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Real-time signals anticipating credit booms in Euro Area countries

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Abstract

This paper identifies credit booms in 11 Euro Area countries by tracking private loans from the banking sector. The events are associated with both financial crises and specific macro fluctuations, but the standard identification through threshold methods does not allow to catch credit booms in real time data. Thus, an early warning model is employed to predict the explosive dynamics of credit through several macro-financial indicators. The model catches a large part of the in-sample events and signals correctly both the global financial crisis and the sovereign debt crisis in an out-of-sample setting by issuing signals in real-time data. Moreover, while tranquil booms are driven by global dynamics, crisis-booms are related to the resilience of domestic banking systems to adverse financial shocks. The results suggest an ex-ante policy intervention can avoid dangerous credit booms by focusing on the solvency of the domestic banking system and financial market's overheating.

Keywords: Credit Boom, Euro Area, Early Warning, Multivariate Logit

JEL Classification: C32, G01, E32, E51

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1 Introduction

The legacy of the Global Financial Crises prompted a widespread debate about ex-ante policy, that is an early intervention of policymakers during economic expansions, in order to make the economic system more resilient to adverse financial shocks and to avoid expensive ex-post measures, like bank bailouts or unconventional policies during downturns. This paper provides empirical evidence about credit booms and a strategy to provide early signals to introduce an ex-ante intervention with focus on the dynamics of credit of several Euro Area countries. A preliminary analysis confirms the well-established findings that credit booms are frequent events and that they are strictly related with states of macroeconomic and financial instability. These facts motivate to build an early warning model which signals coming credit booms and shows whether those signals are useful indicators of future crises.

A widespread empirical literature highlights the importance of the financial cycle in triggering long-lasting real crises and the potential amplification mechanisms that it can engender, in particular through banking crises (Borio [2014]). Yet, many authors stressed the pre-emptive power of credit and asset prices in signaling systemic financial risks (Borio and Lowe [2002]). Important works like Jordà et al. [2015, 2013]; Schularick and Taylor [2012] build long-run analyses to study the historical determinants of financial crises. They find that credit growth is a key predictor of financial crises and suggest that credit aggregates are superior policy indicator to pursue financial stability. Mendoza and Terrones [2012, 2008] (henceforth MT) find credit booms are source of economic turbulence and identify these as unusual expansions in the cyclical component of private credit.

This paper identifies credit booms through a threshold method like in MT, then it employs an early warning model (EW henceforth) in the same spirit of Schularick and Taylor [2012]. However, three main differences characterize the analysis here. First, credit booms are identified exploiting real-time information exclusively. Second, the EW predicts states that anticipate the starting date of the event, that is *credit-boom buildups*. Third, in line with further works, the EW evaluation criteria are based on the signaling approach — developed by Kaminsky and Reinhart [1999] and extended in Alessi and Detken [2009, 2011]— to provide signals subject to policy preferences. This strategy accounts for the relative aversion of policymakers against Type I errors (not issuing a signal when an event is imminent) and Type II errors (issuing a signal when no event is imminent). The final goal is to compute an optimal threshold to qualify the predicted probability estimated through the EW and to test its predictive power.

Furthermore, the EW developed in this paper takes into account the different adjustment processes of macro variables during crisis states, i.e. the so called crisis and post-crisis bias (Bussiere and Fratzscher [2006]). In the same spirit, a multinomial logit model is implemented also to distinguish credit booms that are followed by crisis from tranquil credit booms. The latter provides useful insight to policymakers to distinguish those booms that reflect adjustment of credit to economic fundamentals.

This work relates to recent EW advancements such as the work of [Sarlin \[2013\]](#), which emphasizes the role of policymakers’ preferences in the optimal threshold determination. Also it relates to [Duca and Peltonen \[2013\]](#) and [Behn et al. \[2016a\]](#) who identify systemic events through a financial stress index and find that global variables have a greater impact with respect to the domestic dimension. Similar analyses can be found in [Behn et al. \[2013\]](#) and [Behn et al. \[2016b\]](#), showing that this model can help policymakers to set counter-cyclical capital buffers and to gauge the benefits of capital ratio macroprudential measures through the estimated probability of having a financial crisis. Yet, the results in this paper are presented so to allow a comparison with the latter.

A recent contribution by [Richter et al. \[2017\]](#) shares many similarities with this paper. However, here credit-boom thresholds are set to identify large displacements from the long-run trend, consistently with the theoretical intuition that credit booms are out-of steady-state phenomena ([Brunnermeier and Sannikov \[2014\]](#)). Moreover, the boom-threshold factor here is based on a real-time standard-deviation of the credit cyclical component, so that the EW might be used for actual predictions or out-of-sample analyses. However, one drawback with respect to [Richter et al. \[2017\]](#) is that, due to a shorter sample, the logistic EW cannot be used to distinguish bad from good credit booms directly. Alternatively, the paper provides estimates of tranquil and bad credit booms through an multinomial logit. The latter allows to highlight new insights about the nature of credit booms which are at odds with [Richter et al. \[2017\]](#).

Though the research have extensively deepened the relevance of credit cycle and its relationship with the real economy, the role of credit booms for policy purposes is much more controversial. This paper encourages EA’s policymakers to use real-time EW models to set ex-ante interventions targeting the credit cycle. Besides to confirm well-known results of the literature and that real-time EWs provide accurate signals anticipating credit booms, the paper adds also another important result. Dangerous credit-boom buildups can be distinguished from tranquil ones, inasmuch the former are significantly characterized by a low capitalization of the domestic banking system and a high stock prices growth.

The paper is structured as follows: Section 2 defines credit booms and filtering techniques to identify them in a sample of EA countries. Also, an event analysis shows the relationship between credit booms and macro-financial patterns, while a frequency analysis shows whether these booms are related with financial crises. Section 3 presents the logistic EW and its evaluation criteria. Section 4 reports baseline results and further analysis. Section 5 collects some concluding remark.

2 Credit filters, booms and financial instability. Stylized facts and macro implications

There are several arguments about financial instability drivers, but a consistent part of the literature relies on the private credit dynamics as a broad measure of the financial cycle.

From an ex-ante perspective, the salient part of its dynamics is linked with buildup phases, when a consistent deviation of private credit from its long-run trend is observed. In this paper credit booms are identified through several strategies, but it follows as a benchmark the one proposed in MT. The latter relies on a threshold method: more specifically, it takes significant and positive deviation of private credit from its long-run trend. Thus, the credit boom is a time period where the following condition holds:

$$l_{i,t} \geq \phi \sigma(l_i) \quad (1)$$

where $l_{i,t}$ is the cyclical component of the private credit for country i at time t , $\sigma(l_i)$ is its standard deviation and ϕ is the boom threshold factor. The latter is set equal to 1.65 because the 5% tail of the standardized normal distribution satisfies $P(l_{i,t}/\sigma(l_i) \geq Q1.65) = 0.05$. However, this specific ϕ 's calibration is subject to hypothesis testing of normality of the cyclical components that are discussed next.

Three points in time are defined to identify the event: the peak ($\hat{t}$), the starting date (t^s) and the ending date (t^e). The peak is the date of the contiguous dates set satisfying the (1) that shows the maximum difference between $l_{i,t}$ and $\phi \sigma(l_i)$. The starting date of the credit boom is defined as a date $t^s < \hat{t}$ yielding the smallest difference $|l_{i,t} - \phi^s \sigma(l_i)|$. The ending date is a date $t^e > \hat{t}$ yielding the smallest difference $|l_{i,t} - \phi^e \sigma(l_i)|$. The start and the end thresholds, ϕ^s and ϕ^e respectively, for simplicity are set both equal to one, although robustness checks have been implemented without changing the results. The thresholds setting is so that $\phi^s = \phi^e < \phi$, and the duration of the credit boom is obtained from the difference $t^e - t^s$. Notice that, following this definition, the whole event is described by both the upswing and the downswing of credit deviation. Therefore, in real-time data such an event can be identified only once the credit cycle collapses, i.e. ex-post. Although the credit boom's identification of this section relies on this definition, the EW in next section focuses only on the buildup phases of the event, so as to generate timely signals to implement an ex-ante policy intervention.

In MT the credit-cycle component of the credit is obtained through a two-sided [Hodrick and Prescott \[1997\]](#) (HP) filter with smoothing parameter set equal to $\lambda = 1600$ for quarterly data. However, the use of the HP filter has been recently criticized in [Hamilton \[2018\]](#). The Hamilton filter regresses an actual observation on its past observations for a given time horizon, so that the cyclical component is just the error term coming from this regression. In other words, the long-run trend is conceived as all of what can be explained using historical data. With two-sided HP, instead, cycle-waves are shaped on the whole information available in the sample and forecasts would be then flawed by this extra-information.

