioneered by Kaminsky and Reinhart, 1999). However, this method of signal extraction may not be ideal as highlighted by Demirgüç-Kunt and Detragiache (1998), given the incentives for regulators to overweight the risk of type 1 errors. Borio and Lowe (2002) and Borio and Drehmann (2009) offer the simple alternative of minimizing the noise-to-signal ratio with the proviso that at least two-thirds of the crises are correctly predicted.

This paper relies on a more precise method of balancing the cost-benefit trade-off of choosing indicator thresholds through the construction of a correct classification frontier (CCF) or receiver operating characteristics (ROC) curve (see Jordà and Taylor, 2011; Berge and Jordà, 2011, and Drehmann et al., 2011). In particular, Berge and Jordà (2011) discuss the use of ROC curve analysis to evaluate the historical predictive ability of indicator variables when the utility trade-offs across outcomes are unknown. Jordà (2011) describes the chronology of indicator variables as potentially embodying the latent state of the financial cycle. Observable financial conditions variables are generated by a mixture of distribution with each state (non-crisis and crisis) determined by the indicator chronology. Comparisons of the empirical distributions obtained by sorting the indicator and financial conditions variables by state will determine the information content of each indicator chronology. Berge and Jordà (2011) present two non-parametric statistics which can be used to gauge correct classification, the Kolmogorov-Smirnov (KS) statistic and Wilcoxon-Mann-Whitney (WMW) rank statistic (see Kolmorgorov, 1933; Smirnov, 1939; Mann and Whitney, 1947; Wilcoxon, 1945).

3. BEHAVIOR OF CONDITIONING VARIABLES AROUND DOMESTIC CRISIS EPISODES

The potential conditioning variables are measured based on deviations of variables from their trends to reflect their underlying cyclicality. As discussed above, all gaps are calculated as differences from a one-sided Hodrick-Prescott filter. Hence, the trend considers only historical information up to time *t* for each variable and excludes the future path of the given variable.

As discussed in Drehmann et al. (2010, 2011), the variables can be classified into three categories: the *macroeconomy*, *banking sector activity* and *funding costs*. The variables evaluated in this paper are similar to those in Drehmann et al. (2010, 2011). However, this paper also considers the relative behavior of *credit to the public sector* as well as *investment in public sector securities* given the dominant role of the public sector in the economy throughout the sample period.

The variables that relate to the macroeconomy include: credit (private and public)-to-real GDP, real credit growth, real investment growth, credit plus investment-to-real GDP, credit plus investment growth, investment to real GDP, private sector credit-to-real GDP and public sector credit-to-real GDP[2,3]. Other macroeconomic series evaluated are inflation, real GDP growth, real M2J growth and JSE Index growth. These variables are typically used as leading credit cycle indicators as they tend to display strong growth preceding systemic financial downturns. As shown in Figure 1, credit-to-real GDP, private sector credit-to-real GDP, public sector credit-to-real GDP and credit plus investment-to-real GDP, all rise leading up to a crisis episode, indicating their usefulness for signaling the accumulation phase. In contrast, real GDP growth declines significantly before a crisis, suggesting that it may be a useful variable for the release phase.

