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TOWARDS AN UNDERSTANDING OF CREDIT CYCLES: DO ALL CREDIT BOOMS CAUSE CRISES?

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Towards an understanding of credit cycles: do all credit booms cause crises?[1]

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Towards an understanding of credit cycles: do all credit booms cause crises?

Macroprudential policy is now based around a countercyclical buffer, relating capital requirements for banks to the degree of excess credit in the economy. We consider the construction of the credit to GDP gap looking at different ways of extracting the cyclical indicator for excess credit. We compare different smoothing mechanisms for the credit gap, and demonstrate that some countries require an AR(2) smoother whilst other do not. We embed these different estimates of the credit gap in Logit models of financial crises, and show that the AR(2) cycle is a much better contributor to their explanation than is the HP filter suggested by the BIS and currently in use in policy making. We show that our results are robust to changes in assumptions, and we make criticisms of current policy settings.

Keywords: credit cycle; financial crisis; banks; macro-prudential policy; filtering

1 Introduction

This paper investigates the link between credit cycles and banking crises in order to shed light on the policy justification of countercyclical regulatory capital buffers. The contribution of credit to economic growth has been discussed for decades, following the McKinnon (1973) and Shaw (1973) framework of the 1970s where increased saving flows in a financially liberalised regime were shown to improve both the quantity and quality of investment. In the 1990s, endogenous growth theorists[2] provided an alternative view of the growth-enhancing role of credit, whereby financial intermediaries, via risk pooling and diversification, improve innovation and technological progress. By the 2000s however, the benefits of increased credit flows

[2] King and Levine, (1993); Levine (1997)

became open to question and a cautionary view on the growth of credit evolved in response to the sub-prime crisis of 2007. Economists and regulators (including the Bank for International Settlements, BIS) have increasingly blamed rapid credit growth as a cause of financial instability, arguing that banks' search for yields manifested as risky loan allocations and ultimately, systemic failure. This view has directed the policy debate on regulation, and, in a bid to curb excessive credit growth and financial instability, Basel III now recommends the use of countercyclical buffers based on credit growth as a macroprudential tool[3].

Countercyclical buffers are intended to reduce the amplification of procyclicality, a particular dynamic between credit and house price growth, generated by the banking system. During a cyclical upturn, loan volumes increase (often due to increased risk appetite of banks) and concurrently, this may fuel house price bubbles which in turn stimulate lending via raised collateral values. However, this cyclical causality becomes problematic when asset bubbles burst and the dynamics reverse: banks behave risk aversely and ration credit as non-performing loans rise, which depresses asset prices further[4]. To defend against adverse real economy effects, regulators in the post 2007 crisis environment advocated credit growth based procyclical accumulation of bank capital which could be released to counter the cyclical downturn: Basel III uses the gap between the credit-to-GDP ratio and its long term trend to calibrate the capital accumulation. While regulators recognize that the link between credit-to-GDP gaps and capital buffers is not mechanical, there remains consensus that

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[3] These have been in active use, for instance in the UK immediately after the BREXIT referendum.

[4] This transmission has been discussed over the last decades: described as the financial accelerator by Bernanke and Gertler (1989) and Bernanke et al. (1996) whilst Kiyotaki and Moore (1997) used a theoretical framework to show how the dynamic interaction between credit and assets prices amplify shocks to output.

this gap is an adequate policy indicator for the build-up of vulnerabilities on the financial side (Drehmann and Tsatsaronis, 2014).

Credit-to-GDP ratios represent a practical and appealing way to guide policy given the objective of the buffer. However, a growing literature supports the view that not all credit-to-GDP amplifications are “credit booms gone wrong”, underpinned by “reckless lending” (Freixas et al., 2015; Gorton and Ordoñez, 2016). In these cases, financial intermediation disseminates credit to projects whose net present values are likely to be positive and hence taxing via countercyclical buffers would be socially undesirable. Thus the distinction between credit booms associated with house price bubbles versus those that fund productive investment is an important policy issue since only the former may be associated with financial instability. In such cases, credit and house price cycles can cause each other, leading to the problem of procyclicality.

In this paper, we investigate if and when credit growth leads to banking crises. We test the hypothesis that excessive credit- to-GDP growth causes banking crises in 14 OECD countries during 1978 – 2016[5]. We utilise total credit to the private nonfinancial sector to construct our credit-to-GDP gaps. We initially construct a (“HP filtered”) credit gap to mimic the BIS approach. To probe the role of credit-to-GDP dynamics in more depth, we recognise that a time series can be decomposed in to a trend, a cyclical component and a random element and estimate three additional measures, making specific assumptions on the functional form of the cycle: an AR(1) cycle, an AR(2) and a stochastic cycle. Our rationale is that, while extant studies estimate credit gaps as generalised residuals, by utilising specific cyclical data generating processes, we may

[5] Country and timeframe choices are driven by data availability

provide a better explanation of credit abnormalities in the economy and thus generate higher explanatory power[6].

We subject our gap-measures to an information criteria selection procedure, to isolate the optimal gap measure for each country[7] (similarly to Macchiarelli, 2013). The idea that credit-to-GDP gaps differ across countries, reflecting idiosyncratic factors, is discussed by Drehmann et al. (2012), Grintzalis et al. (2017), and Edge and Meisenzahl (2011). Bassett et al. (2015), particularly note how home mortgages in the US account for a large share of the observed increase in the one-sided trend in the credit-to-GDP ratio. Hence, measures of the credit-to-GDP cycle that explicitly accommodate this persistency are worth exploring.

Our filtering exercise reveals a natural "clustering" of countries into two gap-types: countries for which AR(2) cycles are preferred (Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US) and the remaining group (Denmark, Germany, Japan, the UK, and the Netherlands) where a stochastic cycle is optimal. We find the BIS filtering procedure (which makes no assumptions on the cyclical dynamics) is not selected as the optimal gap in any of our countries.

To evaluate the credit cycles' crisis role in generating crises, we then embed the "optimal" gap for each country within a logit early warning system, using macroeconomic and regulatory variables, including capital adequacy, liquidity and

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[6] To escape the usual criticism of HP-filtered series suffering from end-point bias (see Hamilton, 2017), we retrieve our "HP-filtered" series using a one-sided Kalman filter where restrictions are put on the state space representation of the latter. An advantage of this method is that our filter can be estimated using maximum likelihood (Harvey and Trimbur, 2008; Harvey, 1989).

