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Credit Booms in Commodity Exporters

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Abstract

This paper identifies 101 credit boom episodes, i.e. periods of exceptional credit growth, in a sample of 115 countries for 1960-2014, and compares the results for commodity exporters and non-commodity exporters. I find that there is no difference in the number and duration of credit booms between commodity exporters and non-commodity exporters, but around two thirds of credit booms in the last four decades in commodity exporters have been associated with high commodity prices. In addition, I find that business cycles dynamics are more exacerbated during a credit boom episode in commodity exporters than in non-commodity exporters, and domestic demand variables tend to end below the trend after the peak of a credit boom. A frequency analysis shows that commodity exporters have a higher likelihood of having credit booms ending in a banking crisis and this result is confirmed by a regression analysis. However, commodity exporters do not have a higher incidence of having a credit boom, and net capital inflows and credit growth remain as the main predictors of these episodes.

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1. Introduction

Credit has been growing rapidly in the last decade, in particular in emerging markets and commodity exporters (coinciding with a sustained rise in commodity prices). Rapid credit growth may be beneficial because it may increase the level of financial deepening and boost consumption of durable goods and investment projects (Garcia-Escribano and Han, 2015). On the other hand, excessive credit growth may damage the economic prospects, in particular when these episodes lead to the so-called credit booms, episodes of rapid credit growth above its trend associated with periods of economic distress (Borio et al., 2015). Moreover, in some cases, credit booms can end in banking crises (Mendoza and Terrones, 2008; Calderon and Kubota, 2012). Hence, from the policymaker perspective it is relevant to identify those episodes. Although some methodologies have been developed to identify and examine credit boom episodes (Gourinchas et al., 2012; Mendoza and Terrones, 2008), most of these works have focused mainly on advanced economies and some emerging economies.

Recent literature has stressed the impact of a surge in commodity prices in the business cycle dynamics. It has been shown that in many net commodity exporters, the commodity terms of trade are important drivers of fluctuations within the business cycle, enhancing domestic demand and credit (Cespedes and Velasco, 2012; Aslam et al., 2016). Yet a sustained rise in commodity prices, i.e. a commodity boom, may lead to an overheating of the economy and a widening of the output gap, increasing macroeconomic risks and financial vulnerabilities (International Monetary Fund, 2015). Is it possible that this scenario may trigger a credit boom? Surprisingly, the association between credit booms and commodity booms has received little attention in the recent past. It could be argued that not all credit booms in commodity exporters are linked to high commodity terms of trade, and that other variables such as financial deepening and capital inflows explain better the occurrence of a credit boom episode. But a commodity boom can become an additional source of pressure, magnifying the credit expansion, and even increasing the chance of having a credit boom ending in a crisis.

The main goal of this paper is to identify credit boom episodes and describe their stylized facts in commodity exporters, and compare them to credit booms in non-commodity exporters. Moreover, I aim to answer these questions: (i) Have the credit booms in commodity exporters been related to periods of high commodity prices?; (ii) Are commodity exporters more prone to experiencing a credit boom?; and (iii) Are commodity exporters more prone to having a credit boom followed by a crisis? I use a comprehensive database of real credit per capita and other macro variables covering 115 countries for the 1960-2014 period. To identify the credit boom episodes I use the approaches developed by Gourinchas et al. (2001) and Mendoza and Terrones (2008), and compare their results, and to detect those episodes that coincide with a commodity boom I follow Cespedes' and Velasco's (2012) definition of a commodity boom and use their database. To assess how many credit boom episodes end in banking crises and sudden stops I use frequency analysis based on the databases of Laeven and Valencia (2012) and Calvo (2004) . In addition, I analyse the behaviour of macroeconomic variables during a credit boom episode using event analysis with seven-year windows. Moreover, I measure the probability of having a credit boom and a credit boom ending in a banking crisis using a set of panel logit regressions under different specifications following Calderon and Kubota (2012) and Arena et al. (2015).

I find that there are no significant differences in the duration of a credit boom between commodity exporters and non-commodity exporters, but the macroeconomic dynamics are different between these two groups. Moreover, about two thirds of the credit booms in commodity exporters in the last four decades were linked to periods of high commodity prices, and almost half of them ended in a banking crisis. In contrast, only a quarter of credit booms in non-commodity exporters ended in a banking crisis. This is confirmed by the regression analyses. The set of logit regressions suggest that being a commodity exporter does not affect the incidence of a credit boom, but it does affect the probability of a having credit boom ending in a crisis. They also confirm the key role of capital inflows and credit growth in driving credit booms.

The remainder of the paper is organized as follows: Section 2 provides a brief summary of some theoretical considerations on credit booms and why commodity exporters may have a higher likelihood of experiencing credit booms during a surge in commodity prices. Section 3 presents two methodologies to identify credit boom episodes for my sample of countries, discusses how to assess which credit booms are linked to commodity booms and banking crises, presents an empirical approach to examine the behaviour of the main macroeconomic aggregates around a credit boom, and estimates determinants of credit booms episodes. Section 4 presents the empirical results, and Section 5 provides a conclusion and gives avenues for further research.

2. Literature review

The role of credit in amplifying and propagating business cycle shocks has been widely reported in the last two decades[2]. Of particular interest are the so-called credit booms, episodes of remarkable credit growth that can have negative consequences on economic activity, prices and resource allocation (and may be associated with period of economic turbulence, as suggested by Mendoza and Terrones, 2008). However, not every episode of credit growth is bad since credit expansion can be led by financial deepening or normal cyclical upturns (International Monetary Fund, 2004).

A growing literature has examined credit booms' features and effects on the dynamics of the business cycle and on macro and financial vulnerabilities. It has been repeatedly shown that surges in capital inflows are the primary cause of credit booms.[3] In addition, domestic and external factors play a role in driving credit booms; growth of domestic product, (Arena et al., 2015), productivity gains and financial reforms (Decressin and Terrones, 2011; Mendoza and Terrones, 2012), capital account liberalizations (Dell'Ariccia et al., 2012), and financial deepening (Tornell and Wetermann, 2012; Arena et al., 2015) have also been reported as credit boom triggers.

Credit booms may add distortions to the economy in the short and long-run. Output may fall and never return to its pre-crisis trend, and potential output may fall as well, reducing the growth prospects of any country. Borio et al. (2015) find that credit booms diminish productivity growth and induce resource misallocation. Avdjiev et al. (2012) argue that credit booms add upward pressure on the real exchange rate, thus affecting competitiveness. Elekdag and Wu (2011) report that during credit booms, usually bank and corporate financial soundness indicators deteriorate, increasing future financial frictions. In addition, as noted by Santos (2015), credit booms hinder institutional development and long-term growth.

Furthermore, credit booms can be followed by a financial or banking crisis[4] (and become "bad" credit booms). Most of the banking crises of the last four decades happened in periods of fast credit growth. Angkinand et al. (2010) argue that credit booms may happen as the result of financial liberalization and

[2] See Kiyotaki and Moore (1997) and Bernanke and Gertler (1998) for early works in this field.
[3] Yet Amri et al. (2014) find that there is significant variation in the strength of this relationship depending on how capital inflows are measured. In addition, there are many factors that affect this relation. For instance, Magud et al. (2011) find that exchange rate regime could weaken the linkages between credit booms and a surge in capital inflows. Furceri and Zdzienicka (2011) also find that countercyclical fiscal policies can weaken that link.
[4] Rousseau and Wachtel (2015) argue that credit booms associated with financial deepening promote growth and are less likely to end in a bad credit boom.

this could lead to a crisis in the banking system. Amri et al. (2012) claim that the mechanism through which credit growth may lead to a banking crisis is by exacerbating the fragility of the system. In that sense, Barajas et al. (2007) find that more prolonged booms concurring with a higher inflation and low growth have a higher probability of ending in crisis, and that this probability is reduced by improved banking supervision and greater trade openness[5]. Credit growth and capital flows can help predict financial crises. A long-term analysis of 14 advanced economies by Schularick and Taylor (2009) and Jorda et al. (2011) for the last century shows that credit growth is the single most powerful and accurate predictor of financial crises. Gourinchas and Obstfled (2012) add real currency appreciation and show that both variables combined are the most robust and significant predictors of financial crises for advanced and emerging countries. Caballero (2016) finds that a surge in net capital inflows augment the probability of banking crises, most of the times through a credit boom episode. However, Arena et al. (2015) claim that although most banking crises have been preceded by a credit boom episode, the opposite is not true. Why should the policy makers care about financial-crisis recessions? Recent evidence shows that recessions caused by financial crises are more costly in terms of output than normal recessions, and credit-intensive expansions are usually followed by slower recoveries and deeper recessions (Reinhart and Rogoff, 2011; Jorda et al., 2011; Gourinchas and Obstfeld, 2012).