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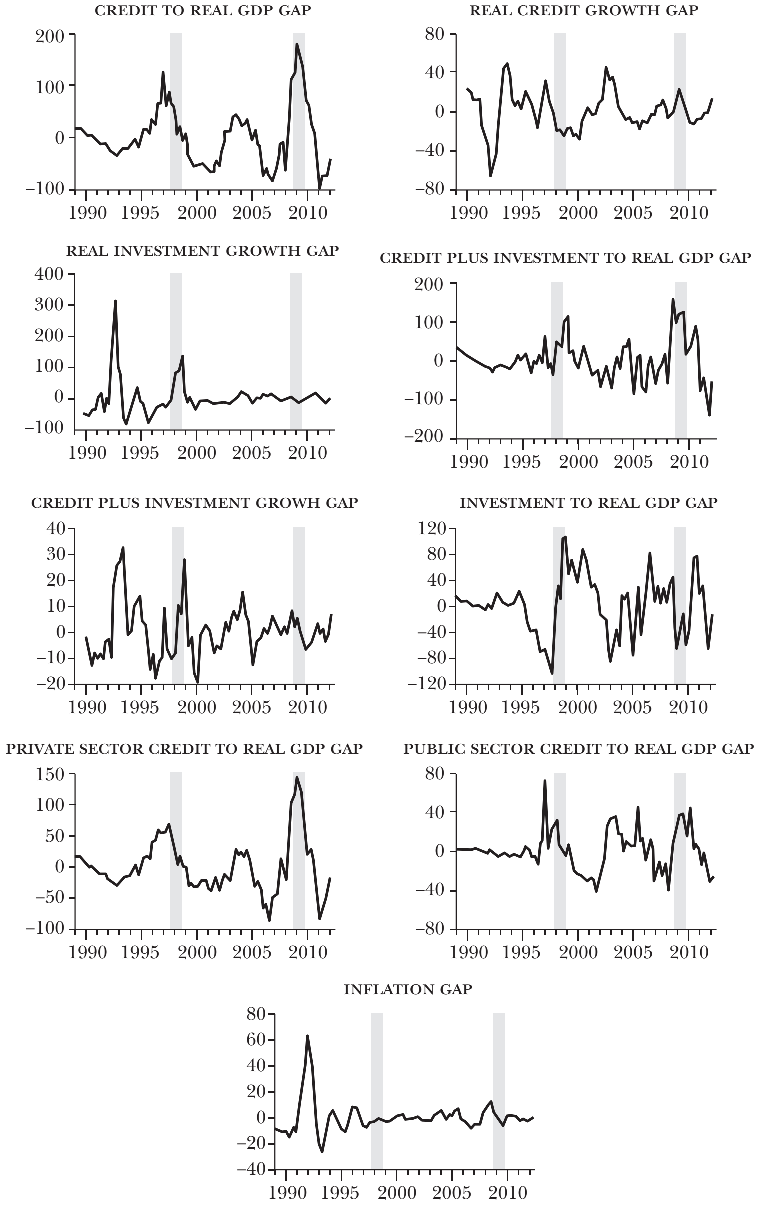
2 Real GDP is used as the normalizing variable given the unavailability of a long enough official series for nominal GDP.

3 Growth variables are calculated as the four-quarter change (in percent).

Figure 1a

BEHAVIOR OF CONDITIONING VARIABLES AROUND CRISES[1]

(Percentage)

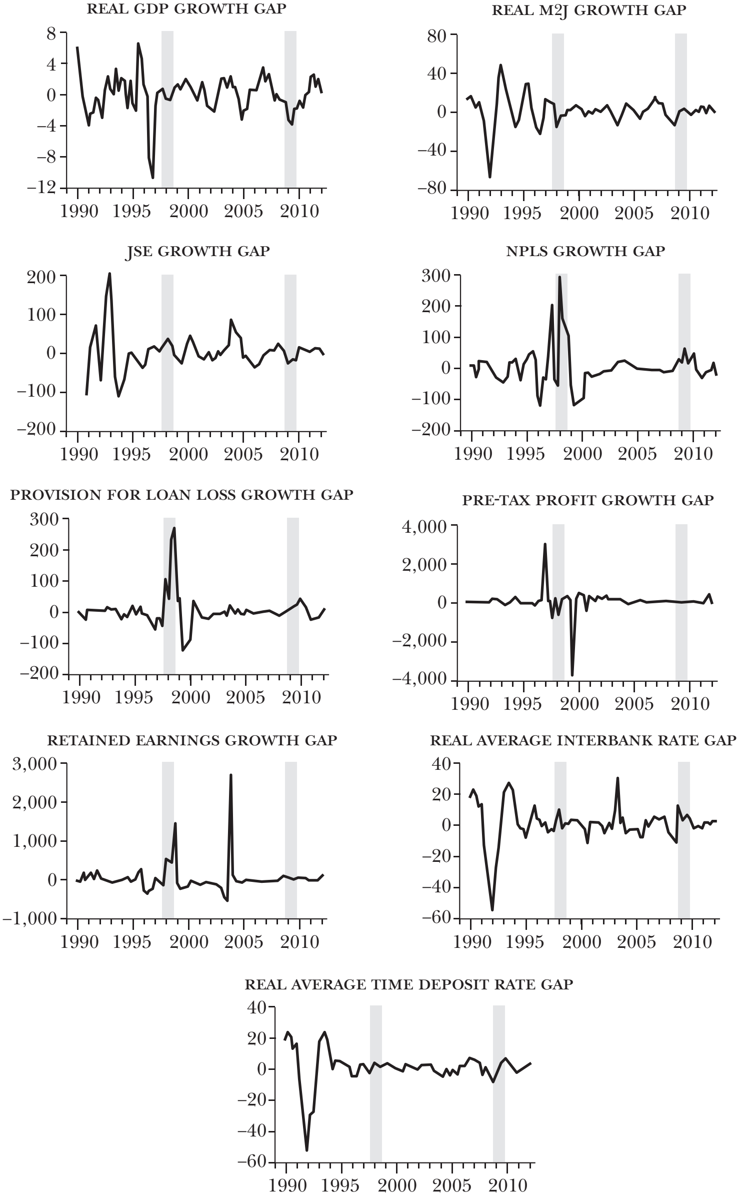


[1] Areas shaded in gray denote crisis episodes.