[7] All cycles are calibrated so the financial cycle is of medium term duration, consistent with the extant literature (Drehmann and Tsatsaronis, 2014).

property price growth, as standard controls. We also compare the efficacy of our cycle estimators. In the overall sample, we find that a mix of stochastic and AR2 cycles best describes crisis probabilities in terms of informational criteria. The AR2 cycle seems to apply to countries where credit growth and house prices interact and feed each other. Granger tests suggest in these countries, house price growth raised collateral values which propagated risky lending.

As a robustness test, we vary crisis timing to check the stability of our results. Additionally, we use end-point observations on the cycles to confirm the robustness of our credit-gap effects. Again, these tests suggest that credit-to-GDP growth in itself is not risky, but when it combines with feedback from house prices, regulation becomes warranted. The policy implication of our results is that financial regulators should carefully identify the nature of credit growth before taxing banks in order to minimise social welfare losses from financial disintermediation.

Our paper is structured as follows: section 2 reviews literature that links credit growth to banking vulnerabilities and the surrounding regulation. We also discuss the alternative filtering methodologies that are available for credit-to-GDP gap construction. Section 3 describes our filtering and early warning methodologies, including Receiver Operating Curves as information criteria. Section 4 discusses our data and in section 5 we present our results. Section 6 concludes.

2 Credit Cycles, Bank Capital and Macro-Prudential Regulation

For many years, the management of financial system operations was mandated to Central Bank control, alongside management of the currency. Avoiding financial crises or ameliorating their effects was an important objective up until the 1929-1933 recession. Financial repression and the Bretton Woods fixed exchange rate system combined to ensure that there were no financial crises in advanced economies in the period from 1940 to 1972. Systemic risk appeared to have disappeared, and consequently, after the 1970s, Central Bankers and regulators increasingly focused on inflation and micro-prudential regulation. However, from 1970 to 2000, decade by decade, although financial crises in advanced economies became more common, they were still not seen as a major focus of policy: the majority of the economics profession became convinced that macroprudential policy[8] was unneeded as systemic risk was either absent or unavoidable[9].

The financial crises that broke in 2007 and 2008 in the US, the UK and much of the Northern Hemisphere led to a re-evaluation of systemic and endogenous risk, driving the design of a new regulatory framework. In particular, attention was given to the role of credit cycles and their impacts on crisis risks. Whilst the Basel III regulatory architecture is still under implementation, the implications for credit growth, at least as far as this research is concerned, are in place. Both the quantity and quality of capital that individual banks must hold has increased, and systemically important banks are required to conserve more capital. In addition, there are two entirely new capital based buffers, the countercyclical buffer and conservation buffer. The conservation buffer (2.5 percent of risk weighted assets) allows regulators to impose capital distribution constraints when common equity capital (i.e. high quality Tier 1 capital) falls below 7%. These changes to core capital and the conservation buffer are micro-prudential

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[8]A term probably coined by Andrew Crockett when he was the Managing Director if the BIS

[9] This view of exogenous risk not requiring regulation was put forward by Alan Greenspan when he was Chairman of the Federal Reserve, and given some support by the academic research summarised in *Financial Crises* by Allen and Gale (2007).

(individual bank based), although it is clear that the more capital the banks hold, the less risk there is of a systemic crisis developing (Barrell et. al (2010)).

The focus of this paper however, centres on the current macro-prudential framework which specifies a countercyclical buffer. In summary, as credit increases excessively, it is presumed that more potentially non-performing loans are issued and the balance sheets of banks face future deterioration. When macro-economic conditions worsen, there is a materialisation of credit risk and consequently the core capital of the banking system becomes compromised which curtails further lending. This creates solvency and liquidity risk for borrowers as their project net present values approach negative in the macroeconomic downturn. They exhibit even higher default rates and induce further reductions in bank capital. The buffer construction is therefore based on the assumption that this cyclical transmission between credit and asset values drives credit gaps and relies on results showing credit cycles to be good crisis predictors (BCBS 2010 a,b).

An obvious source of this transmission is the build-up of excessively risky lending that is driven by house price bubbles. At least in countries where debt default has low costs, mortgage borrowers effectively hold put options against the bank, which they can exercise by defaulting when property price bubbles burst. This behaviour was especially apparent in the US sub-prime crisis (Reinhart and Rogoff, 2008). As bank capital erodes to cover the defaults, mortgage credit is further rationed and hence house prices continue the decline. This in turn raises the value of the put option from the borrower's perspective and increases mortgage default rates further. Structural changes in the banking industry may exacerbate the procyclicality by incentivising increased lending during the upturn. Such changes may manifest as new approaches to firm behaviour (e.g. increased focus on shareholder value and performance based bonuses) or technological innovations (e.g. growth of internet banking).

However, it is not always the case that the above stylised transmission will hold: asset price bubbles can arise from reasons exogenous to the banking system. Credit growth can also be rapid in periods when higher lending is simply a rational response to profitable returns on lending. House prices for example have risen in real terms over decades in many countries reflecting structural changes in demographics and urbanisation[10]. Gorton and Ordonez (2016) suggest that credit booms are initiated by positive total factor and labour productivity shocks but only those where the shock dissipates quickly will transform into “bad booms”. Regulating against credit growth via extra capital requirements when productivity growth is high, can lead to a reduction in good lending for sound projects, impacting on economic output. Dell’Ariccia et. al (2012) note that only one third of post-1970s credit booms are associated with subsequent crises. Hence the output costs of regulation should be offset against the benefits of the reductions to crisis probabilities and the ameliorated costs of crises.

Important long run studies such as Schularick and Taylor (2012), Jorda et. al (2011, 2013) and Reinhart and Rogoff (2008) examine historical data sets and wide groups of countries when analysing crises and cycles, as justified by the relative infrequence of crisis episodes and their tendency to cluster in time. Reinhart and Rogoff (2008) note banking crises are often associated with the growth of external debt, and this is supported by Karim et. al (2013) using the current account and Jorda et. al (2013)

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[10] House prices in London, for instance have been rising in real terms almost continuously for 70 years, and this may reflect shifting demand toward the city within a growing world economy, with assets being sold to foreign residents.

who note the link between external imbalances and crises has strengthened in the last 60 years.