What is the link between booms in commodity prices and credit booms? A commodity boom can exacerbate the growth of credit through many channels[6]. Cespedes and Velasco (2012) report wealth effects as the main channel, so as commodity prices rise so does income and consequently consumption and investment[7], thus boosting domestic demand and stimulating domestic production, and subsequently demand for credit. As noted by the International Monetary Fund (2015), during a rise in commodity prices: (i) there is a feedback effect between income, consumption and investment, as higher investment boosts the rest of the economy and in turn raises income; (ii) future price expectations also increase, thus increasing demand in period t and in the future; and (iii) this process is usually accompanied by an overheating of the economy. Also, fiscal policy can become a channel through which commodity price shocks are transmitted: if commodity revenues represent a significant share of

[5] In addition, they find that the level of financial development is directly related to the probability of having a crisis.
[6] It is evident that the channels depend on the country's characteristics. Adler and Sosa (2011) suggest that the impact of a terms of trade shock depend on the degree of financial openness of a country, the strength of the external and fiscal position, the exchange rate regime, and the level of financial dollarization.
[7] Investment in non-commodity sector also increase as there is a spillover effect from investment in commodity sectors (Fornero and Kirchner, 2014).

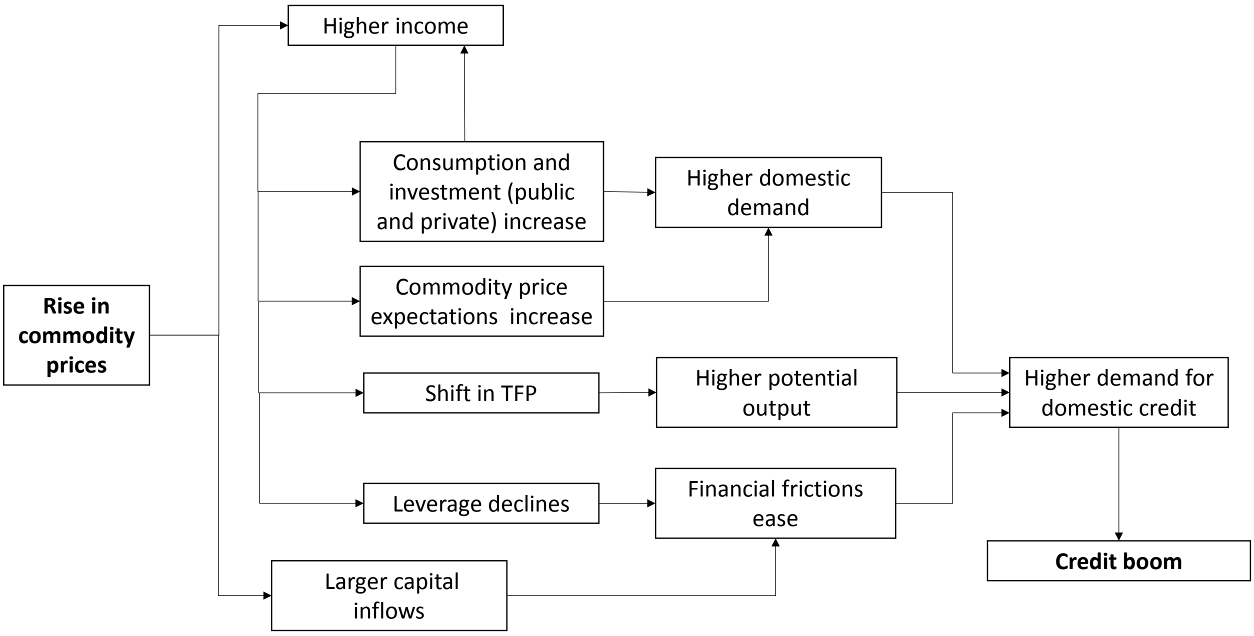
total fiscal revenues, fiscal policy is often procyclical with respect to the terms of trade. Moreno et al. (2014) note that domestic private credit acceleration results in a more sensitive real activity to shocks in terms of trade.

In regard to financial frictions, these are usually relaxed during a commodity boom. As argued by Shousha (2016), if the shock in commodity prices also increase the price of non-tradable goods, bank leverage may decline, reducing banks costs and pushing further the supply of credit. Moreover, Aslam et al. (2016) note that as returns increase, net worth improves and the firm's leverage declines, reducing the cost of financing, relaxing financial frictions, and in turn boosting income. Adler and Sosa (2011) find that in countries with high financial dollarization this effect is amplified. As mentioned by Aslam et al. (2016) current account deficit worsens and net capital inflows (one of the main causes of credit booms) are higher during the upswing of a commodity boom. Castillo and Rojas (2014) show that terms of trade also have short and long term effects on total-factor productivity (TFP)[8]. If higher investment leads to greater spending on research and development, and there is faster adoption of technology, or a sustainable sectoral reallocation, potential output may increase, boosting aggregate demand and the appetite for loanable funds. Figure 1 shows a simplified version of the mechanisms that may arise during a rise in commodity prices and can lead to a credit boom.

This paper contributes to the existing literature in many ways. First, it contributes to the credit boom literature by highlighting the link between high commodity prices and credit booms, and proposing commodity booms as a trigger factor for credit booms. Second, it also contributes to the literature on the effects of high commodity prices on the business cycle of commodity exporters by examining the behaviour of credit and other macroeconomic aggregates during a credit boom in commodity exporters. Moreover, it shows that commodity exporters are more vulnerable to bad credit booms. Third, in contrast to most of the previous empirical research in this area that has mainly focused on advanced economies and some emerging economies, I expand the sample to include a large group of emerging and low-income countries.

[8] Castillo and Rojas (2014) show that for Mexico, Peru and Chile terms of trade shocks have temporary and permanent effects on TFP, and can explain more than a quarter of the TFP growth.

Figure 1 A rise in commodity prices can lead to a credit boom



Source: Own elaboration based on Aslam et al. (2016), Cespedes and Velasco (2012), Castillo and Rojas (2014), the International Monetary Fund (2015), and Shousha (2016).

3. Data and methodology

To identify credit booms I build a comprehensive annual data set for 115 countries, 39 commodity exporters[9] and 76 non-commodity exporters, from 1960 to 2014 on credit and other macroeconomic aggregates that are linked to credit booms. See Appendix 2 for the sources and description of the variables.

Credit booms identification

There are two standard approaches to identify a credit boom. The first, developed by Gourinchas, Valdes and Landerretche (2001) (henceforth GVL), estimates the percentage deviation of the ratio of nominal credit to nominal GDP[10] with respect to its trend. The trend is estimated using an expanding Hodrick-Prescott filter (with the smooth parameter, λ, equal to 1000), and then is compared to a boom threshold. There will be a credit boom when the deviation of the ratio from the trend exceeds a given threshold:

[9] I follow the International Monetary Fund (2015) classification of commodity exporters: "A commodity exporter is classified as that if its exports of commodities exceed 35 percent of the country's total exports on average in the period 1962 – 2014; and net commodity exports account for at least 5 percent of the total trade in the same period". Although the IMF classification considers only emerging economies and low-income economies in the commodity exporter group, I have included Australia, Canada and Norway in this group as these countries are traditionally classified as commodity exporters.

[10] GVL takes the geometric average of GDP in year t and year $t+1$ as the adequate measure of GDP.

$$\frac{\left[(Credit/GDP)_{i,t} - (Credit/GDP)_{i,t}^{Expanding\ HP}\right]}{(Credit/GDP)_{i,t}^{Expanding\ HP}} \geq \varphi^{*}$$

The peak of a credit boom takes place at the date of the largest deviation and the starting date is the year before the peak at which the deviation exceeds a limit threshold (for the end date, this is the date after the peak where the deviation is larger than the limit threshold). Therefore, the boom threshold is used to identify episodes and the limit threshold determines the start and the end of a credit boom. The duration of an episode is the difference between the end date and the start date. Following GVL, I set $\varphi^{*} = 0.195$ and the limit threshold at 0.05. It is worthy to note that under this approach the threshold is invariant across countries.