In [Richter et al. \[2017\]](#) the use of the Hamilton filter is central for the identification of credit booms. However, [Drehmann and Yetman \[2018\]](#) find that de-trended credit-to-GDP ratio obtained through one-sided HP filter, with an higher smoothing parameter $\lambda = 400000$, outperforms many other measure of credit gap in predicting financial crisis.

Figures 1-3 show the series of the cyclical component of the (log) CPI-deflated credit of the banking system obtained through the three filtering techniques.¹ These are obtained in a sample of 11 Euro-Area countries (EA)² for the largest time span available at quarterly frequency (1974:Q1–2018:Q1) in order to minimize the loss of information and reported from 1990:Q1. The Hamilton filtered cycles (red lines) are the one presenting more amplified swings.

Table 2 reports peak-dates of credit cycle for the Hamilton, one-sided and two-sided HP filters. Peaks are identified by employing the [Harding and Pagan \[2002\]](#) algorithm with a minimum length of each phase of four quarters. The number of cycle-peaks are 31, 9 and 22 respectively. Notice that the latter do not identify always a credit-boom event. All the filters indicate credit-cycle peaks in the around of the dot-com bubble (1998–2002) for the largest part of EA countries. The Hamilton and the two-sided HP filters peak in period 1990–1992 in Finland, France and Italy. The latter indicate also a peak in the around of the global financial crisis (2005–2009) in almost all countries of the sample.

Before to identify credit-boom events, it is safer to test the assumption that credit cycles come from normal distributions, which justifies to calibrate the boom-threshold factor $\phi = 1.65$. The (one-sample) Kolmogorov-Smirnov test indicates to what extent the observed credit-cycles deviate from a normal distribution, so that if the null hypothesis is true this deviation is likely small. Table 4 reports the D-statistic³ and the relative p-values for credit cycles obtained with the three filters for each country in the sample. In most cases a failure to reject the null hypothesis is recorded. Specifically, in all countries when credit cycles are obtained through one-sided HP filter. In 9 countries in the case of the two-sided HP and 8 in the Hamilton filter case.

By applying the threshold method of MT, the Hamilton filter is the one that identifies more credit booms (20 events), followed by the two-sided HP filter (18 events) and the one-sided HP filter (only 8 events). Though the two-sided filter by using past, present and future information provides a genuine representation of the long-run trend, the resulting credit cycles would be less useful for forecasting purpose. Therefore, for the purpose of predicting excessive credit dynamics through the EW model, in what follows the Hamilton-filtered credit cycle will be used as benchmark to identify credit-boom events. However the one-sided HP is taken as benchmark for Germany, Greece and Italy to meet the assumption of normality of the boom-threshold factor.

¹The smoothing-parameters are $\lambda = 400000$ for one-sided and $\lambda = 1600$ for two-sided HP filters. The Hamilton filter projection horizon of 20 quarters to reflect the long duration of credit cycles as in [Hamilton \[2018\]](#) and [Drehmann and Yetman \[2018\]](#).

²Austria (AT), Belgium (BE), Finland (FI), France (FR), Germany (DE), Greece (GR), Ireland (IE), Italy (IT), Netherlands (NL), Portugal (PT) and Spain (ES).

³This indicates maximal absolute difference between the observed and the normal cumulative relative frequencies.

2.1 Stylized facts on credit dynamics within the Euro Area

In this subsection credit booms are identified in order to study their cross-country frequency and the behavior of macro-financial variables in the neighborhood of the event. The sample in object collects quarterly data for 11 EA countries from 1991:Q2 to 2017:Q4. The advantage of this sample is twofold: on the one hand, there are enough post-2008 observations to analyze the behavior of the main macro variables in the aftermath of the global financial crisis. On the other hand, since the focus is on countries adopting Euro convergence criteria, periods of exchange rates overheating are excluded for the most part of the sample period. The time-series used for the identification is the cyclical component of real private credit (deflated by the CPI) sourced by the Bank of International Settlements (BIS), that captures both loans and debt security instruments. In principle, there are two versions of this series: one is the private credit from domestic banking systems, the other is the private credit from the whole financial sector. These two series share a similar path up to the beginning of the global financial crisis, then the former slows down and the latter increases rapidly. They track almost the same boom episodes, but since the analysis keeps a close watch on banking crises and since EA countries are mostly bank-based, the focus will be on the first one.⁴

Overall, 21 credit booms are identified, ranging from 1 to 3 episodes per country with an average duration of 8 quarters. Nine countries experienced a credit-boom between 1996:Q1 and 2000:Q1, before the collapse of the dot-com bubble, while five between 2007:Q1 and 2008:Q3, before the collapse of Lehman Brothers.⁵ The sample average standard deviation of credit's cyclical components, $\sigma(\bar{l})$, is 3% above the trend.

The event analysis shows cross-country means and medians of macro-financial variables (Figures 7–10). Of course, there is no causal interpretation for these figures, but they show that characteristic patterns around credit booms belong to both the time and the cross-sectional dimension. For the large part of the variables, average dynamics are not influenced by outliers since there are no significant differences from their respective median dynamics. The figures show a five-years window (21 quarters) centered at the peak of the credit boom ($\hat{t}$ is normalized to $t = 0$). Figure 7 shows real private loans and real GDP cycles. This suggests that credit booms are associated with a specific pattern of the business cycle across countries, which is the same regularity that MT find for advanced economies during the period 1960-2010.

Panel (a) shows that, on average, the credit cycle is symmetric around the peak and that it starts to cross the trend about a year and an half before the farthest deviation. The average peak is about 7% above the trend. In the following quarters, on average, the credit falls about 2 points below its trend. Panel (b) shows that the GDP cycle rises suddenly

⁴By using loans from the whole financial sector three more episodes are identified in Portugal and an additional event in other two countries although they last no more than three quarters.

⁵Dot-com bubble: AT, ES, FI, FR, GR, IE, IT, NL and PT. Global financial crisis: AT, ES, FI, FR and IE.

during the buildup of the boom, about 2% above the trend, and drops up to 1 point below it during the downswing. Notice that, less than 50% of credit booms are concomitant to GDP booms tracked through the same threshold method. However, the business cycle around the booms reveals also several differences among countries.

Figure 8 shows country-specific events occurred during the period 2007:Q1-2008:Q3, before the Lehman Brothers collapse. Also in this case the peak of the boom is centered at $t = 0$. Credit increases rapidly in Ireland, Greece and Belgium, while Spain and France experience a slower buildup phase (Panel a). Belgium and Ireland are also those countries that experience a severe bust phase up to 12 points below the trend. Almost all countries present large fluctuations of real GDP cycle, but Spain and Greece show an asymmetric pattern after the peak. Moreover, apart from Spain, all countries experience a severe GDP fall about 2% below the long-run trend within the two years that follow the peak.

Figure 9 presents the event analysis for lending margins of EA banking systems. These credit spreads indicate bank's profitability, and are calculated as the difference between the average lending rates and the average deposit rate to both households and non-financial corporations (NFCs henceforth). Figure 9 is split between lending margins to new loans/deposits and outstanding loans/deposits. Since these data are available from 2003, we can include only credit booms related to the global financial crisis and the sovereign debt crisis. The analysis shows an average downward pattern before the peak and a sudden increase after the boom. However, margins on outstanding amounts have a deeper downward tendency also after the peak, while, margins on new businesses are flatter before the boom and jump suddenly at the peak date. Indeed, margins on new businesses are less sluggish and capture recent developments in bank interest income in a more timely fashion.⁶

Figure 10 shows the event analysis for other macro variables. The cycles of current accounts as percentage of the GDP, a stock index (deflated by the CPI), an house price index and the CPI inflation rate (quarter-on-quarter). The current account displays a deficit greater than 0.8% of GDP at the peak, but it gradually turns into a surplus up to 0.6% of GDP. The house price index records on average a 10% increase at the peak and a fall in the downswing about the same extent, showing a pattern similar to that of real credit cycle. The stock price index shows a similar pattern to the real GDP cycle: it increases about 20% during the buildup of the boom and it falls in the after the peak on a similar extent. The inflation rate has not particular tendency around the event since, showing only an above-trend pattern around the quarters close to the peak at median level.

Another important question is how frequently credit booms relate to crisis states. To study this relationship one need a clear definition of crisis states that clearly distinguishes financial from other types of crises. This paper follows the classification made in [Duprey et al. \[2017\]](#), which identify systemic financial stress dates using a Markov-switching model selection. One reason to use it is that the model captures on average 100% of the banking

⁶See ECB, Monthly Bulletin, Jan (2009).

crises identified by [Laeven and Valencia \[2013\]](#) that is generally accepted as benchmark for crises identification. More specifically, the model selects financial stress episodes that are associated with prolonged declines in real economic activities. These are defined as at least six consecutive months of negative annual industrial production growth concomitant to a decline in real GDP during at least two quarters. Moreover, the model allows to construct an EU crisis simultaneity index that preserves cross-country comparability. Crises dates are reported in Table 3. The frequency analysis reveals that 70% of credit booms are associated with crisis states, of which 80% relates to banking crises, while the rest to equity crashes in the private sector. Almost 70% of credit booms start prior to the crisis, ranging from 2 to 9 quarters before. However, 30% of these do not end up in crises and they have a maximum duration of four quarters. Finally, on average, countries have more than 50% of probability of experiencing a credit boom (that in MT definition includes also credit downswings after a peak) once the starting threshold is crossed.