Schulerick and Taylor (2012), use a 140 year panel of 14 developed economies to analyse bank credit growth and crises: broad money and credit cycles grew together in a generally stable fashion pre-1950, and both are good predictors of financial crises, but post- 1950, only credit predicts crises. This reflects the break down in the relation between credit growth and bank deposits that resulted from financial innovations in the last 60 years, in particular the increasing use of nonmonetary liabilities to increase leverage. Jorda, et. al (2013) examine the relation been financial crises and 200 economic downturns in their 140 year panel, and find that post-crisis downturns are worse than others. However, it is not obvious from this work that credit causes financial crises; standard controls, including known defences of crises such as capital and liquidity are omitted as are drivers of credit such as house prices[11]. The exclusions reflect a paucity of data availability for such long run studies[12] which means key post – 1945 trends in house prices and bank regulation cannot be assessed for their impact on credit dynamics[13].

It is clear from this literature that an alternative method for analysing excessive credit growth should accommodate underlying output growth. The credit-GDP gap is therefore an obvious candidate for inclusion given the current macroprudential

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[12] Schularick and Taylor (2012) include stock prices in one set or regressions as these are the only asset price series available for such long runs. The growth in lagged nominal stock prices is insignificant in terms of explaining crisis probabilities whilst the first lag of real changes is significant.

[13] See also Aikman et. al (2015) and Summers (2016) who replicate the results of Schularick and Taylor (2012) but again, omit the control variables that we include.

framework based on the BIS (2010a, b), Borio and Lowe (2002, 2004), Drehmann et. al (2010), Drehman et. al (2011) and supported by Alessi and Detken (2014). In this context, the role of the filter becomes crucial since the gap's reliability (as either an early warning indicator or calibrator of countercyclical buffers) is contingent on the filter used for extraction. A common view is that financial cycles last longer than business cycles. Drehmann et al. (2012), for instance, examined variables across a number of countries and found the average duration of the financial cycle to be about 16 years. Basset et al. (2015) suggest that some types of credit (government sponsored enterprises and other nonbank) are persistent well beyond business cycle frequencies, and are thus excluded from the extracted gap.

Methodologies for estimating credit gaps range from statistical models that extract information from observed series, to those using economic priors. The most popular filtering techniques typically include: *trends* (linear; split or spline), *univariate filters* (Baxter-King or band pass,[14] Hodrick-Prescott (1997); Beveridge-Nelson (1981)[15], Kalman (see Harvey, 1989)) and *economic* methods (Structural VARs)[16]. The univariate filters exist in multivariate version as well, where the filter's information set is conditional on a set of (exogenous) variables relevant in explaining the series long run behaviour.

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[14] The trend is obtained by "eliminating" the very low moving trend components and the very high frequency components while keeping intermediate business cycle components.

[15] This method shows how any ARIMA(p,1,q) process can be decomposed into a permanent and transitory component. This requires some important assumptions, i.e. the trend of a series is described by a random walk process and the error terms in both components are highly correlated

[16] The equilibrium is estimated based on structural assumptions about the nature of the economic disturbances.

Among the different methodologies, the Hodrick-Prescott filter's simplicity makes it an appealing estimation method for retrieving credit-to GDP gaps, based on a trend. The latter is extracted by introducing a weighting parameter, λ, which trades off goodness of fit against smoothness. However, the filter is often criticised for generating biased end of sample values and also because it produces series with spurious dynamics that do not reflect the underlying data-generating process (Hamilton, 2017; Edge and Meisenzahl, 2011). Additionally, its statistical formalization produces values for the smoothing parameter at odds with common practice, particularly at quarterly frequencies (Hamilton, 2017; Ravn and Uhlig, 2002).

Alternative specifications make additional assumptions on the cycle's functional form, for instance. autoregressive dynamics or stochastic cycles à la Harvey and Jaeger (1993) and Koopman et al. (2006). These representations can accommodate alternative credit dynamics with different degrees of persistency. Whereas extant policy approaches estimate credit gaps as generalised residuals (i.e. the difference between the actual credit-to-GDP ratio and its trend), by utilising specific data generating processes for the cycle, these alternatives may better explain business-cycle irregularities in the economy. They may have the added benefit of being able identify the trend while capturing (some of) the persistency characterizing the observed housing boom-and-bust cycle (see Reinhart and Rogoff, 2008; Aßmann et al., 2011). The limit to such approaches is that housing cycles generating long lasting recessions (booms) and considerable losses (gains) in output, may require different trend descriptions (Basset et al., 2015), to the extent that these changes are structural (Jannsen, 2010; Boysen-Hogrefe et al., 2016; Cerra and Saxena, 2008).

3 Methodology

3.1 Optimally Choosing Cyclical Indicators

We initially mimic the BIS gap approach using identical parameters. In the standard specification of Borio and Drehmann (2011), Bank of England (2013), Borio and Lowe (2002; 2004), the cycle is taken as the residual or irregular component between the actual series and the HP filtered trend. A recursive one-sided framework is used, reflecting the idea that policy makers can only access information available at time *t*. However, to escape the usual criticism of HP-filtered series suffering from end-point bias, we retrieve our one-sided HP-filtered series using a Kalman filter (as opposed to a Kalman smoother) using maximum likelihood (Harvey and Trimbur, 2008; Harvey, 1989). This will not affect our crisis estimation as this ends well before our data stops.

Harvey and Trimbur (2008) have noted how the HP filter is equivalent to the smoothed trend obtained from an unobserved component model of the type:

$$y_t = \mu_t + \epsilon_t \tag{1.1}$$

Where

$$\mu_t = \mu_{t-1} + \beta_{t-1} \tag{1.2}$$

and

$$\beta_t = \beta_{t-1} + \zeta_t$$

The irregular and slope disturbances, ε and ζ, respectively, are mutually independent and normally and independently distributed with mean zero and variance σ^2. The signal-noise ratio, $q = \sigma_\zeta^2 / \sigma_\varepsilon^2$, plays the key role in determining how observations should be weighted for prediction and signal extraction. The higher is q, the more past observations are discounted in forecasting the future.