Figure 1b

BEHAVIOR OF CONDITIONING VARIABLES AROUND CRISES[1]

(Percentage)



[1] Areas shaded in gray denote crisis episodes.

The banking sector variables evaluated are growth in NPLs, provision for loan loss growth, pre-tax profits growth and retained earnings growth. Changes in the two former variables appear to be fairly coincident with the financial cycle. Growth in provision of loan loss, in particular, seems to be a good candidate for the release phase. Pre-tax profits growth and retained earnings growth exhibit weak performance for both the accumulation and release phases, especially for the second crisis episode. Finally, real monthly average (mid-point) interbank and real weighted average time deposit rates are the funding cost variables evaluated. Signals from these measures appear relatively noisy and do not perform well around the crisis episodes.

4. EVALUATION OF INDICATORS AND THRESHOLDS USING ROC CURVE ANALYSIS

Let $S_t \in \{0,1\}$ denote an observed financial conditions variable, with 1 indicating that t is a crisis period (quarter), and y_{t-h} be an indicator variable at time $t-h$ for h=0,1,2...H. Also let $\hat{S}_t(h) = I(y_{t-h} > c_h)$ denote a probability prediction about S_t, where the $I(.)$ indicator function equals 1 if true and c_h denotes the threshold related to the h-period ahead prediction. Assuming h=0, define the following conditional probabilities:

$$TP(c) = P[y_t \geq c \mid S_t = 1] \tag{1}$$

$$FP(c) = P[y_t \geq c \mid S_t = 0], \tag{2}$$

where $TP(c)$ is the true positive, sensitivity or recall rate and $FP(c)$ is the false positive, 1-specificity rate or type 1 error. The relationship between $TP(c)$ and $FP(c)$ describes the ROC curve. The threshold or cut-off value provides the decision rule to divide the conditioning variable according to the crisis states (see Table 1).

The ROC curve plots the combinations $\{TP(c), FP(c)\}$ for $c \in \{-\infty, \infty\}$. When $c \to \infty, TP(c) = FP(c) = 0$ and, alternatively, when $c \to -\infty, TP(c) = FP(c) = 1$. The ROC curve may be represented with the Cartesian convention $\{ROC(r), r\}_{r=0}^{1}$, where $ROC(r) = TP(c)$ and $r = FP(c)$. If y_t is uninformative regarding the crisis period, $TP(c) = FP(c) \forall c$ and the ROC curve would be the 45° line in [0, 1]×[0, 1] space. Conversely, if y_t is perfectly informative, then the ROC curve would hug the north-east corner in [0, 1]×[0, 1].

Table 1

RESULTS FROM DECISION RULE

		Observed	
		Crisis	*No crisis*
Decision	Above threshold	True positive prediction (sensitivity)	False Positive prediction (1-specificity)
	Below threshold	False negative prediction (1-sensitivity)	True negative prediction (specificity)

As an alternative to the noise-to-signal approach for indicator evaluation, consider the expected utility given the cost-benefit trade-off of each type of error given by:

$$U(r) = U_{11} ROC(r)\pi + U_{01}(1 - ROC(r))\pi + U_{10} r(1-\pi), \quad U_{00}(1-r)(1-\pi) \tag{3}$$

where U_{ij} is the utility associated with the prediction i given that the true state is j, $i, j \in \{0,1\}$ and π is the unconditional probability of observing a crisis episode over a specific horizon.

Maximization of [3] indicates that the optimum, c^*, can be obtained by solving:

$$\frac{dROC}{dr} = \frac{U_{00} - U_{10}}{U_{11} - U_{01}} \frac{(1-\pi)}{\pi} \quad , \tag{4}$$

which is the point where the slope of the ROC curve equals the expected marginal rate of substitution between net utility of accurate crisis and non-crisis prediction.