The second approach, developed by Mendoza and Terrones (2008) (henceforth MT), defines a credit boom as an episode in which the amount of credit to the private sector exceeds its typical expansion over the business cycle. This approach estimates the deviation from the long-run trend and its corresponding standard deviation for the logarithm of real credit per capita. The long-run trend is estimated using the Hodrick-Prescott filter (setting $\lambda = 100$). A country experiences a credit boom episode when the credit deviation from the trend exceeds the usual deviation by a factor of φ or more.

$$Credit_{i,t} \geq \varphi\sigma({Credit^{HP}}_{i})$$

I follow MT and set $\varphi = 1.65$ because for a standardized normal distribution it is satisfied that $rob(Credit_{i,t}/\sigma({Credit^{HP}}_{i}) \geq 1.65) = 0.05$ [11]. The approach to find the peak of the credit boom and the start and end date is similar to GVL, but the limit threshold is equal to 1. In this case, I also evaluate the sensitivity of the average duration of a credit boom to this parameter.

Although both approaches seem similar, GVL tends to overestimate the number and the duration of the credit boom episodes (for a detailed comparison between these two approaches see Mendoza and Terrones, 2008). For robustness, I plan to identify episodes under both approaches, and compare the results; but will only work with the results from the MT methodology[12].

[11] Yet it is possible to use a lower φ. For instance, Benigno et al. (2015) set $\varphi = 1$ to identify boom episodes for net capital inflows. Although the results are not presented for the different values of the parameter φ, I found that the results are robust for any parameter above 1.5, whereas for threshold values below 1 the results can change dramatically.

[12] Arena et al. (2015) check MT robustness using the MT approach with credit-to-GDP instead of real credit per capita and find that the correlation between the credit booms identified with the former and the latter is around 50 percent.

It is worth noting that the results for both methods are sensitive to the chosen detrending filter or the use of no filter at all. For instance, Meller and Metiu (2014) use the Christiano-Fitzgerald filter due to its power to extract medium-frequency components compared to the Hodrick-Prescott filter and the absence of the endpoint problem, thus identifying more credit boom episodes. Gordon and Ordoñez (2016) propose an approach in the MT fashion to identify credit boom episodes relying on levels and not deviations from the trend and argue that detrending misses relevant characteristics of the data in large samples. Under their approach, the length of the boom increases.

Once the credit booms have been identified, I use Velasco's and Cespedes's (2012) database on booms in commodity prices[13], and find those commodity booms that take place between two years before the start of a credit boom and the credit boom peak.

It is also of interest to analyze how many credit booms become bad credit booms and if there is any difference between commodity exporters and non-commodity exporters in this regard. I use frequency analysis to examine in my sample the association between credit boom episodes, banking crises and sudden stops. For the banking crises, I use Laeven's and Valencia's (2012)[14] database of financial crises to estimate the coincidence of having a credit boom followed by financial crises. A similar analysis for credit booms that lead to sudden stops is performed using Calvo et al. (2004) database[15]. There will be a coincidence when the banking crisis started between the peak year and two years after the end date of a credit boom.

Event analysis

Next, I perform event analysis to describe the cyclical behavior of the main aggregate economic variables around the peak of a credit boom episode. I compute seven-year windows[16] centered at the peak of credit booms ($t = 0$) that display the cross-country means and medians of the cyclical

[13] The authors construct a weighted country-index for 59 commodity exporters for 1930-2008 and define a boom as the period during which the index surpasses the trend by more than a quarter. The advantage of working with specific country-indexes instead of with a general commodity price index is that it is possible to identify the evolution of the relevant commodity price for each country.
[14] Laeven and Valencia (2012) define a banking crisis as the episode where there are: "(i) significant signs of financial distress in the banking system, and (ii) significant bank policy intervention measures in response to significant loses in the banking system".
[15] Calvo et al. (2004) define a sudden stop as an episode that reflects a "large and an unexpected fall in capital inflows that have costly consequences in terms of economic activity".
[16] Previous literature on the topic has usually constructed seven-year windows (Mendoza and Terrones, 2008 and 2012; Arena et al., 2015) but windows can have any length. For instance, Benigno et al. (2015) use nine-year windows.

components of gross domestic product, private consumption, investment, public consumption, current account, real exchange rate, inflation, and credit across all credit boom episodes. All variables are measured in constant per-capita terms and as deviations from the trend using the Hodrick-Prescott filter (with $\lambda = 100$), except for current account-to-GDP ratio (current prices and not detrended), real exchange rate, and inflation. Following Benigno et al. (2015), to ensure that the composition of the sample does not distort the cyclical patterns, I include only credit booms for which at least five years of data are available.

There are two caveats about the event study analysis discussed by Terrones and Mendoza (2008): (i) it does not show if there is a boom in the macro variables; and (ii) it shows point estimates of the central tendency, but it does not demonstrate whether the results are statically significant[17].

Determinants of credit booms

In the same fashion as Barajas et al. (2007), Calderon and Kubota (2012), Decressin and Terrones (2011) and Arena et al. (2015), I estimate a set of panel logit regressions that links a set of macroeconomic variables to the likelihood of credit boom episodes for the period 1970-2014, and evaluate if there is a difference in the prediction for commodity exporters and non-commodity exporters:

$$P(y_{it} = 1|X) = \Phi(\beta_1 Net\ capital\ inflows_{i,t-1} + \beta_2 \Delta Credit_{i,t-1} + \beta_3 \Delta GDP_{i,t-1} + \beta_4 X_{it-1} + \varepsilon_{it})$$

The dependent variable is the incidence of a credit boom ($y_{it} = 1$ if there is a credit boom in year t for country i, and $y_{it} = 0$ otherwise). $Net\ capital\ inflows$ is the three-year average ratio of capital inflows to GDP (the current account is used as a proxy[18]), $\Delta Credit$ is the growth of real credit, ΔGDP is the growth of real GDP, and X is a matrix of control lagged[19] variables that also includes a dummy for commodity exporter countries[20] that interacts with credit growth, and ε_{it} is the error term. Control variables include: (i) macro variables such as inflation rates (as a proxy of financial stability), measured

[17]To check statistical significance, I run cross-section OLS regressions on a constant for each variable for one period before the peak, the peak and one period after the peak. Although the results are not presented here, many of the coefficients are statistically significant, yet most of the low income countries exhibit large standard errors (a similar result to Arena et al., 2015).
[18] Other proxies of capital inflows considered (but not reported here) are the flow of total external liabilities to GDP (as in Mendoza and Terrones, 2008); and the current account plus the variation in reserves (as in Benigno et al., 2015). The use of these proxies reduce the data availability for this sample.
[19] Control variables are also lagged to avoid potential endogeneity problems.
[20] Another alternative would be to use the change in terms of trade as a proxy for commodity exporters. Yet this variable does not allow the identification of which countries are commodity exporters, and in the case of non-commodity exporters may be misleading.

as the annual percentage change of the CPI, and the ratio of bank credit to the private sector to GDP (as a proxy for the depth of the domestic financial system); (ii) asset price misalignment measured as the deviation of the real exchange rate from its Hodrick-Prescott trend; and (iii) external shocks, measured by the US bills interest rate and the VXO index, an indicator of volatility and risk aversion. To measure the predictive capacity of these models, I estimate the so-called AUC (area under the curve)[21].

This regression analysis can be further used to predict bad credit booms. As argued by Amri et al. (2014), the main issue with the frequency analysis previously presented to detect bad credit booms is that it reveals only a simple correlation but does not support any prediction. Hence, I follow Calderon and Kubota (2012) and use the same model that was used to explain credit boom determinants, but change the dependent variable. Now, $y_{it} = 1$ if there is a bad credit boom in year t for country i, and $y_{it} = 0$ otherwise.

4. Empirical results

Using the MT approach I identify 101 credit boom episodes, of which 31 occurred in commodity exporter countries and 70 in non-commodity exporters (see Table 1 and Appendix 3). Most of the credit booms occurred in the 1990 – 2014 period. The difference in the duration of credit booms for both groups is negligible but it is worthy to note that for commodity exporters, most of the cycle is spent in the upswing part, and this result is robust for different specifications of the start/end threshold (see Table 2). For the non-commodity exporters, most of the credit boom is spend in the downswing. This could be an indicator that the usual overheating of the economy takes longer in the commodity exporters.