Summarizing, the analysis shows that banking credit booms in the EA are associated with specific patterns of many macro-financial variables. On average the event starts with a surge in the cyclical component of GDP, house price indexes, stock indexes, increasing deficits in current accounts and declining lending margins during the buildup phases, followed by an opposite pattern during credit downswings. These results confirm and reinforce MT analysis, notwithstanding their fluctuations result more accentuated around the peak, probably due to a larger sample — both in time and cross-sectional dimensions — that allows them to track many other episodes.

3 An Early Warning system to identify the booming nature of the credit cycle

This section focuses on the left-hand side of credit boom event as in Figure 7. The goal is to obtain a signal that predicts the buildup of the boom in order to provide policymakers with timely information to setup an ex-ante intervention. One caveat of MT’s method is that a credit boom is qualified as such only when the credit cycle crosses its standard deviation times a threshold factor. This method, in fact, is such that credit cycle has to be un-normally far from its long-run trend, so as to avoid concerns about credit dynamics every time this is above its growth path, possibly also in a good shape. However, as the event analysis has shown, the credit cycle crosses its boom threshold about an year before it collapses, therefore contingent pre-emptive signals can be policy relevant. The setup of this section is a multivariate logistic EW model that assesses the power of several variables in predicting credit boom buildups. This section also tests the ability of the EW model to catch credit booms states rather than financial crisis states. As not all credit booms turn into financial crises, this can be a potential source of bias for policy makers that should be taken into account.

Thus, the same model is estimated for two different dependent dummy variables. Since

the latter are binaries, the probability estimated on the left-hand side of the model is a non-linear function of the regressors on the right-hand side. The logistic model is described by the following equation:

$$P(Y_{i,t} = 1) = \frac{e^{\alpha_i + \beta_i X'_{i,t}}}{1 + e^{\alpha_i + \beta_i X'_{i,t}}} \quad (2)$$

The left-hand side variable is the probability of being in a given state for country i at time t . On the right-hand side, α_i catches the unobserved country-heterogeneity, while $X_{i,t}$ is a vector containing macro-financial regressors. The latter consists of growth rates of macro financial variables and other predictors in level.⁷ The latter consists of real GDP, real credit from the banking system, real credit from all financial institutions, the CPI inflation, an house price index, a stock price index, the consolidated banking capitalization (defined as equity on total assets in levels), an average of lending rates and lending margins of consolidated banking systems. Alternatively, by splitting the real credit from the whole financial system, the model is regressed on credit to households and credit to NFCs.

All the specifications allow country fixed effects. The estimation does not include time dummies that would account for heterogeneity in crisis probability over time. Notice that, although time dummies would improve the ex-post fit of the model catching the global time factors—that drive the left-hand-side of the logit—they are unknown ex-ante. Thus, time dummies add little help to the EW evaluation, especially in the out-of-sample forecasting.⁸ However, since the global financial crisis affected almost all countries in the sample, robust standard errors clustered at quarterly level are employed in order to account for potential correlation in the error terms.

As clarified above, the first model specification uses two main dependent variables representing credit boom buildups and financial vulnerability states. As in [Behn et al. \[2016a\]](#), the latter is a binary variable that equals one between 7 and 12 quarters prior to a systemic crisis and zero otherwise. Again, systemic crisis states are identified following [Duprey et al. \[2017\]](#). That way, the dependent variable allows to catch vulnerable states early enough without loosing accuracy. This is set so as to leave sufficient time to policymakers to implement adequate actions. In the same spirit, the second dependent variable anticipates credit downswings, and it equals one between 4 and 9 quarters before the boom threshold is crossed. Thus, on average, this dummy equals one between 7 and 12 quarters before credit cycle collapses after having crossed its boom threshold. As shown in the previous section, those phases are concomitant to the worsening of macro conditions and in many cases they are associated to financial crises. The credit boom dummy is chosen among four main specifications that take different upper bounds as reference points: the peak, the starting date and the whole event rather than the threshold-crossing date. However, the

⁷As pointed out in [Behn et al. \[2013\]](#), Year-on-Year growth rates have much more predictive power than Quarter-on-Quarter growth rates. The analysis here takes YoY rates as benchmark and QoQ for robustness checks.

⁸See both [Schularick and Taylor \[2012\]](#) and [Behn et al. \[2013\]](#) on this point.

latter is preferred for two main reasons: first, it allows to avoid overlaps with crisis states and, second, on average it corresponds to the financial vulnerability dummy every time a financial crisis is anticipated by a credit boom.

Moreover, the estimation avoids the post-crisis bias that may arise when the dependent variable does not discriminate between tranquil periods (when economic fundamentals are sustainable) and crisis states (when macro series are much more volatile). Following [Bussiere and Fratzscher \[2006\]](#), this potential source of bias is addressed first by excluding quarters of crisis states from the estimation and then by performing a multinomial logit as robustness check. In the latter the dependent variables are specified so as to distinguish both tranquil, vulnerable and crisis states (see Section 4).

3.1 Model evaluation

The predictive ability of the EW models are measured following several evaluation criteria. The underlying idea is to compare the predicted probability with the actual outcome in the data, by defining a threshold above which the former signals that an event is about to occur. The signaling approach consists in finding this optimal threshold $\tau \in [0, 1]$, defined as a percentile of the distribution of predicted probability. The latter, $P(\widehat{Y}_{i,t} = 1)$ is transformed into a binary predictor $\widehat{P}_{j,t}$, that equals one when the continuous predictor crosses the threshold and zero otherwise. Thus, signals issued by this binary predictor are compared with the actual outcome, $C_{i,t}$, that equals one for effective realizations observed in the data and zero otherwise. The latter has to be interpreted according to which dependent variable is considered. In the case in object, $C_{i,t}$ equals one if country i experiences a crisis within the following 7-12 quarters (i.e. from $t + 7$ to $t + 12$) and zero otherwise for the financial vulnerability dummy, while, $C_{i,t}$ equals one if the credit cycle crosses the threshold within the following 4-9 quarters (i.e. from $t + 4$ to $t + 9$) and zero otherwise for the credit boom dummy.

Each observation can be then classified in a contingency matrix reported in Table 5. There is a true positive (TP) when the model issues a signal and a realization in the actual class is observed, a false positive (FP) when the model issues a signal that does not correspond to a realization in the actual class, a false negative (FN) when the model does not signal a realization which instead is observed in the actual class, and a true negative (TN) for an observation to which corresponds both no signal and no realization in the actual class.

In order to find the optimal threshold, τ , the policymakers preference has to be set. The latter can be thought as a parameter $\mu \in [0, 1]$ denoting the relative aversion to Type I errors (i.e. the rate of missed realizations, $T_1(\tau) = FN/(TP + FN) \in [0, 1]$) and to Type II errors (i.e. the rate of false alarms, $T_2(\tau) = FP/(TN + FP) \in [0, 1]$). In general, μ is greater than 0.5, reflecting the fact that policymakers are more willing to issue a false alarm than missing a realization because crises are costly. In particular, in the baseline specification $\mu = 0.85$, but other calibrations are set as robustness checks. Therefore, the

optimal threshold has to minimize the following loss function depending on the two errors (T_1 and T_2) weighted for the policymakers' preference (μ):

$$L(\mu, \tau) = \mu P_1 T_1(\tau) + (1 - \mu) P_2 T_2(\tau) \quad (3)$$

As in [Sarlin \[2013\]](#), equation (3) assumes that policymakers are concerned about the absolute number of misclassifications, so as to account for the relative frequencies of the actual class, which are $P_1 = P(C_{i,t} = 1)$ and $P_2 = P(C_{i,t} = 0)$.

A crucial evaluation instrument is the so called usefulness of the EW that can be obtained through the loss function. [Alessi and Detken \[2009\]](#) define the absolute usefulness of an indicator, U_a , as the difference between the minimum loss that the policymaker may reach by ignoring the indicator and the loss that the indicator produces by itself. This is defined as $U_a(\mu) = \min(\mu P_1, (1 - \mu) P_2) - L(\mu, \tau)$. The rationale underlying the latter is that policymakers may achieve a loss equal to $\min(\mu P_1, (1 - \mu) P_2)$ by either always issuing a signal ($T_1(\tau) = 0$) or never issuing a signal ($T_2(\tau) = 0$). Notice that, since in our sample tranquil periods are more frequent than crisis states ($P_2 > P_1$), setting an higher μ —which implies more interest in detecting vulnerable states— makes the indicator more useful in absolute terms.