In addition, the slope of the ROC curve is the likelihood ratio of probability density function (*pdf*), given by θ, for the sub-sample of $y_t \left(y_t^c \right)$ for which S_t=1 and the *pdf* for the sub-sample of $y_t \left(y_t^{nc} \right)$ for which S_t=0 given by φ, so that:

$$\frac{dROC}{dr} = \frac{\varphi\left(\Theta^{-1}(1-r)\right)}{\theta\left(\Theta^{-1}(1-r)\right)} , \tag{5}$$

where Θ is the cumulative *pdf* associated with θ. Furthermore, the (KS) statistic is used to determine the optimal operating point (c^*) by the maximization of the distance between *TP(c)* and *FP(c)*, under the assumptions $U_{ii} = 1$, $U_{ij} = -1$ and $\pi = 0.5$ (see Figure 2).

The measure of overall classification ability is the area under the ROC (AUROC) curve:

$$AUROC = \int_0^1 ROC(r)\,dr; \qquad AUROC \in [0.5,1], \tag{6}$$

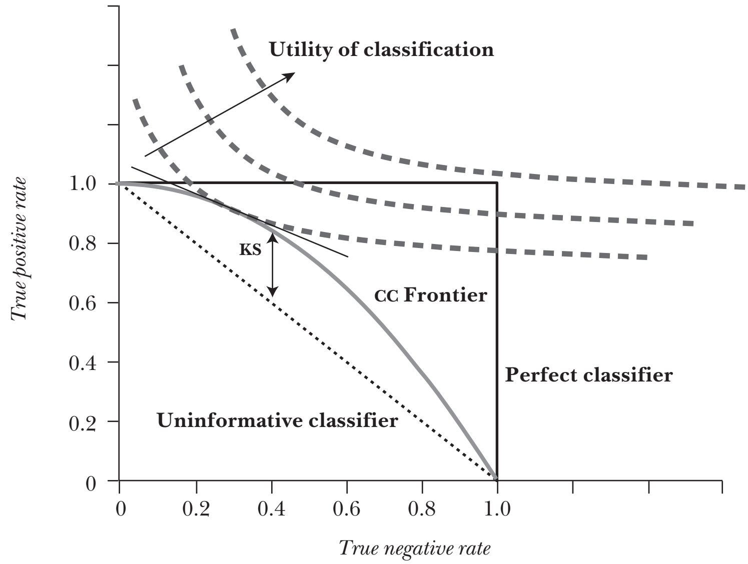
which may be computed as the rank-sum statistic:

$$\widehat{AUROC} = \frac{1}{n_0 n_1} \sum_{j=1}^{n_0} \sum_{i=1}^{n_1} \left\{ I\left(y_j^{nc} < y_i^c\right) + \frac{I\left(y_j^{nc} = y_i^c\right)}{2} \right\}, \tag{7}$$

where $I(\cdot)$ is the indicator function that equals 1 when the argument is true and 0 otherwise, n_0 and n_1 are the number of observations in y_j^{nc} and y_i^c, respectively, and the latter term in

Figure 2

RECEIVER OPERATING CHARACTERISTICS CURVE



Source: O. Jordà, *Discussion of Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates*, Working Paper, University of California, Davis, 2011.

7 is used to correct tied ranks (see Jordà and Taylor, 2010). The AUROC is a WMW rank statistic which is equal to 1 in the case of a perfect classifier and 0.5 (450 line) for a completely uninformative classifier. In addition, under standard regularity conditions (see Hsieh and Turnbull, 1996):

$$\sqrt{n_1}\left(\widehat{AUROC}-0.5\right)\xrightarrow{d}N\left(0,\sigma^2\right) \tag{8}$$

$$\sigma^2=\frac{1}{n_0n_1}\begin{bmatrix}AUROC(1-AUROC)+(n_1-1)\left(\phi_1-AUROC^2\right)+\\+(n_0-1)\left(\phi_2-AUROC^2\right)\end{bmatrix}^{1/2}$$

where $\phi_1=AUROC/(2-AUROC)$

and $\phi_2=2AUROC^2/(1+AUROC)$.