Table 1 Credit boom episodes

	1960-2014	1960-1969	1970-1979	1980-1989	1990-1999	2000-2014
Credit booms (MT methodology)						
All	**101**	**6**	**23**	**20**	**28**	**24**
Commodity exporters	31	1	3	9	10	8
Of which: emerging economies	*17*	*0*	*2*	*4*	*8*	*3*
Non-commodity exporters	70	5	20	11	18	16
Of which: emerging economies	*23*	*0*	*6*	*2*	*10*	*5*
Credit booms (GVL methology)						
All	**169**	**1**	**20**	**35**	**26**	**87**
Commodity exporters	55	1	7	18	8	21
Non-commodity exporters	114	0	13	17	18	66

[21] The AUC ranks the prediction capacity of any specification. If the AUC is greater than 0.5, then it has predictive value. For a detailed explanation see Hsu and Lieli (2015), and for an application see Jorda et al. (2011).

Three quarters of the commodity exporters have experienced a credit boom episode. However, this does not necessarily indicate that commodity exporters have a higher probability of having a credit boom and can be misleading due to sample size and the composition between advanced economies, emerging and developing economies. If we compare only the emerging economies[22], 17 episodes occurred in the commodity exporter group, compared to 23 in the non-commodity exporter group, and the ratio becomes similar: around two thirds of emerging markets in both groups have experienced a credit boom.[23] Note also that advanced economies seem to have more episodes of credit booms, which could be a consequence of the high level of development of their financial system (as argued by Barajas et al., 2007).

Table 2 Credit booms and duration sensitivity to different start/end thresholds

Start/end threshold	Commodity exporters			Non-commodity exporters		
	Duration	Upswing (% of duration)	Downswing (% of duration)	Duration	Upswing (% of duration)	Downswing (% of duration)
Mean						
0.25	6.03	0.42	0.32	6.14	0.33	0.45
0.50	5.26	0.39	0.31	5.40	0.32	0.43
0.75	4.68	0.38	0.29	4.83	0.32	0.39
1.00	4.23	0.36	0.28	4.35	0.29	0.38
Median						
0.25	6.00	0.40	0.33	6.00	0.33	0.43
0.50	5.00	0.40	0.33	5.00	0.33	0.50
0.75	5.00	0.40	0.33	5.00	0.33	0.33
1.00	4.00	0.40	0.25	4.00	0.33	0.33

When using GVL methodology the number of credit booms rises to 169, 55 in commodity exporters and 114 in non-commodity exporters (see Table 1 and Appendix 4). Also, the average duration is larger than under MT. Surprisingly, the GVL approach reports the higher number of credit boom episodes in the 1980-1989 period.

I look for booms in commodity prices that precede or coincide with credit booms in commodity exporters. Out of the 31 credit boom episodes identified, 22 coincide with a boom in the price of the commodities using Cespedes's and Velasco's (2012) definition. Only Argentina (1999), Brazil (1989), Chad (1987), Colombia (1998), Indonesia (1997), Mauritania (1962), Malaysia (1998), Peru (1998), and Zambia

[22] The IMF classifies the world economies as Advanced Economies (39 countries) and Emerging Market and Developing Economies (152 countries). Within the latter group, there are 59 emerging economies.
[23] There are 23 emerging economies in the commodity exporters group and 33 emerging economies in the non-commodity exporters group.

(2000) experienced credit booms where there was no evidence of a commodity boom [24] (see Appendix 5).

Following this, I identify 31 credit booms that are followed by a banking crisis (see Table 3 and Appendix 6). The difference between commodity exporters and non-commodity exporters is revealing: while around a quarter (0.26) of the credit booms in non-commodity exporters ended in bad credit booms, in commodity exporters this share increases up to 0.42 percent. If we consider only emerging economies the difference becomes more remarkable: for the period 1960-2014, more than half of credit booms in emerging markets which were commodity exporters ended in a bad credit boom, while the percentage is only a quarter for emerging markets that are non-commodity exporters. Moreover, bad credit booms last on average one more year for commodity exporters. Not every rise in commodity prices ends in a credit boom (for instance, during the most recent boom in commodity prices, there were fewer credit booms), and not every credit boom ends in a bad credit boom. But based on the evidence shown here, it can be argued that: (i) around two thirds of credit booms in commodity exporters were associated with periods of higher commodity prices; (ii) almost a half of those booms end in bad credit booms; and (iii) the previous result is more remarkable for emerging economies. In addition, I report the frequency for those credit booms that end in sudden stops: although commodity exporters show a higher frequency of sudden stops, all those episodes were related to the Asian crisis and are not representative of a credit boom linked to higher commodity prices.

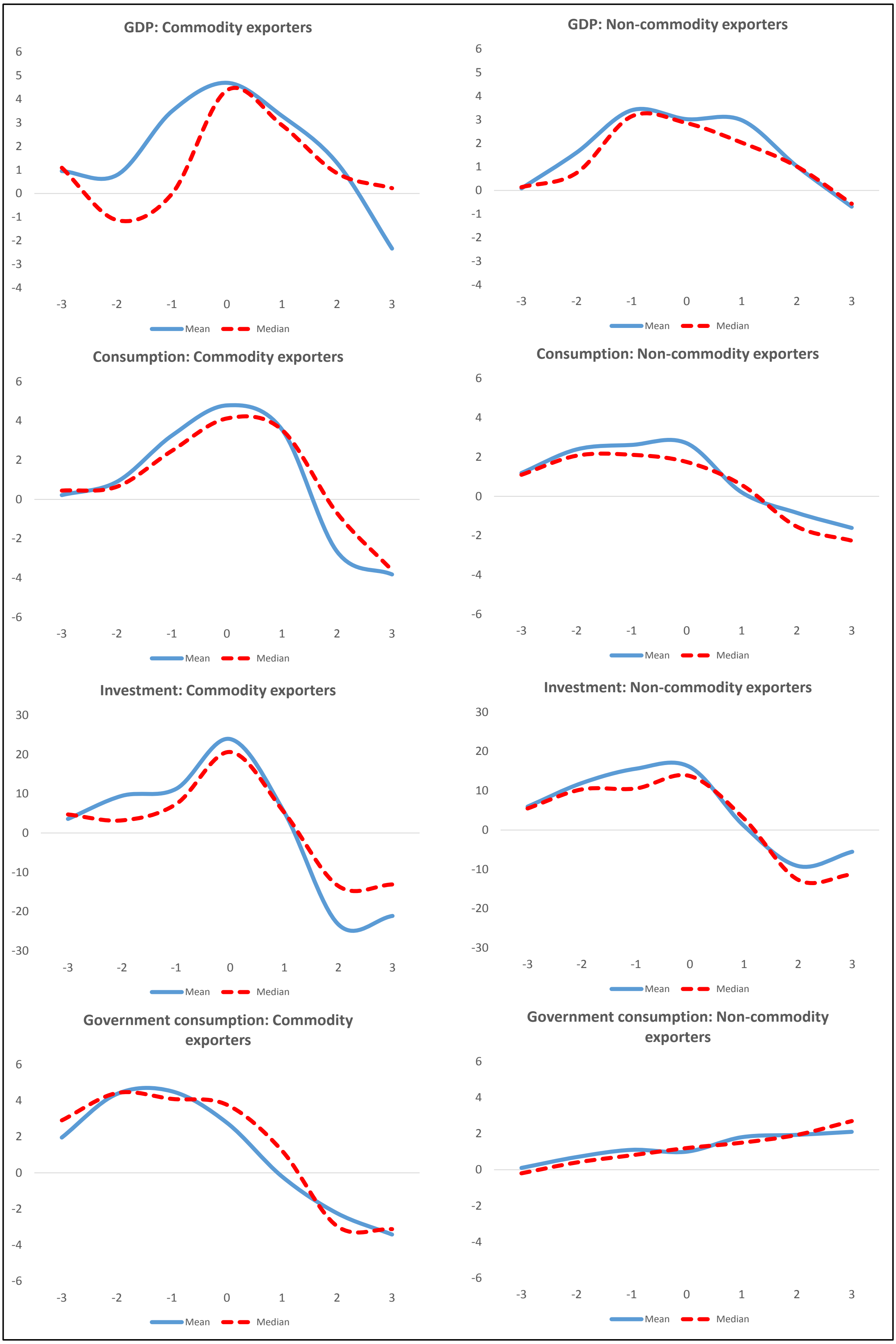
Table 3 Credit booms, banking crises and sudden stops (Frequency analysis)

	Banking crises	Sudden stops
All	**0.31**	**0.09**
Commodity exporters	0.42	0.13
Of which: emerging economies	*0.59*	*0.24*
Non-commodity exporters	0.26	0.07
Of which: emerging economies	*0.26*	*0.17*