However, the concept of relative usefulness is employed to compare different EW model specifications. This is defined as the share of $U_a(\mu)$ that policymakers can achieve through a perfectly performing model:

$$U_r(\mu) = \frac{U_a(\mu)}{\min(\mu P_1, (1 - \mu) P_2)} \quad (4)$$

where the denominator of the (4) is a perfect model achieving $T_1 = T_2 = 0$, so that $L = 0$. The Hosmer-Lemeshow test ([Lemeshow and Hosmer Jr \[1982\]](#)) measures the general goodness of fit of the model, testing whether the actual realization rates match the predicted one in population subgroups.⁹

The receiver operating characteristics curves and its area displays the optimal balance between the true positive rate and the false positive rate at any possible given threshold.¹⁰ This measure provides the accuracy of the signal, starting from a value of 0.5 which indicates that the discriminating ability of the model is like flipping a coin. In other words, the AUROC is the probability that the model ranks a randomly chosen realization $C_{i,t} = 1$ higher than a randomly chosen $C_{i,t} = 0$.

The adjusted noise-to-signal ratio (aNtS) measures the ratio between false signals rate and true signals rate: $aNtS = FPR/TPR = (FP/FP + TN)/(TP/TP + FN)$. An aNtS lower than one is a necessary condition for having a useful indicator (or model).¹¹

⁹In particular, this takes 10 subgroups. The subgroups are compared with a χ^2 to check the significance in the difference between expected and observed events. A p -value ≤ 0.05 indicates poor fit.

¹⁰Notice that, the true positive rate $TPR = \frac{TP}{TP + FN} = 1 - T_1(\tau)$, is the so called sensitivity, while the specificity is the true negative rate $SPC = \frac{TN}{TN + FP} = 1 - T_2(\tau)$.

¹¹See [Alessi and Detken \[2009\]](#) for a discussion on this point.

4 Empirical Results

The first two estimates assess the marginal effects of macro-financial variables on the probability of having a financial crises from 7 to 12 quarters ahead of the observed period and on the probability of having a credit boom from 4 to 9 quarters ahead of the observed period. By assumption policymakers have a strong preference in avoiding crises (or credit booms), at the cost of issuing false alarms, therefore the policy preference is set so to have $\mu = 0.85$. The estimates here give insights about the marginal effect of credit from non-banking institutions, credit to households and to NFCs, the effects of two lending margins and the effects of global variables. Results are reported in Tables 6–7. The sample allows to build the EW on a balanced panel from 1998:Q1¹² to 2016:Q4. When lending rates and margins are included the sample size reduces, because these last are available from 2003:Q1. The latter enter the estimation just in models (3)–(6). The tables report also the *p-value* resulting from the Homser-Lemeshow test, the optimal threshold as percentile of the predicted distribution, the resulting Type I and Type II errors, the aNtS ratio, the AUROC, the relative usefulness and the percentage of correct predictions.

4.1 Sign, significance and predictive ability of the EW

Table 6 is divided in six columns for two dependent variables and three different model specifications. The credit growth from domestic banking systems has positive and significant sign in all specifications. It is worth noticing that the banking component of domestic credit growth is a significant source of financial instability also (models (1) and (3)).

However, one may argue that the inclusion of credit growth among the regressors (as well as the inclusion of GDP growth and inflation) can produce flawed coefficient estimates and it can be a source of reverse causality. This is not incorrect in principle, but even though the dummy is obtained from the credit cycle (or GDP in the case of financial vulnerability), the EW tells whether a regressors at time t , on right-hand side, helps to estimate the probability at time t that something happens in $t + n$, where $n = 4, \dots, 9$ (or for vulnerable states $n = 7, \dots, 12$). In fact, the EW is about predictability of credit events, but it is poorly informative about causality, which would require a more specific experimental design. However, in order to address this issue, the stability of the log-odds is tested in further specifications where the credit component is excluded.

The credit growth from non-banking institutions has significant and negative sign in predicting financial vulnerability, but no significant impact on credit booms formation inasmuch the boom-events build upon banking loans cycles. Models (5) and (6) show that credit to households has a larger and significant impact on both states of financial vulnerability and credit-boom buildups, while credit growth to NFCs impacts negatively. On the one hand, this can be due to the fact that households, by using credit for mortgages

¹²When capital ratios are excluded from the analysis the sample starts from 1991:Q1. The latter specification is preferred for the out-of-sample analysis.

to purchase existing homes, do not actually contribute to GDP and hence they boost house prices which feed credit booms. On the other hand, credit to NFC may contribute to GDP through investment and then it has a negative sign before crises. The latter suggests that it would be useful in the future to provide credit measures which distinguish the productive and unproductive use for both households and firms separately.

The domestic real GDP growth has negative sign in all the specifications, but more significantly for credit booms. It is well understood that financial crises are related with credit overheating, but this in its turn is more likely in countries where domestic growth is weak. This is in line with the fact that the inclusion of credit-to-GDP ratio increases the predictive ability of EW models as highlighted in [Alessi and Detken \[2011\]](#) and [Schularick and Taylor \[2012\]](#). Inflation rate deadens credit booms formation, but their effect is unclear on quarters preceding crises. As expected, both stock index and house price growth have positive sign for both dependent variables, with a greater magnitude of the latter.

Capital ratios of consolidated banking systems have negative and significant sign for both dependent variables. This suggests that the more capitalized domestic banks are, the less the country is likely to experience credit booms and financial crises. This is in line with the idea that the more resilient banking systems are the less they are likely to fail, as their high level of capitalization lowers the probability of having a financial crisis.

Lending margins have mixed effects in predicting credit booms and vulnerable states. Margins on new lending activity anticipate credit booms with a positive sign and with a negative sign financial vulnerability states. While margins on outstanding lending activity anticipates booms with a negative sign and positively vulnerable states.

All models present an aNtS lower than one and the AUROC suggests that they are highly accurate in classifying observations. Indeed, the percentage of correct predictions is stably around the 80%. The results in Table 6 show that detecting credit booms is similar to detect financial instability, but the credit dynamics cannot be considered as a stand-alone warning indicator. Tranquil periods encompass fragility buildups in the credit dynamics which can become the driving force of the financial cycle.

Table 7 reports models for credit booms regressed also on domestic and global variables. The latter include aggregate series of EA, US, UK and JP. This set of models is used as benchmark since it is more powerful in terms of fit and it allows to consider a larger sample. Notice that country-specific thresholds are used for the out-of-sample analysis to get accurate signals. However, the overall predictive goodness of the EW is measured on the model-based optimal policy thresholds. In order to detect this possible source of bias in the threshold, global variables enter the model in two versions, which are unweighted and GDP-weighted.

The coefficients signs of the previous estimations are preserved as well as their significance. Notwithstanding, global credit growth impacts much more than domestic one, while global GDP growth has a negative and significant sign. This confirms that slowdowns in the global growth could favor the buildup of domestic credit booms for highly integrated financial systems. However, when credit to households and credit to NFCs are included

(models (9) and (10)) global growth is not significant anymore. In particular, global credit to households has positive and significant sign, and its impact is stronger than the one at domestic level. This result could be driven by the global financial crisis and it is corroborated by the fact that when credit measures are excluded from the estimation (models (11) and (12)) global house prices have a stronger and significant impact.

Figure ?? shows the AUROC of models (7)–(12). The models including credit to households and NFCs, on the second row of the figure, present the largest AUROC. Models without credit also have a higher AUROC with respect to the models with bank credit. Moreover, the weighted versions performs better than the unweighted, especially for lower values of TPR and FPR. Their optimal threshold is reached in the 74th and 69th percentile of the distribution respectively, and predict correctly 81% and 80% of the observations. However, Model (10) has also the highest relative usefulness. Therefore, the latter is taken as benchmark specification for the following analysis. The in-sample analysis is not helpful predict future states, which is the final goal of the paper. The out-of-sample analysis in the next subsection will reveal whether this EW can be used to set ex-ante measures.

4.2 Out-of-sample analysis and the multinomial logit

In the out-of-sample analysis the estimation horizon is set to 2005:Q1 so as to detect if the EW predicts the booms before the global financial crisis and the sovereign debt crisis. One may assume that policymakers were less worried about credit booms before 2005, so the policy preference is calibrated to both $\mu = 0.85$ and 0.6 for robustness purposes. However, the detected booms in the second case are the same as in the case of policymaker with a strong aversion to Type I errors (results are available upon request).