The trend in eq. (1.1) is an integrated random walk. The statistical treatment of such unobserved component models is based on the state space form described in Harvey (1989). For quarterly data, Hodrick and Prescott (1997) proposed a value of q = 1/1600, where 1600 is referred to as the smoothing constant. Harvey and Jaeger (1993) observed that, for US GDP, the HP filter gives a very similar trend to the one produced by fitting an unobserved components model in which the irregular component in (1.1) is replaced by a stochastic cycle.

We then estimate three additional gaps: these use the same state-space “HP-type” representation of the trend but make additional specific assumptions on the functional form of the cycle. In particular, three functional forms are considered: an AR(1) cycle, an AR(2) and a stochastic cycle -ARMA (2,1)- *à la* Harvey and Jaeger (1993) and Koopman et al. (2006).

The irregular component, ε in the specification in (1.1) in fact may include both a pure measurement error and a cyclical component. This is the case as the specification above makes no assumption on the existing cycle. We thus make the assumption that the irregular component is made up of a pure estimation error (let us call it u_t) and a cyclical component (which we call φ_t).

$$\epsilon_t = u_t + \varphi_t$$

Equation (1.1) thus becomes

$$y_t = \mu_t + \varphi_t + u_t \qquad (1.3)$$

In order to avoid imposing a priori restrictions on the cyclical dynamics, we match the trend (μ_t) with the dynamics of a one-sided HP-filter (we hence use a Kalman filter as opposed to a two-sided filter or smoother), similar to Borio and Lowe (2002).

For these different specifications of the cycle, φ_t, we use the following models:

- ***Model 1*** - *Irregular*: where no explicit assumptions on the cycle are made (hence, the irregular or residual component is considered as a cyclical component, matching Borio and Lowe, 2002).
- ***Model 2*** - *Harvey (1997):* where the statistical specification of the cycle is given by a stochastic cycle
- ***Model 3*** - *AR(1):* where the statistical specification of the cycle is described by a standard order-1 autoregressive process .
- ***Model 4*** - *AR(2):* where the statistical specification of the cycle is described by a standard order-2 autoregressive process

For Model 2, in particular, the stochastic cycle takes the following form

$$\begin{bmatrix}\varphi_t\\ \varphi_t^*\end{bmatrix} = \rho_\varphi \begin{bmatrix}cos\lambda_c & sin\lambda_c\\ -sin\lambda_c & cos\lambda_c\end{bmatrix}\begin{bmatrix}\varphi_{t-1}\\ \varphi_{t-1}^*\end{bmatrix} + \begin{bmatrix}k_t\\ k_t^*\end{bmatrix} \qquad (1.4)$$

where ρ_φ, in the range $0 < \rho_\varphi \leq 1$, is a damping factor, λ_c is the cycle's frequency in radians, in the range, $0 < \lambda_c \leq \pi$; k_t and k_t^* are two mutually uncorrelated NID disturbances with zero mean and common variance σ_k^2.

We subject our different cycles or gap-measures to an "optimal" selection procedure based on the information criteria using the results of our trend-cycle decomposition. This allows us to isolate the best gap measure for each country while remaining agnostic with respect to the cyclical component in each country.

3.2 Logit Early Warning Systems

In this study we look at relatively parsimonious logit models to explain crises, and include standard significant variables from studies such as Barrell et al (2010, 2016) and Karim et al (2013) which are unweighted capital, bank liquidity, house price growth, the current account and the credit gap. We exclude variables that are insignificant in wider studies, such as Claessens et al (2012) and Rose et al (2011).

Before presenting the model, we note how we avoid misspecification and bias in our models. Barrell and Karim (2013) show for a group of emerging markets, country heterogeneity induced biases when comparing pooled versus homogenous samples (in that case, economies with financially constrained markets showed a strong role for credit growth as a crisis determinant, whereas financially liberalised economies did not). By focusing on OECD economies which are market based and financially developed we avoid heterogeneity bias. We also specify a parsimonious model and include only variables that have been shown to significantly affect crisis probabilities. Aside from the practical benefits to policy makers, this has the added advantage of reducing bias from over specification: Greene (2012), p 178, notes that including a variable that is irrelevant (i.e. not orthogonal to other regressors) will induce biases in the coefficients on the other included variable

We use the cumulative logistic distribution which relates the probability that the dummy for crises takes a value of one to the logit of the vector of n explanatory variables:

$$Prob\ (Y_{it} = 1) = F(\beta X_{it}) = \frac{e^{\beta' X_{it}}}{1+e^{\beta' X_{it}}} \qquad (1.5)$$

where Y_{it} is the banking crisis dummy for country i at time t, β is the vector of coefficients, X_{it} is the vector of explanatory variables and $F(\beta X_{it})$ is the cumulative logistic distribution.

The log likelihood function which is used to obtain actual parameter estimates is given by:

$$Log_e L = \sum_{i=1}^{n} \sum_{t=1}^{T} [(Y_{it} \log_e F(\beta' X_{it})) + (1 - Y_{it}) log_e \left(1 - F(\beta' X_{it})\right)] \quad (1.6)$$

3.3 Choosing between Logit models

There are several criteria that are available to identify the best logit early warning specification. The simplest is the Akaike information criterion which is the standard goodness of fit measure that trades-off against overfitting. However, this does not evaluate the predictive ability of the model. For early warning systems, the predictive power of independent variables is as important as their significance and is a function of the probability threshold ($0 \leq p \geq 1$) we set when making a forecast. The noise to signal ratio trades-off false alarms against missed crisis calls at a given p which is subject to policy makers' discretion. A better global measure, based on radar technology investigations, uses the entire set of the thresholds. These Receiver Operating Characteristics (ROCS) and the associated Area Under the ROC (the AUROC) have been used in the banking crisis context by Schularick and Talylor, 2012, Giese et. al, 2014 and Barrell et al. 2016. The ROC curve for each logit model plots a function of false alarms against missed calls for all p values and the integral, the AUROC, is used to select the best model in terms of predictive ability. The intuition is that an AUROC of 50% implies the model is unable to outperform a random coin toss in terms of predicting crises and thus the higher the AUROC, the better the model.

4. Data

Our models use data for 14 OECD countries[17] during 1978 – 2016. Regressions use data from 1978-2013, with the remaining three years being retained for out-of-sample forecasting. We use the same variables as Barrell, Davis, Karim and Liadze

[17] Belgium, Canada, Denmark, Finland, France, Germany, Italy, Japan, Netherlands, Norway, Spain, Sweden, UK and US.