Next, I compare the cycles of the main aggregate variables around the peak of a credit boom (where $t = 0$) for both groups of countries (see Figure 2). Credit booms are associated with an economic boom: GDP is above the trend for both groups of countries during the peak of a credit boom, but the deviation from the trend is larger

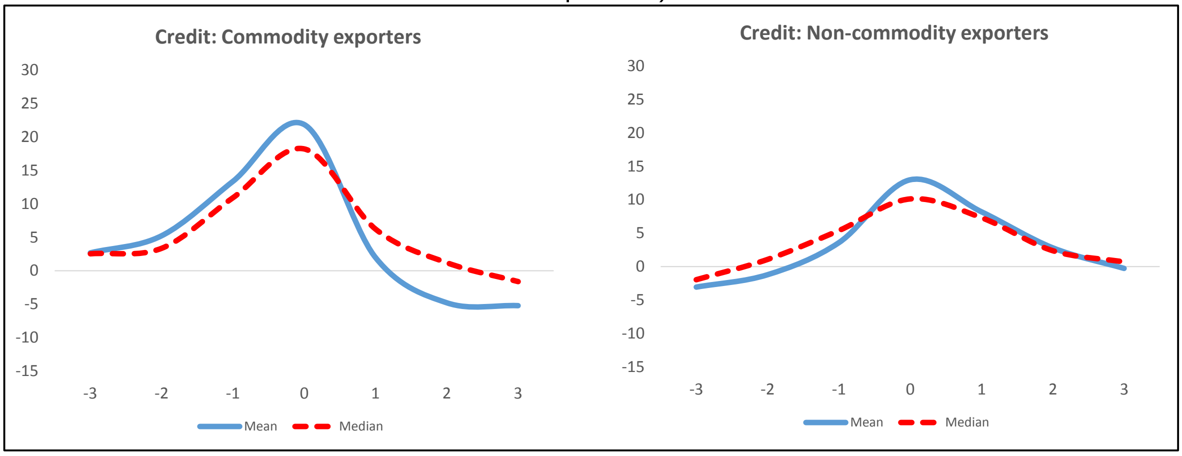
[24] Most of these credit boom episodes took place during the 90s and were associated to financial deregulation, the Asian crisis (1997) and the Russian crisis (1998).

Figure 2 Credit booms and domestic demand (Cross-country means and medians of cyclical components)



for the commodity exporter group (around five percent compared to three percent). Also, the fall below the trend in GDP is more pronounced at the end of the credit boom for commodity exporters. What does explain the rise in GDP? A boom in consumption and investment. As in the case of GDP, these variables display a well-defined pattern: an increase during the upswing phase and decrease during the downswing phase (more pronounced for commodity exporters). In particular investment displays a larger expansion and recession: it increases up to 24 percent above trend and decreases up to 22 percent two years after the peak, while in non-commodity exporters it rises up to 16 percent during the peak and declines nine percent two years after the peak. Credit shows a higher expansion during a credit boom episode in commodity exporters (see Figure 3), rising more than 20 percent above the trend; in non-commodity exporters the magnitude is smaller (13 percent above the trend).

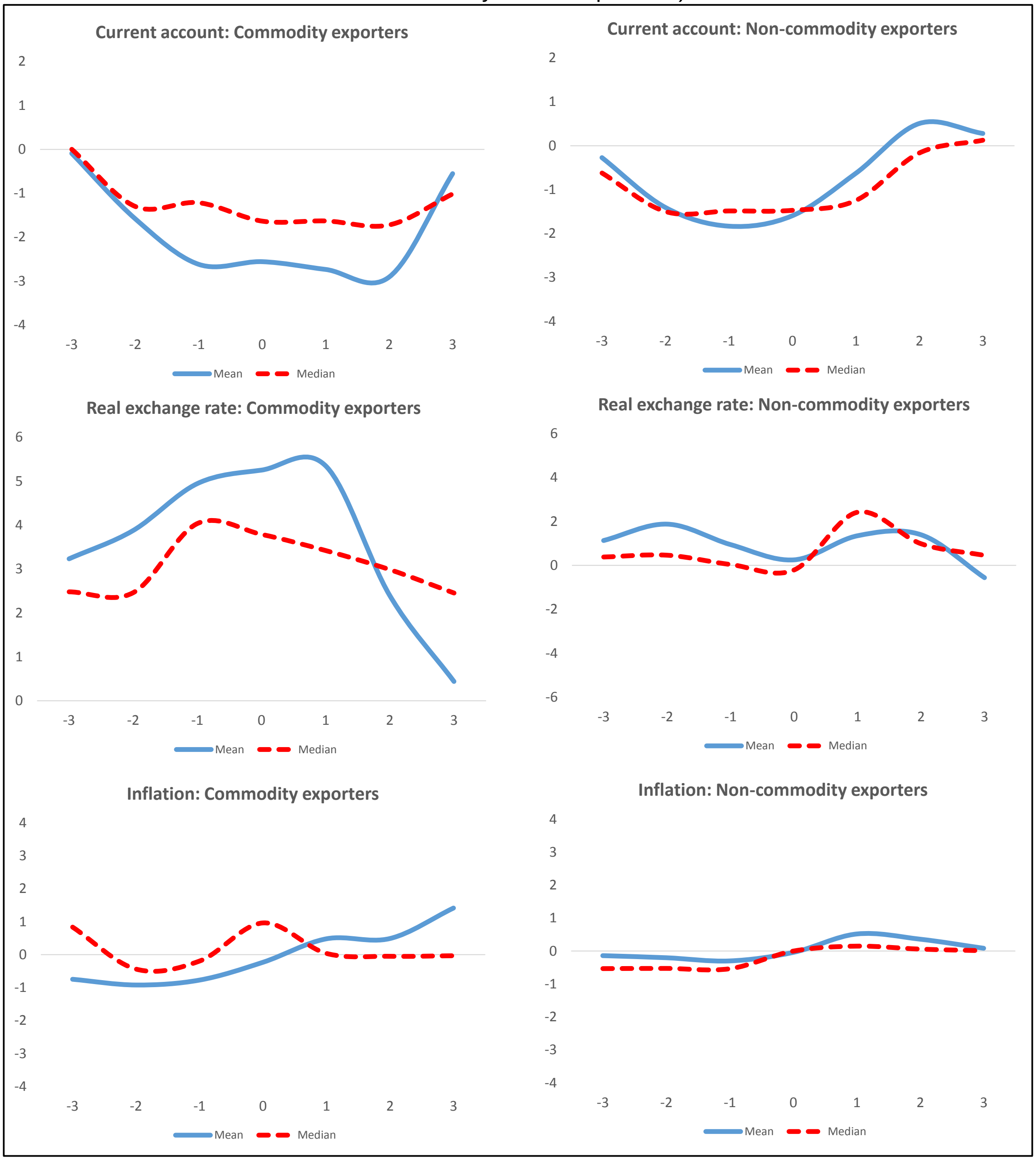
Figure 3 Credit booms and real credit per capita (Cross-country means and medians of cyclical components)



Government consumption exhibits a procyclical pattern in commodity exporters: during the building phase of a credit boom the fiscal expenditure increases and starts declining after the peak. This effect has been highlighted before[25], and is more noticeable in countries where commodities represent a large share of the government's revenue. In contrast, there is a constant increase of the government consumption in non-commodity exporters, which can be interpreted as a moderate counter cyclical fiscal policy. Current account deficit is exacerbated during a credit boom in both groups, but it is more persistent for the commodity exporters: it remains below the trend for all of the duration of the credit boom, while it reverses to the trend for the non-commodity exporters.

[25] See Cespedes and Velasco (2012).

Figure 4 Credit booms, current account, exchange rate and prices (Cross-country means and medians of cyclical components)



The real exchange rate exhibits the typical appreciation expected in a boom[26]: for the commodity exporters, the real exchange rate appreciates by five percent at the peak, while in the non-commodity exporters group it only does so by two percent. Moreover, the real exchange rate appreciation is sustained during the credit boom in non-commodity exporters, while it reverses after the peak in

[26] As stressed in the literature, a commodity exports boom will result in a real appreciation most of the time, although the perception of its time horizon may affect the result. In addition, it is very likely that there may exist some misalignments with respect to the equilibrium real exchange rate, although this will depend on the exchange regime that the country has adopted (Edwards, 1986; Spatafora and Starev, 2003).

commodity exporters. In the case of inflation, there are no evident dynamics, which confirms Mendoza and Terrones's (2012) result that credit booms are not linked to surges in inflation. Nevertheless, it is worthy to note that inflation in commodity exporters is higher at the peak of the boom, which can be related to a higher domestic demand (see Figure 4).