Figure 12 shows country-specific predicted probabilities model (11)¹³ (blue line), the credit cycle (red line), periods of financial crisis (red-shaded area), periods of boom buildups (grey-shaded areas) and country-specific optimal thresholds for $\mu = 0.85$ (horizontal black line). The EW issues a signal for 10 countries of 7 experiencing a credit boom before the GFC, while it issues 9 signals before the sovereign debt crisis. The signals reach the highest out-of-sample values between 2008 and 2010 in all countries, though, the Netherlands is the only country experiencing a credit boom the following years. The information available in 2005 would have signaled the boom which leads to the crises that hit the EA countries. However, some source of variation in macro-financial indicators wrongly inform the EW that a credit boom is coming, while the sovereign debt crisis is imminent. This issue is addressed next.

Tables 8 and 9 report the results for the multinomial logit models, where the dependent variables is allowed to assume at least one specification more than zero-one values. The two versions of model (10) and (12) are repeated with and without capital ratio so to allow a larger sample size.

¹³This specification allows to take the largest sample starting from 1991:Q1.

The first model (Table 8) addresses the post-crisis bias, so that the dependent variable equals 0 for tranquil periods, 1 for credit boom buildups, and 2 for crisis states up to 4 quarters after the crisis periods. That way log-odds should help to account for the different dynamics of the regressors during crisis and booming periods. In principle the key difference is that during booms buildups economic fundamentals are sustainable, while in a crisis/post-crisis state (like in the post-GFC in EA) credit might increase because the economy needs to recover. The log-odds for credit booms are consistent with previous specifications. Their sign and significance are both preserved, but the reduction in their magnitude witnesses that the multinomial logit captures the post-crisis bias better than a binary logit which ignores crisis states. Concerning crisis and post-crisis states there are important reversions in signs. Slowdowns in both domestic credit to households and GDP growth rates characterize crisis states. Also, crisis states are characterized by falls in both house prices and global credit to NFCs growth.

The second multinomial (Table 9) estimates credit booms leading to financial crises (the dependent variable equals 1) and booms that are not related with real losses (the dependent variable equals 2). This model should help policymaker to distinguish bad from good credit dynamics earlier than a credit boom materializes. The log-odds for bad booms are significantly consistent with the baseline specification, even though there is a reduction in their magnitude. In particular, an increase in domestic credit growth to households increases the probability of passing from a tranquil period to a good boom buildup more than to a bad boom buildup. However, substantial differences in the significance level characterize the distinction between leading-crisis and tranquil booms. In the latter case, log-odds of domestic GDP, house prices, capital ratios and most of the global variables are non-significant anymore. The sign of domestic inflation turns into positive, while domestic house prices into negative. Tranquil-booms seems mostly driven by global and domestic dynamics of credit and domestic stock market overheating. On the contrary, internal fragility of the banking system, housing market overheating accompanied by global slow downs of the economic growth seems to be at the ground of booms leading to crises. The analysis here is not intended to provide a causal explanation of credit boom formation, rather it provides the policymakers with a guidance about the nature of an EW signals of model (10) and (12). European policymakers in 2005 would have corroborated her model (12) with such information

5 Concluding Remarks

This paper analyses credit booms within EA countries, their connections with financial crises and the predictive power of global and domestic macro-financial indicators in signaling these events. Credit booms identified through the Hamilton filter and the MT method correspond to specific patterns of real GDP, current account balance, house prices, stock prices and lending margins. Overall, 70% of these episodes are associated with financial

crises in the quarters that following their starting date.

As in this paper, the latter is a well established finding of the empirical literature which motivates the identification of credit booms to set up ex-ante policy measures. However, measures flagging the credit dynamics can be costly for real economy, so that accurate and timely identifications combined with sounding information about the detrimental nature of the boom, are two empirical challenges that this paper addresses.

Real-time filtering techniques identify events detected through an EW system. The novelty of the paper is that the EW detects credit boom buildups, rather than periods anticipating financial crises. The boom-buildups are defined as phases anticipating the date in which the credit cycle crosses the real-time standard-deviation times a boom-threshold factor. The paper compares different EWs with models catching states of financial vulnerability (which are states that anticipate financial crises). Besides accelerations in credit growth, credit booms are likely to materialize when both real GDP growth and inflation rates are weak. This significant relation does not hold when the EW is set to predict financial vulnerable states.

Moreover, credit booms are more likely to occur in weak capitalized banking systems, in contrast with the findings of [Richter et al. \[2017\]](#). An important result is that expansions of credit growth to household is the leading component of credit booms in the EA, while lending to NFCs seems to play an opposite role. This result indicate that cyclical anomalies in credit dynamic might concern the unproductive use of credit, that for these EA countries is related to housing market overheat.

Further, the analysis indicate that the inclusion of global variables improve the predictive ability of the EW. The log-odds of global GDP and global inflation rates account much more than the domestic ones. However, even in this case domestic variables related to internal fragility of the banking system and financial markets overheat remain strongly significant.

The predictive ability of the EW is then tested in an out-of-sample analysis. The model predicts credit booms related to the global financial crisis in 10 countries where 7 countries actually experienced the pre-GFC boom. Then, the benchmark model issues the highest signal in all counties between 2008 and 2010, just before the European sovereign debt crisis. The out-of-sample performance of the EW suggests that the information used would have been a precious signal of imminent crises since 2005, but also that in EA the EW is not able to distinguish credit-boom buildups from the post-GFC period that preceded the sovereign crisis.

In other words, the estimation might be biased by what [Bussiere and Fratzscher \[2006\]](#) called post-crisis bias. A multinomial logistic model addresses this issue, controlling for both crisis and recovery states. Besides the stability of the log-odds when the EW predicts credit boom buildups, the model shows that, differently from the latter, crisis and post crisis states are characterized neither by the domestic slow down in the economic growth, nor by the internal fragility of the banking system. This result explains why the benchmark EW logit provide the highest signal before the sovereign crisis.

However, not all credit booms end up in crises as they might be economic responses to improved fundamentals. A second multinomial logit distinguishes credit booms that do not lead to real losses from credit booms related to financial crises and also in this case its log-odds are stable. Most importantly, the exercise provides policymaker with relevant information to distinguish EW signals: while tranquil-boom buildups are driven mainly by global macro dynamics and corresponding increase in the domestic credit component, crisis-boom buildups are much more related to the domestic capitalization of the banking system and house prices growth.

These findings are in line with the theoretical prescription that fluctuations in asset prices are source of financial instability that operates through adverse feedback loops across the financial market and banks balance sheets ([Brunnermeier and Sannikov \[2014\]](#)). The latter can be, as instance, a consequence of an improper incentive systems and a lack of constraints imposed to banking institutions ([Mitnik and Semmler \[2013\]](#)).

Though any causal interpretation would be misleading, overall these results may inform policymakers about the nature of credit booms. Once the EW provides clear signals of adverse credit overheats, timely policies addressing the resilience of the banking system and financial turmoil might actually lower the probability that credit growth turns to be dangerously excessive in the following years. Clearly, these ex-ante goals call two main policy tools in. On the one hand, the macroprudential capital regulation can improve the solvency of banks' balance sheets. On the other hand, a leaning against the wind of the central bank might aim at deflating financial bubbles. Further research should focus on whether the former policy, the latter or both would be successful in achieving credit and financial stability. In this sense, empirical and theoretical challenges are open to see "what's next" policies implemented after the EW signals.

References

- L. Alessi and C. Detken. 'Real time'early warning indicators for costly asset price boom/bust cycles: a role for global liquidity. *ECB WP*, Mar. 2009. URL <https://ideas.repec.org/p/ecb/ecbwps/20091039.html>. 1, 3.1, 11
- L. Alessi and C. Detken. Quasi real time early warning indicators for costly asset price boom/bust cycles: A role for global liquidity. *European Journal of Political Economy*, 27(3):520–533, 2011. 1, 4.1
- M. Behn, C. Detken, T. A. Peltonen, and W. Schudel. Setting countercyclical capital buffers based on early warning models: would it work? *ECB Working Paper No. 1604*, 2013. 1, 7, 8
- M. Behn, C. Detken, T. Peltonen, and W. Schudel. Predicting vulnerabilities in the EU banking sector: the role of global and domestic factors. *ESRB WP*, (29), Nov. 2016a. URL <https://ideas.repec.org/p/srk/srkwps/201629.html>. 1, 3
- M. Behn, M. Gross, and T. A. Peltonen. Assessing the costs and benefits of capital-based macroprudential policy. *ECB Working Paper No. 1935*, 2016b. 1
- C. Borio. The financial cycle and macroeconomics: What have we learnt? *Journal of Banking & Finance*, 45(C):182–198, 2014. doi: 10.1016/j.jbankfin.2013.0. URL <https://ideas.repec.org/a/eee/jbfin/v45y2014icp182-198.html>. 1
- C. E. Borio and P. W. Lowe. Asset prices, financial and monetary stability: exploring the nexus. *BIS Working Paper No. 114*, 2002. 1
- M. K. Brunnermeier and Y. Sannikov. A macroeconomic model with a financial sector. *American Economic Review*, 104(2):379–421, 2014. 1, 5
- M. Bussiere and M. Fratzscher. Towards a new early warning system of financial crises. *Journal of International Money and Finance*, 25(6):953–973, 2006. 1, 3, 5, 8
- M. Drehmann and J. Yetman. Why you should use the hodrick-prescott filter—at least to generate credit gaps. *BIS Working Paper No. 744*, 2018. 2, 1
- M. L. Duca and T. A. Peltonen. Assessing systemic risks and predicting systemic events. *Journal of Banking & Finance*, 37(7):2183–2195, 2013. 1
- T. Duprey, B. Klaus, and T. Peltonen. Dating systemic financial stress episodes in the eu countries. *Journal of Financial Stability*, 32:30–56, 2017. 2.1, 3, 3
- J. D. Hamilton. Why you should never use the hodrick-prescott filter. *Review of Economics and Statistics*, 100(5):831–843, 2018. 2, 1