(2010): unweighted bank capital adequacy (bank capital/total bank assets), bank liquidity ratios (liquidity as a proportion of total bank assets) and real house price growth. We also add the current account as a driving variable, as in Karim et al (2013). The unweighted bank capital variable primarily comes from the OECD Consolidated Banking Statistics Database but missing values are supplemented using IMF/World Bank data and Norwegian and Swedish Central Bank sources. Liquidity data is drawn from the IMF's International Financial Statistics Database and national central banks, as are the data on the current account as a percent of GDP. Real house price growth and credit growth data are obtained from the BIS which publishes the time series used for its own gap estimations.

The timing and duration of crises are subjective to an extent, although work by Demirguc and Detragiachi (1998) set initial rules to identify systemic episodes: the proportion of non-performing loans to total banking system assets > 10%, or the public bailout cost >2% of GDP, or systemic crisis caused large scale bank nationalisation, alternatively bank runs were observed and if not, emergency government intervention was sustained. They focused on the 1997 Asian crises, but post-sub Prime it was recognised that revisions to international crisis episodes were required. As a result, subsequent work by the World Bank and IMF has updated the dating of crises, albeit using a more restrictive set of criteria and in combination, the two sources allow us to consistently estimate up to 2013, as all crises after 2007 were severe.

To construct our binary banking crisis dummy we use the World Bank Crisis Database covering 1974-2002, (Caprio *et al* ., 2003) as well as Laeven and Valencia (2013) for the subsequent crises. The former have crises in Canada (1983), Denmark (1987), the US (1988), Italy and Norway (1990), Finland, Sweden and Japan (1991), France (1994), and the UK (crises in 1984, 1991 and 1995).

Laeven and Valencia (2013) classified Belgium, Denmark, France, Germany, the Netherlands, Spain and Sweden in crisis by 2008 and the US and UK in 2007. The authors treat the 2008 crisis in the US and the UK as a continuation of 2007 crisis, while we treat it as separate crises since 2008 was induced by the collapse of Lehman Brothers. These dating criteria underpin our results which we present in the next section.

5. Results

We first present the results of our filtering exercises and then discuss the performance of the alternative gap measures when embedded in our logit models.

5.1 Optimal Filters

We describe the results for our filtering process in Table 1. For each country we undertake four filtering exercises, and in each case we report four information related diagnostic tests, the log likelihood, the Schwartz Criteria, the Hannan-Quinn and the Aikake Information Criteria. In 13 of the countries all four criteria point to a single cyclical process being optimal, with only the Netherlands showing a conflict, with three indicating that the Harvey (1997) smoother is optimal, and one, the Schwartz criterion, suggesting an AR(1) process is to be preferred. The AR(2) process is optimal in Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US, whilst the Harvey (1997) is optimal in Denmark, Germany, Japan, the UK, and we allocate the Netherlands to this group as well.

Insert Table 1 here

5.2 Logit Results

We report the results for the crisis logits in Table 2, and in each case we include one lag on credit growth, capital, liquidity and the current account. House prices are lagged by three periods, consistent with the Early Warning model of Barell et al. (2010). Within this model, we embed our variables of interest: credit growth and cyclical indicators for the credit to GDP gap. We choose the current version of this indicator because it is a smoothing process almost entirely dependent on past data, and hence it can be used in an Early Warning System as it is available in real time (at the current period). We report five logits, and in each case we also summarise the information content of the logit with the AUC at the bottom of the column.

Insert Table 2 here

Our previous exercise has been to identify the optimal cycle to individual countries, and we use these in the first logit (column 1; table 2), with nine countries taking the AR(2) cycle as an optimal indicator of the credit to GDP gap and five taking the Stochastic (Harvey, 1997) cycle. This "mixed cycle" variable is significant and has a positive sign, suggesting as the gap widens the probability of a crisis increases given the level of the other indicators. The presence of a significant credit to GDP gap, not surprisingly, is associated with a negative and insignificant coefficient on credit growth which remains insignificant even when the gap is excluded from the logit. Thus the gap indicator appears to contain all the information we need about credit in order to be able to predict crises

Other coefficients are consistent with previous results in Barrell et al (2010) and Karim et al (2013). Capital has a negative and significant coefficient, as does liquidity, confirming that strong systemic defences against bank failure reduce the probability of a crisis occurring. Omitting these significant and relevant variables would bias the results for other coefficients, and would lead to a misunderstanding of factors driving crises. As in Karim et. al (2013), we find that recent current account deficits raise the risk of a crisis occurring, as does an increase in house prices three years previously. Both may lead to poor quality borrowing and lending, fuelled by capital inflows and inflated collateral values, which may increase unexpected loan defaults and cause subsequent bank failures and crises.

In column 2 we split the two cycles and include them only for the countries where they were optimal. Although they have approximately the same coefficient as each other which is similar to that in the mixed regression, only the AR(2) cycle is a significant determinant of the probability of facing a crisis. However, including the two cycles separately appears to be a marginally better explanation of events (as judged by the AUC criterion) than that where they are constrained to have the same coefficient possibly because they are able to capture differences in credit dynamics across countries when entered separately

In column 3 we impose the AR(2) cycle on all countries, and it has a significant and positive coefficient, much as in columns 1 and 2, and the other variables have similar coefficients. Although this is an adequate explanation of the probability of a crisis, our information indicator, the AUC, suggests it signalling quality is lower than the previous two regressions. The same is true in column 4, where we impose the stochastic cycle from Harvey (1997) for all countries. The coefficients are similar, but in general slightly less significant. This reflects that fact that it is a less good explanation of the probability of having a crisis than those contained in columns one to three, as can be judged by its lower AUC.

Our preferred credit to GDP gaps are one component of a decomposition of the credit to GDP ratio into a trend, a cyclical component and a random component. It is of course possible to add the random component back in to the cyclical component and produce an unsmoothed gap. This indeed is the indicator proposed by the BIS in various papers. We include this Hodrick Prescott based indicator in our crisis determination model in column 5 (table 2). The coefficients on capital, liquidity (the defences against crises), current account and house price growth (the causes of crises) remain significant, suggesting these leading indicators of crises are well anchored. However, lagged credit growth and the HP credit to GDP gap are not significant and clearly contribute little to the explanation of crises, as can be seen by the low level of the AUC for this regression.