These results confirm the hypothesis that credit booms in commodity exporters do exhibit a different pattern than in non-commodity exporters and that there are feedback effects between consumption, investment and income. Not only the amplitude of the fluctuations is larger, but credit booms in commodity exporters end with output, consumption and investment with a higher deviation below the trend.

One of the issues that arises when aggregating the different cycles is the presence of heterogeneity among countries within commodity exporters and non-commodity exporters. This is more evident in the non-commodity exporters groups because the sample is larger and the group of advanced economies is more predominant. Also, it would be naïve to assume that the commodity exporters are a homogenous group of countries which exhibit the same features[27]. An alternative analysis would compare commodity exporters and non-commodity exporters for countries with similar features. As a robustness check, the results were compared only for emerging markets, but the qualitative results remain unchanged. This comparison reveals that although the difference between commodity exporters and non-commodity exporters in output, consumption and investment declines in magnitude, the main differences remain, i.e. commodity exporters still exhibit larger fluctuations and end below the trend at the end of the credit boom.

The logit results confirm that larger capital inflows and higher credit growth are good predictors of credit boom episodes; Table 4 shows the results under different specifications. The model with net capital inflows and credit growth as the main predictors exhibit an AUC higher than 0.5, which shows evidence of its predictive power, and the sign and statistical significance of the determinants are as expected. GDP growth is not statistically significant, and neither is the dummy for commodity exporter countries. When more control variables are added the predictive capacity improves marginally. Only under the full specification, and controlling for macro variables, asset prices and external shocks, is the dummy

[27] As argued by the International Monetary Fund (2015): "commodity exporters differ across many other dimensions, in terms of weight of commodities in their aggregate production, the nature of the commodities they export, and their levels of economic and institutional development".

variable for commodity exporters associated to a higher incidence of credit booms, but this model does not add extra information compared to the simpler model of the first specification. On the other hand, macro variables, with the exception of financial depth, do not show any evidence of an effect on the incidence of credit booms. While the sign of these variables is correct, they are not statistically significant.

Table 4 Credit booms and their determinants

($y_{it} = 1$ when there is a credit boom)

	(1)	(2)	(3)	(4)
Net Capital Inflows	0.325**	0.282*	0.276*	0.313***
	(0.164)	(0.162)	(0.154)	(0.125)
Credit Growth	1.675***	1.582***	1.982***	2.35***
	(0.462)	(0.478)	(0.530)	(0.601)
GDP Growth	0.132	0.178**	0.312	0.358
	(0.083)	(0.091)	(0.451)	(0.457)
REER Overaluation		0.073	0.145**	0.157*
		(0.054)	(0.062)	(0.091)
Interest rate			-0.217	-0.184
			(0.178)	(0.195)
VXO			0.049	0.032
			(0.112)	(0.130)
Financial Depth			0.483**	0.421*
			(0.212)	(0.248)
Financial Stability			-0.0135	0.0865
			(0.493)	(0.115)
Commodity Exporter Dummy	-0.013	0.006	0.010	0.015***
	(0.011)	(0.009)	(0.006)	(0.006)
Number of observations	2781	2781	2781	2781
Pseudo R-squared	0.082	0.138	0.123	0.105
AUC	0.67	0.67	0.69	0.70

Note: ***, ** and * denote significance at the 1, 5 and 10 percent level.
Robust standard errors are reported in parentheses.

The second logit analysis for bad credit booms confirms the predictive capacity of net capital inflows and credit growth, but shows some key differences with respect to the first analysis: (i) the specification with the higher AUC is the one that takes into account the change in the real exchange rate; and (ii) the dummy for commodity exporters is significant under all the different specifications proposed here. The specifications that control for macro variables and external shocks add only marginal information. Hence, the incidence of a bad credit boom is positively associated with net capital inflows, credit growth, changes in the exchange rate and being a commodity exporter. To a lesser extent, GDP growth and financial depth have predictive power on the incidence of a bad credit boom.

Table 5 Bad credit booms and their determinants

($y_{it} = 1$ when there is a bad credit boom)

	(1)	(2)	(3)	(4)
Net Capital Inflows	0.244**	0.207**	0.187**	0.284**
	(0.104)	(0.092)	(0.092)	(0.145)
Credit Growth	1.031**	0.897*	1.368***	1.708***
	(0.540)	(0.516)	(0.444)	(0.356)
GDP Growth	0.040	0.034**	0.022**	0.02*
	(0.028)	(0.018)	(0.012)	(0.012)
REER Overaluation		0.079	0.155***	0.172***
		(0.043)	(0.049)	(0.049)
Interest rate			0.021	0.042
			(0.157)	(0.123)
VXO			-0.0392	-0.025248
			(0.035)	(0.022)
Financial Depth			0.783***	0.352**
			(0.112)	(0.178)
Financial Stability			0.00945	0.07785
			(0.345)	(0.141)
Commodity Exporter Dummy	0.341***	0.197*	0.301**	0.269**
	(0.110)	(0.121)	(0.107)	(0.140)
Number of observations	2781	2781	2781	2781
Pseudo R-squared	0.135	0.158	0.198	0.176
AUC	0.64	0.74	0.74	0.75

Note: ***, ** and * denote significance at the 1, 5 and 10 percent level.
Robust standard errors are reported in parentheses.

5. Concluding remarks

In this paper, I have identified 101 credit boom episodes for a large sample of 116 countries for the period 1960-2014, and I have compared the results for commodity exporters and non-commodity exporters. There is no major difference in the number and duration of the episodes. Based on Cespedes' and Velasco's (2012) definition of commodity boom, I show that two thirds of the credit booms in commodity exporter countries of the last four decades were associated with commodity boom episodes. The event analysis shows that commodity exporters exhibit an amplified business cycle in the presence of a credit boom due to more pronounced income effects and more relaxed financial frictions, and domestic demand variables end below the trend at the end of the credit boom. When we compare emerging countries only, the difference in the cycle is less pronounced for investment, consumption and product, but the results still hold.

In addition, a simple frequency analysis reveals that around 40 percent of the credit boom episodes in commodity exporter countries ended in a banking crises, compared to 26 percent in non-commodity exporters. A regression analysis to assess the probability of having a credit boom and a bad credit boom has been carried out. The results show that net capital inflows and credit growth are the main predictors of credit booms and bad credit booms. Exchange rate overvaluation and a being a commodity exporter have predictive power for bad credit booms, but not for credit booms. Moreover, macro variables and external shocks add only marginal information in both cases.

These results are also important from a policy perspective. Credit growth should be closely monitored in commodity exporters, mainly during a favorable terms of trade episode. What may appear as the "normal" growth of credit due to a higher income effect may lead to a bad credit boom and a banking crisis. Yet it also has to be acknowledged that not all increases in prices lead to a credit boom; for instance, the recent boom in commodity prices did not generate a credit boom in most of the commodity exporters. Moreover, measuring credit growth may lead to wrong identification, as the relevant measure is the deviation from the trend.

Many avenues of research remain open. For instance, the analysis could be further extended to assess the effect of credit booms on labor and TFP by measuring misallocation in tradable and non-tradable sectors; and to characterize the cyclical properties of prices such as stock market and real estate prices during a credit boom episode. Moreover, the empirical analysis could be further strengthened with a DSGE model in order to capture the feedback effects and to analyze impulse response functions and evaluate policies. From a policy point of view it would be relevant to assess the capacity and efficiency of different policies to manage credit booms.