5. EMPIRICAL RESULTS

Before conducting the ROC curve assessment, the signal extraction method was employed to assess the performance of potential conditioning variables over different thresholds and horizons. Specifically, the values of thresholds to be examined for each indicator were based on visual assessments of the data vis-à-vis the crisis periods (see Figure 1). Signals, $S(y_{t-h})$, can either take on the value of 0 or 1 depending on whether y_{t-h} is below or above the threshold value, c_h. A signal of 1 (0) was judged to be correct only if a crisis (no crisis) occurred at the end of the prediction horizon[4]. One-year-ahead, three-months-ahead and zero-year-ahead prediction horizons were examined. Notably, these horizons, particularly the latter two, would give the Central Bank a relatively short lead time to implement capital buffers. Longer horizons of two and three years were also examined, but with inferior results. This shortcoming of relatively high volatility in the indicator series may be a feature of small developing economies.

As discussed earlier, given that the preferences of regulators are not observed, the best threshold is determined when using the signals extraction method by minimizing the noise-to-signal ratios conditional on at least two-thirds of the crises being correctly predicted (see Borio and Drehmann, 2009). As depicted in Table 2, bold fonts are used in the columns labeled *Predicted* to indicate threshold values that are consistent with a condition of a crisis prediction rate of at least 66%. In addition, bold fonts and shaded cells in columns labeled N/S indicate the lowest noise-to-signal ratio for threshold values that satisfy the condition.

For the one-year-ahead horizon, private sector credit-to-real GDP gap at the 20% threshold value, achieved the lowest noise-to-signal ratio of 22% as well as the highest percent of correct

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[4] This is a more conservative definition compared to Borio and Lowe (2002) and Drehmann et al (2010, 2011) where signals of 1 (0) are judged to be correct if a crisis (no crisis) occurred *at any time* within the prediction horizon.

predictions of 81%. Thresholds of 30% and 40% for this variable also achieve above two-thirds successful predictive rates, albeit, at slight higher noise-to-signal ratios. Credit (private and public)-to-real GDP gap is the only other variable to satisfy the condition of a crisis prediction rate of at least 66% (75%) and achieved a noise-to-signal ratio of 29% at a 25% threshold value.

At the three-month-ahead horizon, the results are a bit different. Credit-to-real GDP gap still satisfies the condition of a crisis prediction rate of at least 66%, but now at both the 25% threshold value (with noise-to-signal ratio of 21%) and 50% threshold value (with noise-to-signal ratio of 26%). However, in contrast to results for the one-year-ahead horizon, private sector credit-to-real GDP gap did not attain the minimum condition for the prediction ratio.

The results at contemporaneous horizon are similar to those for the three-month-ahead horizon. Only credit-to-real GDP gap satisfies the condition of a crisis prediction rate of at least 66% (81%). Similar to the results for the three-month-ahead horizon, this condition is held at both the 25% and 50% threshold values.

Table 3 presents the AUROC for each indicator over the three horizons. Consistent with the signal extraction method discussed above, the AUROC for the HP-filtered credit-to-real GDP gap, credit plus investment-to-real GDP gap, private sector credit-to-real GDP gap and public sector credit-to-real GDP gap all have significant predictive value for crisis episodes. In contrast to the alternative method, however, is the fact that significant predictive values for these variables are attained for all horizons considered.

Table 2

PERFORMANCE OF POTENTIAL CONDITIONING VARIABLES FOR DIFFERENT SIGNALING HORIZONS

Conditioning variables	*Threshold*	*1-year-ahead prediction (%)*				*3-month-ahead prediction (%)*				*0-year-ahead prediction (%)*			
		Type 1	*Type 2*	*Predicted*	*N/S*	*Type 1*	*Type 2*	*Predicted*	*N/S*	*Type 1*	*Type 2*	*Predicted*	*N/S*
Credit to real GDP	25	14	25	**75**	**29**	9	19	**81**	**21**	9	25	**75**	28
	50	8	38	63	41	3	25	**75**	26	1	25	**75**	**25**
	75	5	69	31	73	1	56	44	57	1	56	44	57
Real credit growth	15	18	88	13	106	15	88	13	103	15	88	13	103
	20	16	88	13	105	14	88	13	101	14	88	13	101
	30	11	94	6	105	8	94	6	102	8	94	6	102
Real investment growth	15	18	94	6	114	12	81	19	93	11	75	25	84
	20	16	94	6	112	11	81	19	91	10	75	25	83
	25	15	94	6	110	10	81	19	90	8	75	25	82
Credit and investment to real GDP	30	21	69	31	87	12	38	63	43	12	38	63	43
	40	14	63	38	72	4	50	50	52	4	44	56	46
	50	11	69	31	77	3	56	44	58	4	56	44	59
Credit and investment growth	5	26	94	6	127	22	81	19	104	21	81	19	102
	10	15	100	0	118	12	100	0	114	11	94	6	105
	15	10	100	0	111	7	100	0	107	5	94	6	99