It would appear that if we wish to use a credit to GDP gap to explain crises, we have to select the most useful indicator, with the AR(2) smoothed gap being a good tool in an Early Warning System for some countries, but not for others. It clearly contains information about bad lending, probably related to the housing market as we show below. However, the simple HP indicator has no information content and calibrating macro-prudential policy off this credit to GDP gap will do little to reduce the probability of an impending crisis.

5.3 Granger Causality, Cycles and House Prices

The observation that house prices and credit growth (related to the cyclical component of output) appear to be associated, can be strengthened by testing the relationship between them. An obvious approach involves bidirectional Granger causality tests between the cyclical components and house price growth. The cyclical component is by construction a stationary series, and our credit growth and house price growth series are also stationary. Hence, we can undertake regressions using pairs of these three variables for two sets of countries, depending on whether the AR(2) or stochastic cycle is preferred[18]. In eight of our AR2 countries (barring Italy) we would

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[18] AR(2) being optimal in Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US.

judge that crises have followed on from house prices cycles, whilst in three of our stochastic cycle countries (Netherlands, Denmark and Germany) we would judge that their crises in 2008 were more related to the international nature of their banking systems activities rather than their domestic house price cycles.

We first run a regression of credit on lagged values of itself[19] and test whether house prices add information to this time series explanation. We then run a regression of the credit to GDP gap on lagged values of itself and check whether house prices are relevant. As we can see (tables 3 and 4), in both cases, house price growth makes a significant contribution. These results suggest that when house prices rise, banks lend more credit and also the credit gap increases on the strength of the higher collateral against which the private sector is able to borrow. We then reverse the question and ask if past credit growth trends are related to house prices and similarly, whether the cyclical component of credit is related to house price growth. In countries where the AR2 cycle best describes credit dynamics, this reverse relationship is also significant: as private sector credit becomes more available, it appears that the increased demand for housing inflates property prices further. This effect is strengthened, the more credit growth deviates from "fundamentals", as indicated by trend output. However for non-AR2 countries, the conclusion is not the same. In these countries, credit dynamics are different as suggested by the stochastic cycle which best describes them. This may explain why credit growth has limited significant impact on the growth of house prices and the credit gap appears to have no impact.

Insert Table 3 and 4 here

[19] In all Granger specifications, 3 lags are used.

It thus appears that in Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US, over our data period, there is a circular pattern with credit growth raising house prices, and rising house prices subsequently raising credit growth. In these circumstances bad lending is possible, as the lending inflates the value of collateral. Conversely, when credit growth slows, house prices begin to grow more slowly or even fall as refinancing of property loans becomes difficult. Collateral for loans thus disappears, and this is a potential cause of banking crises. In our other group of countries (Germany, Denmark, Japan, Netherlands and the UK), a decline in credit growth does not feedback on to house prices, and hence collateral is maintained for loans and default rates will be much lower. These results suggest there may be an association between crises and credit growth in some of our countries, but not in all of them. Hence the major policy related credit gap indicator appears to be relevant in only some countries but not in others.

5.4 Robustness

We subject our optimal logit model to three robustness tests. First we change the timing of a crisis, limiting them to the smaller number of systemic crisis listed in Laevan and Valencia (2013) [20]. Crisis dating varies to an extent across studies (see Barrell et al. 2010) and it could be argued that our optimal model relies on a particular set of dates. Although Laeven and Valencia (2013) use a broader set of policy responses relative to Caprio et al (2003) to identify crisis episodes, two conditions must be met for them to be systemic: 1) Significant signs of financial distress in the banking system (as

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[20] The new set of crisis are Belgium Denmark, France, Germany, Italy, Neths, Spain and Sweden in 2008, the UK and US in 2007, and the US in 1988, Spain in 1978, Sweden, Norway and Finland 1991 and Japan 1997. We use the date range from Laevan and Valencia (2013) for these crises.

indicated by significant bank runs, losses in the banking system, and/or bank liquidations, and 2) Significant banking policy intervention measures in response to significant losses in the banking system. They list six potential policy responses[21], three of which must occur for condition 2) to be met. This means that their definition is more restrictive than that of Caprio et al (2003), and we have preferred to continue to use that definition of a country in a banking crisis.

Our second robustness test repeats our initial Early Warning system estimates using the lagged (rather than current) value of the cyclical indicator. Although we have followed the Basel III suggestion that current credit dynamics affect bank lending behaviour, we test the possibility that utilising lagged credit gaps could change our conclusion. Finally, we test the out-of-sample performance of our optimal model since it could be that our AUROC results are a result of overfitting; in this case the model should not have good out-of-sample performance. For this exercise we use data from 2014-2016.

The new logit is given in Table 5, and we can see that our results are generally robust even after a large change in the dependent variable. Only our housing market indicator changes noticeably in size and significance. This is unsurprising as the 2008 crisis was partly triggered by housing developments in the US, but in some of the 8 countries that experienced a crisis in that year, house price increases had not induced lax lending. This was the case in Germany, for instance, where banking sector involvement in the US subprime market was a major driver behind banking failures.

Insert Table 5 here

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[21] 1) extensive liquidity support (5 percent of deposits and liabilities to nonresidents); 2) bank restructuring gross costs (at least 3 percent of GDP); 3) significant bank nationalizations; 4) significant guarantees put in place; 5) significant asset purchases (at least 5 percent of GDP); 6) deposit freezes and/or bank holidays.

Changing the timing of a cyclical indicator in our Early Warning regressions has much less effect than it would for some other variables as the cycle indicators are slowly emerging filters based on past data. Moving the filter forward by one year adds one new observation and reduces weights on past observations, but the indicator emerges slowly. In Table 6 we compare AUROCs for our six models with row one repeating those from the previous section and row two reporting on those with a lagged cyclical indicator. As we can see there is little change in the overall information content, and we prefer to use the current indicator as it is effectively available in real time, unlike other indicators.

Insert Table 6 here

Table 7 presents the out-of-sample performance of our logit model which shows crisis probability forecasts have been relatively low in most countries where no systemic crises materialised during 2014-2016. Some exceptions are Norway, Finland and to a lesser extent, Sweden in 2014 and 2015, which may be due to a change in the definition of liquidity by the central banks. This is also likely to influence results in Canada, although in most countries, the unprecedented quantitative easing will be an issue. In general, our model performs well out-of-sample with the vast majority of countries having no crisis calls in 2016.