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APPENDIX 1: SAMPLE

Commodity exporters		Non-commodity exporters		
Advanced economies				
Australia		Austria	Italy	Spain
Canada		Belgium	Japan	Sweden
Norway		Denmark	Korea	Switzerland
		Finland	Luxembourg	United Kingdom
		France	Malta	United States
		Greece	Netherlands	
		Iceland	New Zealand	
		Ireland	Portugal	
		Israel	Singapore	
Emerging economies				
Algeria	Libya	Bahamas	India	Sri Lanka
Argentina	Malaysia	Botswana	Jamaica	Suriname
Bahrain	Paraguay	Cabo Verde	Jordan	Swaziland
Bolivia	Peru	China	Mauritius	Thailand
Brazil	Qatar	Costa Rica	Mexico	Tonga
Chile	Saudi Arabia	Cyprus	Morocco	Tunisia
Colombia	Trinidad	Dominica	Pakistan	Turkey
Ecuador	UAE	Dominican Republic	Panama	
Gabon	Uruguay	El Salvador	Philippines	
Guatemala	Venezuela	Egypt	Rwanda	
Indonesia		Fiji	Samoa	
Iran		Germany	Seychelles	
Kuwait		Grenada	South Africa	
Low income economies				
Cameroon	Myanmar	Bangladesh	Haiti	Senegal
Chad	Nicaragua	Benin	Kenya	Swaziland
Congo, Rep.	Niger	Burkina Fasso	Lesotho	Tanzania
Cote d'Ivoire	Sudan	Burundi	Madagascar	Togo
Ghana	Zambia	Central African Republic	Malawi	Tonga
Honduras		Congo, Democratic Rep.	Mali	Uganda
Mauritania		Ethiopia	Nepal	
Mongolia		Gambia	Nigeria	

APPENDIX 2: DATA SOURCES AND DEFINITION

Variable	Source	Definition
Credit	IMF International Financial Statistics, OECD	Claims of the private sector by deposit money banks (IFS line 22) and claims of the private sector by other financial institutions (IFS line 42d) when available
Population	World Development Indicators	Population
Consumer price index	IMF International Financial Statistics, Penn World Tables 7.0	Consumer Price Index (annual average). Inflation is measured by the annual percentage change of the CPI.
Nominal GDP	World Development Indicators, IMF International Financial Statistics	Gross Domesticc Product in current prices, local currency unit
Real GDP	World Development Indicators, IMF International Financial Statistics	Gross Domestic Product in constant prices, international prices
Private consumption	World Development Indicators, Penn World Tables 7.0	Real private consumption, international prices
Government consumption	World Development Indicators, Penn World Tables 7.0	Real public consumption, international prices
Investment	World Development Indicators, Penn World Tables 7.0	Real investment, international prices
Current account balance	World Development Indicators, IMF International Financial Statistics	Current account as percent of GDP
Real exchange rate	IMF International Financial Statistics	Real exchange rate (RER) index
Interest rate	IMF International Financial Statistics	United States federal funds rate
VXO	Bloomberg	Chicago Board Options Exchange S&P 100 Volatility Index. For the period before 1986 the series can be back-casted as suggested in Benigno et al. (2009)

APPENDIX 3: LIST OF EPISODES (MT METHODOLOGY)

COMMODITY EXPORTERS

Country	Start year	End year	Peak year	Duration	Country	Start year	End year	Peak year	Duration
Algeria	1987	1991	1991	5.0	Libya	1974	1977	1975	4.0
Argentina	1997	2001	1999	5.0	Malaysia	1995	1998	1997	4.0
Australia	1989	1991	1989	3.0	Mauritania	1961	1962	1962	2.0
Bolivia	1982	1984	1982	3.0	Myanmar	2000	2002	2001	3.0
Brazil	1988	1989	1989	2.0	Nicaragua	1979	1984	1982	6.0
Cameroon	1989	1991	1991	3.0	Niger	1991	1994	1993	4.0
Canada	2001	2002	2001	2.0	Norway	1985	1990	1987	6.0
Chad	1985	1987	1987	3.0	Peru	1996	2000	1998	5.0
Chile	1977	1984	1980	8.0	Qatar	1991	1992	1992	2.0
Colombia	1993	1998	1997	6.0	Saudi Arabia	1979	1985	1980	7.0
Cote d'Ivoire	1976	1979	1977	4.0	Sudan	2003	2010	2006	8.0
Ecuador	1994	1998	1997	5.0	UAE	1976	1981	1977	6.0
Gabon	2001	2003	2001	3.0	Uruguay	1998	2003	2002	6.0
Ghana	1989	1990	1989	2.0	Venezuela	2006	2009	2007	4.0
Honduras	2006	2008	2007	3.0	Zambia	1996	2000	2000	5.0
Indonesia	1994	1998	1997	5.0					

NON-COMMODITY EXPORTERS

Country	Start year	End year	Peak year	Duration	Country	Start year	End year	Peak year	Duration
Austria	1979	1981	1979	3.0	Madagascar	1990	1994	1993	5.0
Bangladesh	1984	1986	1984	3.0	Mali	1961	1962	1962	2.0
Belgium	1992	1995	1992	4.0	Malta	1969	1973	1970	5.0
Botswana	1974	1977	1976	4.0	Mauritius	1976	1979	1977	4.0
Botswana	1990	1994	1992	5.0	Mexico	1992	1995	1994	4.0
Burkina Faso	1976	1979	1976	4.0	Morocco	1997	2000	1997	4.0
Burkina Faso	1988	1991	1990	4.0	Netherlands	1977	1981	1979	5.0

Country	Start year	End year	Peak year	Duration
Cabo Verde	1993	1997	1993	5.0
Congo, Dem. Rep	1998	2000	1999	3.0
Costa Rica	1977	1980	1979	4.0
Cyprus	2005	2011	2008	7.0
Denmark	2000	2003	2000	4.0
Dominica	1989	1993	1990	5.0
Dominican Republic	1999	2003	2002	5.0
El Salvador	1982	1985	1985	4.0
Ethiopia	1963	1966	1963	4.0
Ethiopia	1995	2001	1996	7.0
Finland	1988	1992	1990	5.0
France	1978	1981	1978	4.0
Germany	1962	1965	1962	4.0
Germany	1998	2001	2000	4.0
Greece	1978	1982	1978	5.0
Hungary	1987	1991	1987	5.0
Iceland	2005	2008	2006	4.0
India	2005	2008	2008	4.0
Ireland	2005	2009	2007	5.0
Israel	1978	1980	1979	3.0
Israel	1982	1984	1984	3.0
Italy	1971	1976	1973	6.0
Italy	1990	1993	1992	4.0
Japan	1970	1973	1972	4.0
Japan	1997	2000	2000	4.0
Korea	1961	1962	1961	2.0
Korea	1968	1971	1969	4.0
Luxembourg	2000	2003	2001	4.0
New Zealand	1988	1991	1988	4.0
Nigeria	2007	2010	2008	4.0
Pakistan	2004	2008	2007	5.0
Philippines	1978	1983	1983	6.0
Philippines	1995	1998	1997	4.0
Portugal	1971	1973	1973	3.0
Portugal	2001	1999	2002	4.0
Samoa	1976	1979	1978	4.0
Senegal	1978	1982	1981	5.0
Seychelles	1977	1982	1979	6.0
Singapore	1972	1973	1973	2.0
South Africa	2006	2009	2007	4.0
Spain	2005	2010	2007	6.0
Sri Lanka	1995	1999	1995	5.0
Suriname	1989	1992	1992	4.0
Sweden	1988	1992	1990	5.0
Sweden	2001	2005	2001	5.0
Switzerland	1969	1973	1970	5.0
Switzerland	1988	1991	1989	4.0
Tanzania	1989	1994	1989	6.0
Thailand	1993	1998	1997	6.0
Togo	1975	1980	1979	6.0
Tonga	1975	1979	1976	5.0
Turkey	1996	1998	1997	3.0
United Kingdom	1972	1975	1973	4.0
United Kingdom	1986	1991	1989	6.0
United States	1986	1990	1989	5.0
United States	2005	2008	2007	4.0

APPENDIX 4: LIST OF EPISODES (GVL METHODOLOGY)

Commodity exporters

Country	Start year	End year	Peak year	Duration
Algeria	1982	1991	1991	10.0
Argentina	1979	1983	1981	5.0
Argentina	1996	2001	1998	6.0
Australia	1989	1991	1989	3.0
Australia	2006	2010	2007	5.0
Bolivia	1996	2000	1998	5.0
Cameroon	1980	1987	1982	8.0
Canada	2001	2002	2001	2.0
Chad	1967	1969	1969	3.0
Chad	1985	1987	1987	3.0
Chile	2006	2008	2007	3.0
Colombia	1993	1998	1997	6.0
Congo	1982	1987	1985	6.0
Cote d'Ivoire	1976	1980	1977	5.0
Ecuador	1976	1982	1981	7.0
Gabon	1974	1978	1977	5.0
Gabon	1984	1987	1986	4.0
Gabon	2001	2003	2001	3.0
Ghana	1969	1972	1971	4.0
Guatemala	1979	1985	1984	7.0
Honduras	1986	1989	1987	4.0
Honduras	2006	2009	2007	4.0
Indonesia	1994	1998	1997	5.0
Iran	2006	2008	2007	3.0
Iran	2010	2012	2011	3.0
Kazakhstan	2006	2009	2007	4.0
Kuwait	1981	1989	1982	9.0