	70	12	100	0	114	10	100	0	111	8	94	6	102
Investment to real GDP	75	11	100	0	112	8	100	0	109	7	94	6	101
	80	11	100	0	112	4	100	0	104	3	94	6	96
	20	13	19	**81**	**22**	17	44	56	53	19	56	44	70
Private sector credit to real GDP	30	6	25	**75**	27	12	63	38	71	14	75	25	88
	40	4	25	**75**	26	9	63	38	69	12	75	25	85
	20	14	69	31	80	8	56	44	61	10	56	44	62
Public sector credit to real GDP	35	8	88	13	95	3	94	6	96	3	75	25	77
	40	5	94	6	99	3	94	6	96	3	94	6	96
	30	11	75	25	84	5	69	31	73	5	63	38	66
Non-performing loans growth	40	11	75	25	84	5	63	38	66	4	56	44	59
	50	16	75	25	90	3	63	38	64	1	56	44	57
	15	21	88	13	110	14	63	38	72	11	50	50	56
Provision for loan loss growth	30	11	88	13	98	5	75	25	79	3	63	38	64
	60	5	94	6	99	1	88	13	89	0	81	19	81
	5	16	63	38	75	15	75	25	88	18	88	13	106
Inflation	10	10	88	13	97	8	88	13	95	8	94	6	102
	-	-	-	-	-	-	-	-	-	-	-	-	-

continues

Conditioning variables	Threshold	1-year-ahead prediction (%)				3-month-ahead prediction (%)				0-year-ahead prediction (%)			
		Type 1	Type 2	Predicted	N/S	Type 1	Type 2	Predicted	N/S	Type 1	Type 2	Predicted	N/S
Real GDP growth	3	10	88	13	97	10	100	0	111	10	100	0	111
	3.5	5	88	13	93	5	100	0	106	5	100	0	106
	4	4	88	13	91	4	100	0	104	4	100	0	104
Real M2J growth	10	16	88	13	105	15	94	6	110	15	94	6	110
	15	11	94	6	105	10	100	0	111	10	100	0	111
	20	10	94	6	104	8	100	0	109	8	100	0	109
Real monthly average inter-bank rate	3	30	56	44	81	30	69	31	98	29	63	38	88
	5	19	81	19	101	16	81	19	97	16	81	19	97
	10	18	94	6	114	16	100	0	120	16	100	0	120
Real weighted average time deposit rate	3	33	88	13	130	32	94	6	137	30	88	13	125
	4	26	100	0	135	23	100	0	130	23	94	6	122
	5	19	100	0	124	16	100	0	120	16	94	6	112

Notes: A signal of 1 (0) was judged to be correct only if a crisis (no crisis) occurred at the end of the prediction horizon.
Type 1 error refers to when no signal is issued and a crisis occurs.
Type 2 error refers to when a signal is issued and no crisis occurs.
Predicted refers to the percentage of crises correctly predicted. Values in bold font in this column indicate that more than 66% of crisis quarters were correctly predicted.
The noise-to-signal ratio (N/S) is defined as the fraction of type 2 errors divided by one minus the fraction of type 1 errors. Values in bold font and shaded cells in this column indicate the lowest N/S ratio among the threshold values that are associated with indicators showing a correct prediction rate of at least 66 percent.

Table 3

PERFORMANCE OF POTENTIAL CONDITIONING VARIABLES USING THE AUROC CURVE FOR DIFFERENT SIGNALING HORIZONS

Conditioning variables	*0 Year*	*3 Months*	*1 Year*
Credit to real GDP	**0.95**	**0.94**	**0.87**
Real credit growth	0.53	0.50	0.54
Real investment growth	0.53	0.51	0.43
Credit and investment to real GDP	**0.81**	**0.81**	**0.73**
Credit and investment growth	0.47	0.45	0.41
Investment to real GDP	0.27	0.29	0.30
Private sector credit to real GDP	**0.66**	**0.71**	**0.82**
Public sector credit to real GDP	**0.86**	**0.77**	**0.64**
Non-performing loans growth	**0.73**	**0.68**	**0.64**
Provision for loan loss growth	**0.64**	0.61	0.58
Inflation	0.42	0.48	0.52
Real GDP growth	0.24	0.24	0.35
Real M2J growth	0.39	0.34	0.37
Real monthly average inter-bank rate	0.53	0.49	0.52
Real weighted average time deposit rate	0.44	0.40	0.40

Notes: AUROC curve of conditioning variables relative to crisis periods for 0-year-ahead, three months-ahead and one year-ahead predictions.
Areas statistically different from 0.5 using the one-tailed WMW test are denoted by bold font and shaded cell at the 99% level of significance and bold font at the 95% level of significance.