Insert Table 7 here

6. Conclusion

To test the hypothesis that excessive credit- to-GDP growth causes banking crises in 14 OECD countries during 1980 – 2013, we construct an HP credit gap to mimic the BIS approach. We then estimate three additional gaps, making additional specific assumptions on the functional form of the cycle: an AR(1) cycle, an AR(2) and a stochastic cycle *à la* Harvey and Jaeger (1993) and Koopman et al. (2006). These representations are designed to accommodate alternative cycle processes. The AR(2) and the stochastic cycle are naturally calibrated so the financial cycle is of medium term duration, consistent with the extant literature (Drehmann and Tsatsaronis, 2014).

We subject our gap measures to an optimal selection procedure based on the information criteria using the results of our trend-cycle decomposition, which allows us to isolate the best gap measure for each country. The results of the filtering exercise point out that there exist a natural statistical "clustering" of countries into two gap-types: countries for which a AR(2) is optimal (Belgium, Canada, Finland, France, Italy, Norway, Sweden, Spain and the US), and a remaining group (Germany, Denmark, Japan, Netherlands, UK) where a stochastic cycle is preferred.

The three cycle indicators are then embedded in a logit model in order to estimate their crisis prediction strength. Our logit early warning system utilises standard data on banking crisis, macroeconomic and regulatory control variables, including capital adequacy, liquidity, the current account and property price growth. We find that a mix of stochastic and AR2 cycles best describes crisis probabilities in terms of AUROCs. The AR2 cycle seems to apply to countries where credit growth and house prices interact and feed each other. Granger tests suggest in these countries, house price growth raised collateral values which propagated risky lending. Our conclusions are robust to changes in crisis timing, the use of lagged credit gaps and out-of-sample testing.

We conclude that credit growth is sometimes a good indicator of potential problems but note that this is restricted to cases where excessive lending fuels a cycle of rising housing prices and hence collateral which in turn propagates further credit growth. This transmission mechanism appears to be captured by only one of the four gap measures. Hence, we suggest that the most commonly used indicators cannot provide useful policy rules since they do not detect financial vulnerabilities. This result contrasts with the prevailing view that excessive credit growth (defined by a different gap measure) requires banks to hold excess regulatory capital. In particular, Basel III uses the “HP-filtered” gap between the credit-to-GDP ratio and its long term trend to guide policy in setting countercyclical capital buffers. We call this conclusion in to question and suggest that it is urgent that regulators change their view of how to measure and respond to the credit to GDP gap.

Credit-to-GDP ratios clearly represent a practical and appealing way to guide policy given the objective of the buffer. However, a growing literature supports the view that not all credit-to-GDP amplifications are “credit booms gone wrong”, underpinned by “reckless lending” (Schularick and Taylor, 2012; Gorton and Ordoñex, 2016). In these cases, financial intermediation disseminates credit towards productivity gains as opposed to risky lending, and hence taxing via countercyclical buffers would be socially undesirable. Hence, these types of credit cycle are unlikely to display high crisis prediction power.

Our results suggest that credit-to-GDP growth per se is not risky but that credit booms driven by house price acceleration require dampening. The policy lesson that we derive from this exercise is that financial regulators should carefully identify the nature of credit growth before taxing banks in order to minimise social welfare losses from financial disintermediation.

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List of Tables

Table 1. Comparing Filters for the Credit to GDP gap

Model	T	p	log-likelihood	SC	HQ	AIC		Model	T	p	log-likelihood	SC	HQ	AIC
CANADA								**JAPAN**						
Irregular	140	1	-291.020	4.1927	4.1803	4.1717		Irregular	140	1	-389.841	5.6045	5.592	5.5834
Harvey (1997)	140	3	-92.165	1.4225	1.3851	1.3595		Harvey (1997)	140	3	-122.174	1.8512*	1.8138*	1.7882*
AR(1)	140	2	-99.776	1.496	1.471	1.4539		AR(1)	140	2	-134.405	1.9907	1.9657	1.9486
AR(2)	140	4	-86.879	1.3823*	1.3324*	1.2983*		AR(2)	140	4	-132.416	2.0328	1.983	1.9488
BELGIUM								**NETHERLANDS**						
Irregular	140	1	-309.420	4.4556	4.4431	4.4346		Irregular	140	1	-287.964	4.1491	4.1366	4.1281
Harvey (1997)	140	3	-106.908	1.6331	1.5957	1.5701		Harvey (1997)	140	3	-109.527	1.6706	1.6331*	1.6075*
AR(1)	140	2	-109.501	1.6349	1.6099	1.5929		AR(1)	140	2	-111.758	1.6671*	1.6422	1.6251
AR(2)	140	4	-94.011	1.4842*	1.4343*	1.4002*		AR(2)	140	4	-112.422	1.7472	1.6973	1.6632
GERMANY								**NORWAY**						
Irregular	138	1	-282.371	4.128	4.1154	4.1068		Irregular	140	1	-367.897	5.291	5.2785	5.27
Harvey (1997)	138	3	-40.462	0.69351*	0.65574*	0.62988*		Harvey (1997)	140	3	-195.782	2.9028	2.8654	2.8397
AR(1)	138	2	-48.688	0.77703	0.75185	0.73461		AR(1)	140	2	-197.701	2.8949	2.87	2.8529
AR(2)	138	4	-43.345	0.77101	0.72064	0.68616		AR(2)	140	4	-192.485	2.8910*	2.8411*	2.8069*
DENMARK								**SWEDEN**						
Irregular	140	1	-393.144	5.6516	5.6392	5.6306		Irregular	140	1	-382.553	5.5003	5.4879	5.4793
Harvey (1997)	140	3	-139.354	2.0967*	2.0592*	2.0336*		Harvey (1997)	140	3	-148.984	2.2342	2.1968	2.1712
AR(1)	140	2	-153.955	2.27	2.245	2.2279		AR(1)	140	2	-158.826	2.3395	2.3146	2.2975
AR(2)	140	4	-140.088	2.1424	2.0926	2.0584		AR(2)	140	4	-139.726	2.1373*	2.0874*	2.0532*