- D. Harding and A. Pagan. Dissecting the cycle: a methodological investigation. *Journal of monetary economics*, 49(2):365–381, 2002. 2
- R. J. Hodrick and E. C. Prescott. Postwar us business cycles: an empirical investigation. *Journal of Money, credit, and Banking*, pages 1–16, 1997. 2
- Ò. Jordà, M. Schularick, and A. M. Taylor. When credit bites back. *Journal of Money, Credit and Banking*, 45(s2):3–28, 2013. 1
- Ò. Jordà, M. Schularick, and A. M. Taylor. Leveraged bubbles. *Journal of Monetary Economics*, 76:S1–S20, 2015. 1
- G. L. Kaminsky and C. M. Reinhart. The twin crises: the causes of banking and balance-of-payments problems. *American economic review*, pages 473–500, 1999. 1
- L. Laeven and F. Valencia. Systemic banking crises database. *IMF Economic Review*, 61(2):225–270, 2013. 2.1
- S. Lemeshow and D. W. Hosmer Jr. A review of goodness of fit statistics for use in the development of logistic regression models. *American journal of epidemiology*, 115(1):92–106, 1982. 3.1
- E. G. Mendoza and M. E. Terrones. An anatomy of credit booms: evidence from macro aggregates and micro data. *National Bureau of Economic Research*, 2008. 1
- E. G. Mendoza and M. E. Terrones. An anatomy of credit booms and their demise. Technical report, National Bureau of Economic Research, 2012. 1
- S. Mitnik and W. Semmler. The real consequences of financial stress. *Journal of Economic Dynamics and Control*, 37(8):1479–1499, 2013. 5
- B. Richter, M. Schularick, P. Wachtel, et al. When to lean against the wind. Technical report, CEPR Discussion Papers, 2017. 1, 2, 5, 9
- P. Sarlin. On policymakers’ loss functions and the evaluation of early warning systems. *Economics Letters*, 119(1):1–7, 2013. 1, 3.1
- M. Schularick and A. M. Taylor. Credit booms gone bust: monetary policy, leverage cycles, and financial crises, 1870–2008. *The American Economic Review*, 102(2):1029–1061, 2012. 1, 8, 4.1

Appendix

Data sources

Quarterly level data: bank credit, total credit, total credit to households and NFCs have been taken from BIS. All these are adjusted for the breaks. Nominal GDP is taken from OECD data, while Current Account-to-GDP from bloomberg. House and stock prices from mixed sources (BIS, National central banks, Eurostat, Bloomberg). Total assets of MFIs, the capital and reserves of MFIs, the lending rates and are taken from the Statistical Data Warehouse of the ECB.

Table 1: Summary of the variables

Variable	Obs	Mean	Std.Dev.	Min	Max
Real Credit Growth from Banks	1078	3.911	7.683	-22.87	35.77
Real Credit Growth from All	1078	4.706	6.838	-12.65	58.44
Real Credit Growth to Household	1003	5.237	7.799	-8.544	36.07
Real Credit Growth to NFCs	1003	3.996	7.579	-14.56	87.22
Credit-to-GDP	1078	2.217	6.708	-40.28	25.08
Real GDP Growth	1078	1.697	4.189	-17.23	37.55
Inflation	1078	2.242	1.989	-6.109	16.14
Stock Price Growth	1078	8.473	28.10	-66.2	167.2
House Price Growth	1055	4.823	7.516	-23.14	32.21
Banking Capitalization	789	2.917	13.92	-54.19	206.1
Avg. Lending Rates	605	3.995	1.101	1.450	6.390
Lending Margin (New Business)	605	1.624	0.633	0.308	4.122
Lending Margin (Outstanding)	605	1.800	0.789	0.195	4.375
Real Global Credit from Banks	1078	0.127	0.104	-0.116	0.313
Real Global Credit to Households	1078	0.160	0.114	-0.0346	0.363
Real Global Credit to NFCs	1078	0.131	0.116	-0.130	0.343
Real Global GDP	1078	0.117	0.0680	-0.183	0.215
Global Inflation	1078	0.0679	0.0370	-0.0289	0.198
Global House Price Growth	1078	0.0912	0.124	-0.261	0.373
Global Stock Price Growth	1078	0.207	0.518	-1.142	1.328

Figure 1: Credit cycles obtained through two-sided HP filter and $\lambda = 16000$ (black), one-sided HP filter $\lambda = 400000$ (blue) and the Hamilton filter (red). Credit is (log) CPI-deflated and it consists of loans and debt securities instruments of the domestic banking system.

Figure 2: Credit cycles obtained through two-sided HP filter and $\lambda = 16000$ (black), one-sided HP filter $\lambda = 400000$ (blue) and the Hamilton filter (red). Credit is (log) CPI-deflated and it consists of loans and debt securities instruments of the domestic banking system.

Figure 3: Credit cycles obtained through two-sided HP filter and $\lambda = 16000$ (black), one-sided HP filter $\lambda = 400000$ (blue) and the Hamilton filter (red). Credit is (log) CPI-deflated and it consists of loans and debt securities instruments of the domestic banking system.

	Hamilton	One-sided HP	Two-sided HP
AT	1990:Q3; 1998:Q3; 2000:Q1; 2006:Q4	2005:Q3	2000q4
BE	2015:Q2	2015:Q1	2000:Q3; 2008:Q1
DE	1991:Q2; 2000:Q1		2000:Q2; 2001:Q1
ES	1999:Q3; 2000:Q1; 2007:Q1		2007:Q3
FI	1999:Q4; 2001:Q2; 2002:Q3; 2004:Q3; 2006:Q1	1999:Q1; 2001:Q2	1990:Q3; 2001:Q2
FR	1990:Q1; 2001:Q2; 2007:Q3	1998:Q2; 2000:Q3	1990:Q1; 2001:Q3; 2008:Q1; 2009:Q1
GR	2002:Q2; 2005:Q2; 2006:Q2	1996:Q1	1990:Q1; 2009:Q1
IE	2000:Q1; 2006:Q1		2000:Q1; 2008:Q1; 2009:Q3
IT	1990:Q4; 2000:Q4; 2007:Q4	2000:Q2	1992:Q1; 2011:Q3
NL	1995:Q4; 1997:Q3; 2000:Q1		2001:Q1; 2011:Q2
PT	1999:Q3; 2000:Q1	1999:Q1	2000:Q2; 2001:Q1

Table 2: Peaks of credit cycles identified with Hamilton, one-sided HP and two-sided HP filters respectively.

	Crisis period
AT	1991:Q1-1993:Q2; 2008:Q1-2010:Q3
BE	1991:Q2-1993:Q3; 2007:Q4-2013:Q1
FI	1991:Q2-1996:Q2; 2001:Q1-2001:Q3; 2008:Q4-2010:Q3; 2012:Q3-2013:Q2
FR	1991:Q2-1993:Q1; 2002:Q3-2003:Q2; 2008:Q1-2012:Q3
DE	1992:Q3-1994:Q3; 2001:Q4-2003:Q3; 2008:Q3-2010:Q2
ES	1992:Q3-1992:Q3; 2008:Q1-2013:Q3
GR	2008:Q1-2013:Q2
IE	2007:Q3-2012:Q2
IT	1991:Q3-1996:Q3; 2008:Q1-2013:Q2
NL	2002:Q2-2004:Q2; 2008:Q1-2010:Q3; 2011:Q3-2012:Q2
PT	2008:Q1-2013:Q3

Table 3: Crisis periods. Crises dates are taken from Duprey et al. [2017]. These are periods of financial stress followed by significant losses on the real side.