Furthermore, credit plus investment-to-real GDP gap, public sector credit-to-real GDP gap, NPLs growth gap and provision for loan loss growth gap all show significant predictive power especially for the contemporary horizon. Notably, these indicators were not supported as being useful under the conditions of the signal extraction method. Notwithstanding, the more robust AUROC method provides strong support for the two latter indicator variables, in particular, to be used as lagging indicators to guide the release phase. Specifically, as indicated by the BCBS, release of the buffer add-on should be considered when in a situation of system-wide banking system losses. Accordingly, NPLs growth gap and provision for loan loss growth gap both satisfy this scenario in sufficiently promptly signaling the timing of the release.

Basel Committee (2010) offers guidelines for countries operating the countercyclical capital buffer regime. The Committee also developed a formula that offers a buffer level that varies with the size of the deviation of the cyclical components of conditioning variables from their long-term trends. The formula links a conditioning variable to a capital adjustment factor. This add-on factor equals zero in bad times and increases linearly in the conditioning variable to a set maximum level. In practice, each national authority makes its own decision on the choice of conditioning variables and the statistical tool that splits these variables into their trend and cyclical components.

The formula for the countercyclical add-on may be presented as:

$$k_t = \begin{cases} 0 & \text{if } y_t < L \\ \dfrac{y_t - L}{H - L} k_{max} & \text{if } L \le y_t \le H \\ k_{max} i & \text{if } H < y_t \end{cases} \tag{9}$$

The choice of lower and upper threshold gap levels, L and H, are critical to the speed and timing of buffer adjustment in relation to the buildup of systemic risk. The Basel Committee has established broad criteria to determine threshold gap levels as a starting guide to the relevant authorities for deciding the buffer add-on (BCBS, 2010):

> *1) L* should be low enough, so that banks are able to build up capital in a gradual fashion before a potential crisis. As banks are given one year to raise additional capital, this means that the indicator should breach the minimum at least 2-3 years prior to a crisis,
>
> *2) L* should be high enough, so that no additional capital is required during normal times,
>
> *3) H* should be low enough, so that the buffer would be at its maximum prior to major banking crises.

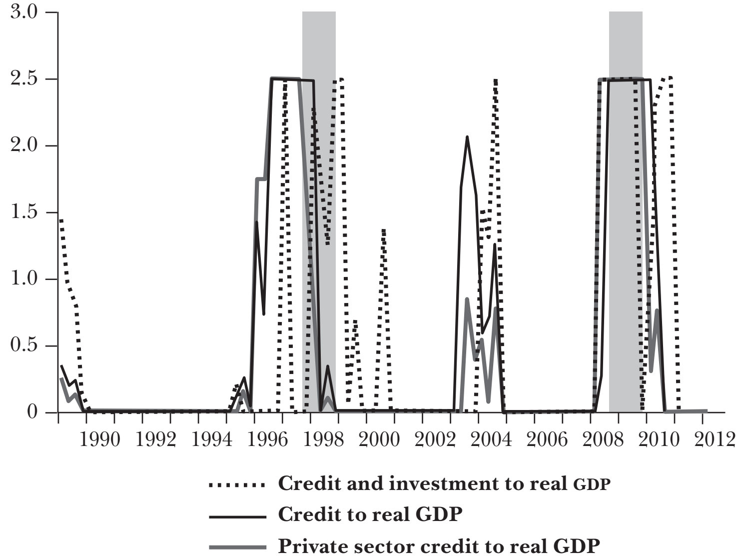
Figure 3 illustrates how the countercyclical buffers would have affected Jamaica's commercial banks using the HP-filtered credit-to-real GDP gap, credit and investment-to-real GDP gap and private sector credit-to-real GDP gap as conditioning variables (as supported by the AUROC method) over the sample period of this study. In accordance with the Basel (2010) guidelines, the maximum buffer add-on (Kmax) was set at 2.5% of risk-weighted assets. The Figure depicts that evolution of capital add-on when *L*=15% and *H*=50% for purely exposition purposes. For both crisis periods, the buffer would reach the maximum value prior to the onset of the crisis. This feature of the conditioning variables provides justification for setting $\lambda = 16{,}000$ which is below the $\lambda = 400{,}000$ used for studies on advanced countries.