FINLAND								**SPAIN**						
Irregular	140	1	-378.177	5.4378	5.4253	5.4168		Irregular	140	1	-414.176	5.9521	5.9396	5.9311
Harvey (1997)	140	3	-134.766	2.0311	1.9937	1.9681		Harvey (1997)	140	4	-86.551	1.3776	1.3277	1.2936
AR(1)	140	2	-145.876	2.1545	2.1296	2.1125		AR(1)	140	2	-127.113	1.8865	1.8616	1.8445
AR(2)	140	4	-130.162	2.0007*	1.9508*	1.9166*		AR(2)	140	4	-80.390	1.2896*	1.2397*	1.2056*
FRANCE								**UK**						
Irregular	140	1	-237.509	3.4283	3.4158	3.4073		Irregular	140	1	-335.455	4.8275	4.815	4.8065
Harvey (1997)	140	3	-32.630	0.57204	0.53462	0.509		Harvey (1997)	140	3	-112.320	1.7105*	1.6730*	1.6474*
AR(1)	140	2	-37.756	0.60997	0.58502	0.56794		AR(1)	140	2	-122.766	1.8244	1.7994	1.7824
AR(2)	140	4	-28.109	0.54275*	0.49285*	0.45870*		AR(2)	140	4	-113.002	1.7555	1.7056	1.6715
ITALY								**US**						
Irregular	140	1	-267.644	3.8588	3.8463	3.8378		Irregular	140	1	-294.751	4.246	4.2336	4.225
Harvey (1997)	140	4	-77.501	1.2483	1.1985	1.1643		Harvey (1997)	140	3	-5.379	0.18273	0.14531	0.1197
AR(1)	140	3	-84.611	1.3146	1.2772	1.2516		AR(1)	140	2	-35.067	0.57155	0.5466	0.52952
AR(2)	140	4	-73.757	1.1949*	1.1450*	1.1108*		AR(2)	140	4	2.563	0.10458*	0.054684*	0.020530*

T = no. of observations; p=parameters; SC = Schwarz criterion; HQ = Hannan-Quinn Criterion; AIC = Akaike information criterion

Table 2. Choosing Cyclical credit indicators in logit models

	(1) Mixed	(2) Split	(3) AR2	(4) Stochastic	(5) Irregular
Credit (-1)	-0.013 (0.803)	-0.013 (0.802)	-0.018 (0.726	-0.014 (0.786)	-0.029 (0.614)
Cycle (**Mixed**)	**0.051** **(0.022)**				
Stochastic Cycle		0.051 (0.295)		**0.033** **(0.04)**	
AR2 Cycle		**0.052** **(0.03)**	**0.049** **(0.038)**		
Irregular Cycle					0.015 (0.493)
Capital (-1)	**-0.347** **(0.000)**	**-0.347** **(0.000)**	**-0.332** **(0.000)**	**-0.347** **(0.000)**	**-0.301** **(0.000)**
Current Account (-1)	**-0.139** **(0.013)**	**-0.139** **(0.013)**	**-0.13** **(0.018)**	**-0.123** **(0.022)**	**-0.119** **(0.033)**
Real House Price Growth (-3)	**0.079** **(0.019)**	**0.079** **(0.019)**	**0.082** **(0.014)**	**0.084** **(0.012)**	**0.083** **(0.013)**
Liquidity (-1)	**-0.128** **(0.000)**	**-0.128** **(0.000)**	**-0.13** **(0.000)**	**-0.126** **(0.000)**	**-0.129** **(0.000)**
Area Under the Curve AUROC	0.7698	0.7702	0.7648	0.7608	0.7553

p-values in parentheses; 1978 - 2013; binary logit estimator

Table 3. Granger Causality between Credit Growth or Cyclical Components and House Price Growth for Countries where the AR2 Cycle is Optimal

	F-Statistic	Prob.
REAL HOUSE PRICE GROWTH (X) → Credit Growth (Y)	14.879	0.000
Credit Growth (X) → REAL HOUSE PRICE GROWTH (Y)	2.723	0.029
REAL HOUSE PRICE GROWTH (X) → Cycle (Y)	18.002	0.000
Cycle (X) → REAL HOUSE PRICE GROWTH (Y)	3.095	0.027

. Null Hypothesis: X does not Granger Cause Y

Table 4: Granger Causality between Credit Growth or Cyclical Components and House Price Growth for Countries where the AR2 Cycle is NOT Optimal

	F-Statistic	Prob.
REAL HOUSE PRICE GROWTH (X) → CREDIT GROWTH (Y)	10.666	0.000
CREDIT GROWTH (X) → REAL HOUSE PRICE GROWTH (Y)	2.211	0.068
REAL HOUSE PRICE GROWTH (X) → Cycle (Y)	2.506	0.059
Cycle (X) → REAL HOUSE PRICE GROWTH (Y)	0.884	0.449

Null Hypothesis: X does not Granger Cause Y

Table 5. Changing crisis dates

Credit (-1)	-0.171	(0.000)
Cycle **(Mixed)**	0.146	(0.000)
Capital (1)	-0.121	(0.038)
Current Account (-1)	-0.142	(0.002)
Real House Price Growth (-3)	0.044	(0.092)
Liquidity (-1)	-0.104	(0.000)

p-values in parentheses; 1981 - 2013; binary logit estimator

Table 6. Changing Lags: Impact on Area Under the Roc Curves (AUCs)

Cycle Type	Mixed	AR2 + Stochastic Decomposition	AR2	Stochastic	Irregular
Lags on Cycle: None	0.7698	0.7702	0.7648	0.7608	0.7553
Lags on Cycle: One	0.7573	0.7734	0.7609	0.7622	0.7491

Table 7. Forecast Crisis Probabilities (%)

Table 7: Forecast Crisis Probabilities (%)							
	2014	2015	2016		2014	2015	2016
Belgium	3.0	6.5	5.9	Japan	0.0	0.1	0.0
Canada	19.1	15.7	15.4	Netherlands	5.5	4.1	4.9
Denmark	2.3	0.7	0.7	Norway	31.4	4.9	5.2
Finland	10.5	13.3	7.0	Sweden	8.9	7.7	6.3
France	5.7	9.3	6.6	Spain	1.6	1.2	0.9
Germany	1.7	3.1	1.7	UK	2.2	1.6	1.1
Italy	0.9	0.5	0.4	USA	0.0	0.0	0.1