	Hamilton		HP one-sided		HP two-sided	
	Difference	<i>p-value</i>	Difference	<i>p-value</i>	Difference	<i>p-value</i>
AT	0.072964	<i>0.187943</i>	0.039903	<i>0.574587</i>	0.025483	<i>0.797733</i>
BE	0.06992	<i>0.215444</i>	0.048926	<i>0.434744</i>	0.099553	<i>0.031781</i>
DE	0.134997	<i>0.003272</i>	0.077817	<i>0.121569</i>	0.05659	<i>0.328108</i>
ES	0.087448	<i>0.090611</i>	0.044522	<i>0.501684</i>	0.061525	<i>0.267868</i>
FI	0.066005	<i>0.254624</i>	0.083172	<i>0.090062</i>	0.123661	<i>0.004885</i>
FR	0.031536	<i>0.731787</i>	0.041241	<i>0.553296</i>	0.059196	<i>0.295395</i>
GR	0.146176	<i>0.00122</i>	0.067469	<i>0.205133</i>	0.049977	<i>0.419293</i>
IE	0.044301	<i>0.539967</i>	0.062117	<i>0.261125</i>	0.045187	<i>0.491374</i>
IT	0.10726	<i>0.026986</i>	0.046104	<i>0.47726</i>	0.055076	<i>0.347983</i>
NL	0.051835	<i>0.430126</i>	0.052313	<i>0.385844</i>	0.051543	<i>0.396728</i>
PT	0.086999	<i>0.092868</i>	0.065735	<i>0.222301</i>	0.055221	<i>0.346056</i>

Table 4: One-sample Kolmogorov-Smirnov test for normality. The table reports the D-statistic for each country in the sample and for three different filtered credit cycles.

Figure 4: Credit Boom identification per country. The figure reports credit cycle identified with only the Hamilton filter.

Figure 5: Credit Boom identification per country. The figure reports credit cycle identified with only the Hamilton filter.

Figure 6: Credit Boom identification per country. The figure reports credit cycle identified with only the Hamilton filter.

Figure 7: Credit Boom event: cross-country means (blue) and medians (red) of real loans and real GDP cycles. Long-run trend here are obtained through Hamilton filter.

Figure 10: Credit Boom event for other macro variables' cycles. Long-run trends are obtained through Hamilton filter.

Figure 8: Credit Boom event before Lehman Brother collapse for selected countries

8.1. Deviations of Real Credit from long-run trend obtained through Hamilton filter.

8.2. Deviations of Real GDP from long-run trend obtained through Hamilton filter.

Figure 9: Lending margins on new loans and outstanding loans in correspondence of credit events.

		<i>Actual Class</i>	
		$C_{i,t} = 1$	$C_{i,t} = 0$
<i>Predicted Class</i>	$P_{i,t} = 1$	TP	FP
	$P_{i,t} = 0$	FN	TN

Table 5: Contingency Matrix. A *TP* when the model issues a signal and we observe an actual realization, a *FP* when the model issues a signal that does not correspond to an actual realization, a *FN* when the model does not signal an actual realization which instead is observed and a *TN* when there are no signal and no realization at all.

	Vulnerability (1)	Credit boom (2)	Vulnerability (3)	Credit boom (4)	Vulnerability (5)	Credit boom (6)
Bank Credit	0.16*** (0.03)	0.10* (0.06)	0.36*** (0.06)	0.11* (0.07)		
Non-banking Credit	-0.13*** (0.02)	-0.04 (0.02)	-0.10*** (0.02)	-0.06 (0.04)		
Credit to NFCs					-0.19*** (0.07)	-0.34*** (0.07)
Credit to Households					0.83*** (0.20)	0.48*** (0.10)
Real GDP	-0.21** (0.10)	-0.19** (0.09)	-0.24* (0.14)	-0.70*** (0.16)	-0.27* (0.16)	-0.71*** (0.18)
CPI Inflation	-0.24 (0.20)	-0.21 (0.17)	0.27 (0.38)	-0.73*** (0.18)	1.32*** (0.46)	-0.72*** (0.25)
Stock Prices	0.03*** (0.01)	0.02*** (0.01)	0.06*** (0.02)	0.02** (0.01)	0.06*** (0.02)	0.02* (0.01)
House Prices	0.21*** (0.04)	0.13*** (0.03)	0.29*** (0.07)	0.30*** (0.06)	0.11* (0.06)	0.24*** (0.07)
Capital Ratio	-0.46*** (0.15)	-0.42*** (0.11)	-0.62** (0.29)	-0.72*** (0.21)	-0.71** (0.36)	-0.47* (0.24)
New Lending Margins			-1.73* (0.97)	1.20 (0.74)	-2.01 (1.24)	2.08** (0.90)
Out. Lending Margins			1.34** (0.65)	-0.02 (0.46)	-0.61 (1.01)	-0.52 (0.57)
Constant	0.40 (1.27)	1.15 (1.14)	-1.22 (2.91)	2.86 (2.57)	-1.61 (3.43)	0.28 (3.10)
Pseudo R-Squared	0.30	0.18	0.44	0.32	0.48	0.41
Homer-Lemeshow	0.99	0.65	0.99	0.92	0.99	0.85
Optimal Threshold	76	41	78	72	78	73
Type I error	0.22	0.06	0.13	0.20	0.12	0.13
Type II error	0.22	0.42	0.19	0.20	0.19	0.18
AUROC	0.84	0.72	0.86	0.87	0.89	0.91
aNtS	0.28	0.06	0.16	0.24	0.14	0.15
Abs. Usefulness	0.06	0.03	0.07	0.07	0.07	0.08
Rel. Usefulness	0.51	0.31	0.60	0.60	0.62	0.69
% Predicted	78.26	63.61	82.22	80.00	82.47	83.16
Observations	621	415	405	285	405	285

Table 6: EW benchmark. The table shows the ability of the logistic model in estimating quarters before crisis states (Vulnerability) and quarters before credit events (Credit Booms). Independent variables are expressed in annual growth rates. Country-fixed effects are included. Robust standard error are clustered at quarterly level. The policymaker preference parameter is $\mu = 0.85$ for any specification.

Credit boom buildups $P(Y_{i,t} = 1)$	No weights (7)	GDP weights (8)	No weights (9)	GDP weights (10)	No weights (11)	GDP weights (12)
Real Credit	0.12* (0.07)	0.09 (0.06)				
Real Credit to Households			0.30*** (0.06)	0.35*** (0.07)		
Real Credit to NFCs			-0.30*** (0.07)	-0.29*** (0.07)		
Real GDP	-0.23** (0.09)	-0.21*** (0.08)	-0.42*** (0.12)	-0.32*** (0.11)	-0.18** (0.08)	-0.18** (0.07)
Inflation	0.08 (0.15)	0.02 (0.13)	-0.54** (0.26)	-0.37 (0.23)	0.12 (0.14)	0.05 (0.13)
Stock Prices	0.03*** (0.01)	0.02** (0.01)	0.05*** (0.02)	0.03** (0.01)	0.03*** (0.01)	0.02** (0.01)
House Prices	0.09** (0.04)	0.10** (0.04)	0.04 (0.05)	0.00 (0.06)	0.09*** (0.03)	0.11*** (0.04)
Capital Ratio	-0.23* (0.13)	-0.26** (0.12)	-0.25 (0.16)	-0.32** (0.16)	-0.33*** (0.10)	-0.35*** (0.09)
Gl. Credit	1.88 (2.39)	0.52** (0.20)			3.44* (2.03)	0.58*** (0.20)
Gl. Credit to Households			7.38*** (2.45)	0.65*** (0.23)		
Gl. Credit to NFCs			1.65 (1.39)	0.10 (0.10)		
Gl. GDP	-9.77*** (3.63)	-0.98** (0.43)	4.68 (5.22)	-0.21 (0.39)	-9.48*** (3.57)	-1.02** (0.43)
Gl. Inflation	-6.21 (5.19)	-0.63 (0.42)	-6.59 (6.85)	-0.43 (0.40)	-7.40 (5.12)	-0.65 (0.41)
Gl. Stock Prices	-0.21 (0.59)	0.04 (0.05)	-1.46* (0.83)	-0.02 (0.05)	-0.03 (0.58)	0.04 (0.05)
Gl. House Prices	5.96** (2.65)	0.49* (0.27)	-3.97 (4.17)	0.08 (0.32)	5.60** (2.36)	0.48* (0.27)
Constant	-0.51 (1.25)	-0.38 (1.16)	-0.89 (1.69)	0.23 (1.65)	0.12 (1.02)	0.20 (0.91)
Pseudo R-Squared	0.22	0.22	0.34	0.35	0.21	0.21
Homer-Lemeshow	0.37	0.25	0.92	0.05	0.45	0.07
Optimal Threshold	53	56	71	72	61	69
Type I error	0.25	0.20	0.18	0.18	0.23	0.33
Type II error	0.29	0.28	0.19	0.19	0.27	0.17
AUROC	0.74	0.75	0.88	0.88	0.75	0.76
aNtS	0.33	0.25	0.23	0.23	0.30	0.50
Abs. Usefulness	0.04	0.04	0.06	0.06	0.04	0.04
Rel. Usefulness	0.36	0.34	0.60	0.61	0.38	0.37
% Predicted	72.05	73.01	81.46	81.22	73.73	80.00
Observations	415	415	410	410	415	415

Table 7: EW and Global Variables. The latter include data from EU, UK, US and JP. Independent variables are expressed in annual growth rates. Country-fixed effects are included. Robust standard error are clustered at quarterly level. The policymaker preference parameter is $\mu = 0.85$ for any specification.