Whereas the build-up phase associated with these conditioning variables is sufficient for the first crisis episode (two years), it is short (one quarter) in the case of the second crisis period. Interestingly, the conditioning variables indicate a build-up of buffer capital in the 2003 to 2004 period, albeit, with a shorter duration and smaller magnitude compared to the crisis episodes. However, this period is not considered a crisis episode given the maintenance of low NPL levels in the banking sector as well as the presence of abundant market liquidity. Notwithstanding the absence of an *official* crisis, commercial banks

Figure 3

HISTORICAL PERFORMANCE OF COUNTERCYCLICAL CAPITAL BUFFERS FOR JAMAICA'S COMMERCIAL BANKS

(Percentage)



Source: O. Jordà, *Discussion of Anchoring Countercyclical Capital Buffers: The Role of Credit Aggregates*, Working Paper, University of California, Davis, 2011.

operated within a severely challenging macroeconomic environment within this period triggered by the announcement of a large fiscal disjuncture and a downgrade in the rating of Jamaica's sovereign debt by Standard and Poor's at the end of 2002. Given the deteriorated domestic financial conditions, particularly in the foreign exchange market, the Central Bank instituted a Special Deposit reserve requirement for DTIs on 10 January 2003 and adjusted interest rates sharply upward on three occasions during the first half of 2003 in order to constrict the excess market liquidity. Hence, in the context of the tightening in monetary policy during 2003, it can be reasonably argued that the actions of the Central Bank averted a looming boom-bust cycle at that time of weakened sovereign creditworthiness.

6. CONCLUSION AND POLICY IMPLICATIONS

This paper provides support for the findings of other studies (eg., Borio and Drehmann, 2009) that policymakers can be guided by conditioning variables at one-year and three-month horizons such as credit-to-GDP, NPLs growth and provisions for loan loss growth in their design of countercyclical capital buffers. It is acknowledged that reliance on these relatively short horizons, which may be due to relatively high volatility in the indicator series, would give policymakers relatively little implementation lead time. This shortcoming may be a feature of small developing economies.

The novelty of this paper comes from the finding that banking sector variables reflecting sovereign risk build-up (namely the level of public sector credit and investments in public sector securities) perform successfully as conditioning variables for Jamaica. Hence, other economies with a history of fiscal dominance and public sector crowding out of private sector credit should explore variables that reflect sovereign risk build-up in guiding the accumulation and release phases of a capital buffer requirement for their banking sectors.

Importantly, the accurate timing of implementing a countercyclical capital buffer would be crucial, as it would have to be established only in a clear up-cycle period. Otherwise, it could have negative implications in terms of banks' financial strength, stakeholders' perceived confidence in the sector and the reputation of the central bank. Against this pre-requisite, although this paper focuses on computing the long-run trend by the HP filter as a guide for the buffer to be consistent with the proposed method of the BCBS, alternative statistical filters may be applied to obtain comparative results for robustness checks[5]. Nonetheless, experimenting with other statistical detrending approaches is unlikely to dramatically improve the performance of the indicators. Indeed, an alternative approach such as that proposed by Geršl and Seidler (2010)

[5] Alternative filters include Beveridge and Nelson (1981) and band-pass, among others.

could be explored which relies on an out-of-sample technique to estimate the fundamental-based equilibrium credit level and may be more appropriate for small developing economies such as Jamaica.

In addition, Jamaica's macroprudential authorities will need to build up a longer time series of data on these indicators to strengthen the decision-making framework regarding implementing countercyclical capital buffers. Then further disaggregation of variables should be explored to refine the efficiency of relevant information contained in the indicators. For example, credit could be further broken down by institution size, currency and economic sector.

Importantly, the regulatory approach to mitigating procyclicality of the financial system should be all-inclusive, covering all financial institutions to mitigate arbitrage opportunities. In addition to the countercyclical buffer requirement, other elements of the prudential framework should also be utilized. For instance, excessive credit growth (and subsequent downward shift in credit quality) stems essentially from inadequate risk management practices. While the central bank may be in the best position to assign the capital requirements commensurate to the degree of risk taken by banks during times of credit growth, it should not be left as a holistic rule-based mechanism.

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