Figure 11: Receiver operating characteristic curve. The figure reports the ROC curves of models (7)–(12). Models (7)–(8) have banking credit growth among regressors. Models (9)–(10), with credit to households and to NFCs among the regressors, provide the highest AUROC. Interestingly, though in models (11)–(12) credit growth is excluded from the estimation, they provide an highest AUROC with respect to models (7)–(8).

Boom vs crisis $P(Y_{i,t} = 1, 2)$	$Y_{i,t} = 1$ (13)	$Y_{i,t} = 2$ (14)	$Y_{i,t} = 1$ (15)	$Y_{i,t} = 2$ (16)	$Y_{i,t} = 1$ (17)	$Y_{i,t} = 2$ (18)	$Y_{i,t} = 1$ (19)	$Y_{i,t} = 2$ (20)
Real Credit to Households					0.06*** (-0.02)	-0.06*** (-0.02)	0.06** (-0.02)	-0.07*** (-0.02)
Real Credit to NFCs					-0.12*** (-0.02)	-0.09*** (-0.03)	-0.13*** (-0.04)	-0.15*** (-0.03)
Real GDP	-0.08** (-0.04)	-0.07* (-0.04)	-0.16*** (-0.06)	-0.05 (-0.05)	-0.14*** (-0.04)	0.04 (-0.05)	-0.18*** (-0.06)	0.13** (-0.06)
Inflation	0.29*** (-0.07)	-0.09 (-0.08)	-0.07 (-0.12)	-0.05 (-0.1)	0.26*** (-0.1)	-0.06 (-0.09)	-0.29** (-0.14)	0.02 (-0.12)
Stock Prices	0.02*** (-0.01)	0.02*** (-0.01)	0.01 (-0.01)	0.02** (-0.01)	0.03*** (-0.01)	0.02** (-0.01)	0.02 (-0.01)	0.02** (-0.01)
House Prices	0.03* (-0.02)	-0.04** (-0.02)	0.10*** (-0.03)	-0.06*** (-0.02)	0.08*** (-0.02)	-0.03 (-0.02)	0.14*** (-0.03)	-0.07*** (-0.02)
Capital Ratio			-0.31*** (-0.07)	0.03 (-0.04)			-0.34*** (-0.08)	-0.07 (-0.04)
Gl. Credit	0.59*** (-0.15)	-0.56*** (-0.13)	0.54*** (-0.17)	-0.89*** (-0.15)				
Gl. Credit to Households					0.45*** (-0.17)	0.37*** (-0.09)	0.40*** (-0.15)	0.32** (-0.13)
Gl. Credit to NFCs					0.14 (-0.11)	-0.65*** (-0.09)	0.07 (-0.1)	-0.75*** (-0.11)
Gl. GDP	-1.21*** (-0.3)	0.43** (-0.19)	-1.31*** (-0.43)	0.46 (-0.29)	-0.84*** (-0.27)	0.2 (-0.2)	-0.71** (-0.3)	0.06 (-0.29)
Gl. Inflation	-0.64* (-0.35)	0.11 (-0.23)	-0.61* (-0.34)	0 (-0.35)	-0.75* (-0.42)	0.03 (-0.25)	-0.57* (-0.33)	0.18 (-0.38)
Gl. Stock Prices	0.04 (-0.02)	0.03 (-0.02)	0.07* (-0.04)	0.06* (-0.03)	0.02 (-0.03)	0.02 (-0.03)	0.03 (-0.04)	0 (-0.04)
Gl. House Prices	0.52*** (-0.16)	0.06 (-0.14)	0.63*** (-0.22)	0.34* (-0.2)	0.28* (-0.17)	-0.31*** (-0.11)	0.22 (-0.2)	-0.1 (-0.18)
Pseudo R-Squared		0.13		0.19		0.21		0.27
Observations		1055		833		994		811

Table 8: The table reports the log-odds of the multinomial logit that compares credit boom buildups and crisis/post-crisis states. The aim is to address the so-called post-crisis bias as in [Bussiere and Fratzscher \[2006\]](#). The dependent variables $Y_{i,t}$ takes values 0, 1 and 2, according to be in a tranquil, boom buildup and crisis and post-crisis period respectively. The robustness check takes as benchmark EWs the model specifications (10) and (12). The same models are repeated in two versions with and without capital ratios, that is available only since 1998:Q1.

Bad vs good booms $P(Y_{i,t} = 1, 2)$	$Y_{i,t} = 1$ (21)	$Y_{i,t} = 2$ (22)	$Y_{i,t} = 1$ (23)	$Y_{i,t} = 2$ (24)	$Y_{i,t} = 1$ (25)	$Y_{i,t} = 2$ (26)	$Y_{i,t} = 1$ (27)	$Y_{i,t} = 2$ (28)
Real Credit to Households					0.03*	0.10***	0.04*	0.10***
					(-0.02)	(-0.03)	(-0.02)	(-0.03)
Real Credit to NFCs					-0.12***	-0.10***	-0.14***	-0.14**
					(-0.03)	(-0.03)	(-0.04)	(-0.05)
Real GDP	-0.22***	0.04	-0.20***	-0.14*	-0.21***	-0.06	-0.19***	-0.13
	(-0.06)	(-0.03)	(-0.07)	(-0.08)	(-0.05)	(-0.07)	(-0.06)	(-0.11)
Inflation	-0.1	0.53***	-0.09	-0.24*	-0.22**	0.64***	-0.26*	-0.37***
	(-0.09)	(-0.1)	(-0.11)	(-0.13)	(-0.11)	(-0.16)	(-0.14)	(-0.13)
Stock Prices	0	0.03***	0.01	0.03***	0.01	0.04***	0.01	0.03***
	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)	(-0.01)
House Prices	0.15***	-0.05***	0.14***	0.01	0.19***	-0.05*	0.19***	0
	(-0.02)	(-0.01)	(-0.03)	(-0.03)	(-0.03)	(-0.03)	(-0.03)	(-0.03)
Capital Ratio			-0.38***	-0.13			-0.39***	-0.21*
			(-0.07)	(-0.09)			(-0.08)	(-0.12)
Gl. Credit	0.52***	0.51**	0.40**	0.41				
	(-0.15)	(-0.21)	(-0.17)	(-0.26)				
Gl. Credit to Households					0.51***	-0.11	0.46***	-0.14
					(-0.14)	(-0.32)	(-0.13)	(-0.29)
Gl. Credit to NFCs					0.1	0.44**	0.07	0.40**
					(-0.08)	(-0.18)	(-0.07)	(-0.16)
Gl. GDP	-1.23***	-0.19	-1.03***	-0.54	-0.92***	0.15	-0.68***	-0.3
	(-0.32)	(-0.42)	(-0.37)	(-0.48)	(-0.24)	(-0.43)	(-0.25)	(-0.38)
Gl. Inflation	-0.42	-1.75***	-0.42	-1.24**	-0.6	-1.62***	-0.55*	-1.05**
	(-0.26)	(-0.63)	(-0.27)	(-0.51)	(-0.36)	(-0.57)	(-0.32)	(-0.44)
Gl. Stock Prices	0.08**	0.04	0.07*	0.05	0.05	0.03	0.04	0.04
	(-0.04)	(-0.03)	(-0.04)	(-0.03)	(-0.04)	(-0.05)	(-0.04)	(-0.04)
Gl. House Prices	0.59***	-0.11	0.53***	0.37	0.26*	0.07	0.14	0.32
	(-0.16)	(-0.2)	(-0.18)	(-0.28)	(-0.15)	(-0.19)	(-0.15)	(-0.28)
Pseudo R-Squared		0.17		0.18		0.24		0.24
Observations		1055		833		994		811

Table 9: The table reports the log-odds of the multinomial logit that compares credit boom buildups leading to crisis states with the ones that do not lead to real-economy losses. The aim is to find significant distinctions that allow policymakers to distinguish the nature of the predicted credit boom, as also in [Richter et al. \[2017\]](#). The dependent variables $Y_{i,t}$ takes values 0, 1 and 2, according to be in a normal, bad and good boom buildup respectively. The robustness check takes as benchmark EWs the model specifications (10) and (12). The same models are repeated in two versions with and without capital ratios, that is available only since 1998:Q1.

Figure 12: Out-of-sample forecasting 2008 Global Financial Crisis. The estimation sample goes from 1998:Q1 to 2005:Q1. EW optimal thresholds are country-specific.

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