Country	Start year	End year	Peak year	Duration
Kuwait	1981	1989	1989	9.0
Kuwait	2006	2009	2007	4.0
Libya	1981	1982	1981	2.0
Malaysia	1995	2000	1997	6.0
Mauritania	1975	1978	1977	4.0
Myanmar	2000	2002	2001	3.0
Myanmar	2013	2014	2014	2.0
Nicaragua	1978	1982	1982	5.0
Niger	1979	1983	1980	5.0
Norway	2005	2006	2006	2.0
Paraguay	2013	2014	2014	2.0
Peru	1981	1985	1983	5.0
Peru	1996	2000	1998	5.0
Qatar	1977	1982	1977	6.0
Qatar	2005	2009	2007	5.0
Saudi Arabia	2005	2009	2008	5.0
Sudan	1981	1984	1982	4.0
Sudan	2005	2010	2006	6.0
Trinidad	1977	1984	1982	8.0
Trinidad	2001	2008	2001	8.0
Trinidad	2001	2008	2007	8.0
UAE	1976	1982	1977	7.0
Uruguay	1998	2002	1999	5.0
Uruguay	1998	2002	2002	5.0
Venezuela	1975	1979	1978	5.0
Venezuela	1986	1988	1986	3.0
Venezuela	2006	2009	2007	4.0

Non-commodity exporters									
Country	**Start year**	**End year**	**Peak year**	**Duration**	**Country**	**Start year**	**End year**	**Peak year**	**Duration**
Austria	2006	2011.0	2008	6.0	Korea	2001	2003.0	2002	3.0
Bahamas	1969	1970.0	1970	2.0	Korea	2006	2010.0	2008	5.0
Bahamas	2006	2010.0	2007	5.0	Lesotho	1998	2002.0	2001	5.0
Bangladesh	2010	2013.0	2012	4.0	Lesotho	2012	2014.0	2014	3.0
Belgium	1992	1996.0	1992	5.0	Luxembourg	2000	2003.0	2001	4.0
Belgium	2006	2008.0	2007	3.0	Luxembourg	2007	2009.0	2008	3.0
Benin	1982	1988.0	1982	7.0	Madagascar	1970	1972.0	1971	3.0
Benin	1982	1988.0	1985	7.0	Madagascar	1979	1980.0	1980	2.0
Botswana	1990	1994.0	1992	5.0	Malawi	2009	2012.0	2010	4.0
Burkina Faso	1976	1979.0	1978	4.0	Mali	2002	2004.0	2004	3.0
Burkina Faso	1988	1991.0	1990	4.0	Malta	2006	2011.0	2008	6.0
Burkina Faso	2013	2014.0	2014	2.0	Mauritius	2003	2005.0	2003	3.0
Burundi	1990	1994.0	1993	5.0	Mauritius	2013	2014.0	2014	2.0
Burundi	2002	2004.0	2002	3.0	Mexico	1992	1995.0	1994	4.0
Cabo Verde	1999	2000.0	1999	2.0	Morocco	1997	2000.0	1997	4.0
Cabo Verde	2008	2012.0	2011	5.0	Morocco	2008	2012.0	2011	5.0
Central African R.	2010	2012.0	2012	3.0	Nepal	2008	2012.0	2009	5.0
China	2010	2014.0	2014	5.0	Netherlands	1977	1981.0	1979	5.0
Costa Rica	1977	1980.0	1979	4.0	Netherlands	1999	2001.0	2001	3.0
Costa Rica	2007	2009.0	2008	3.0	Netherlands	2007	2009.0	2008	3.0
Cyprus	2007	2012.0	2008	6.0	New Zealand	1988	1990.0	1988	3.0
Denmark	2000	2002.0	2000	3.0	New Zealand	2006	2008.0	2007	3.0
Denmark	2006	2010.0	2007	5.0	Nigeria	2007	2010.0	2008	4.0
Dominican Republic	1999	2003.0	2002	5.0	Pakistan	2004	2009.0	2007	6.0
Salvador	1973	1974.0	1973	2.0	Panama	1998	2001.0	1999	4.0
Salvador	1977	1979.0	1978	3.0	Panama	2010	2012.0	2012	3.0
Salvador	1983	1985.0	1985	3.0	Philippines	1978	1983.0	1983	6.0
Egypt	1998	2008.0	2001	11.0	Philippines	1995	1999.0	1997	5.0

Country	Start year	End year	Peak year	Duration	Country	Start year	End year	Peak year	Duration
Fiji	2005	2009.0	2006	5.0	Portugal	1999	2002.0	2000	4.0
Finland	1988	1992.0	1990	5.0	Rwanda	1985	1990.0	1989	6.0
Finland	2005	2011.0	2007	7.0	Samoa	1976	1979.0	1978	4.0
France	1978	1981.0	1978	4.0	Samoa	2005	2008.0	2006	4.0
France	1989	1993.0	1990	5.0	Senegal	1978	1983.0	1981	6.0
France	2007	2011.0	2008	5.0	Seychelles	2007	2008.0	2008	2.0
Gambia	1983	1985.0	1985	3.0	Singapore	1995	1999.0	1998	5.0
Germany	1998	2002.0	2000	5.0	Singapore	2013	2014.0	2013	2.0
Greece	2006	2011.0	2008	6.0	South Africa	2006	2009.0	2007	4.0
Greece	2006	2011.0	2010	6.0	Spain	2005	2011.0	2007	7.0
Grenada	2007	2012.0	2010	6.0	Sri Lanka	1995	2000.0	1995	6.0
Haiti	1974	1981.0	1978	8.0	Suriname	1989	1992.0	1992	4.0
Haiti	1988	1991.0	1989	4.0	Swaziland	2005	2009.0	2007	5.0
Hungary	1987	1991.0	1987	5.0	Sweden	1988	1992.0	1990	5.0
Iceland	2005	2008.0	2006	4.0	Sweden	2001	2003.0	2001	3.0
India	2006	2012.0	2008	7.0	Switzerland	1988	1991.0	1989	4.0
India	2006	2012.0	2010	7.0	Thailand	1994	1998.0	1997	5.0
Ireland	2005	2009.0	2007	5.0	Togo	1976	1980.0	1979	5.0
Israel	1978	1980.0	1979	3.0	Togo	1990	1993.0	1991	4.0
Israel	1982	1984.0	1984	3.0	Tonga	2005	2009.0	2007	5.0
Israel	1998	2002.0	2001	5.0	Tunisia	2000	2002.0	2001	3.0
Italy	1990	1993.0	1992	4.0	Tunisia	2010	2012.0	2011	3.0
Italy	2006	2012.0	2007	7.0	Turkey	2013	2014.0	2014	2.0
Jamaica	1972	1976.0	1973	5.0	Uganda	2010	2012.0	2011	3.0
Jamaica	1988	1991.0	1989	4.0	Ukraine	2007	2009.0	2008	3.0
Jamaica	2006	2009.0	2007	4.0	United Kingdom	1986	1991.0	1989	6.0
Japan	1996	2000.0	2000	5.0	United Kingdom	2006	2010.0	2008	5.0
Jordan	1981	1988.0	1987	8.0	United States	1985	1990.0	1989	6.0
Jordan	2005	2009.0	2007	5.0	United States	2004	2008.0	2007	5.0

APPENDIX 5: CREDIT BOOMS AND COMMODITY BOOMS

Country	Start year	End year	Peak year	Commodity boom? 1/
Algeria	1987	1991	1991	Yes
Argentina	1997	2001	1999	No
Australia	1989	1991	1989	Yes
Bolivia	1982	1984	1982	Yes
Brazil	1988	1989	1989	No
Cameroon	1989	1991	1991	Yes
Canada	2001	2002	2001	Yes
Chad	1985	1987	1987	No
Chile	1977	1984	1980	Yes
Colombia	1993	1998	1997	No
Cote d'ivoire	1976	1979	1977	Yes
Ecuador	1994	1998	1997	Yes
Gabon	2001	2003	2001	Yes
Ghana	1989	1990	1989	Yes
Honduras	2006	2008	2007	Yes
Indonesia	1994	1998	1997	No
Libya	1974	1977	1975	Yes
Malaysia	1995	1998	1997	No
Mauritania	1961	1962	1962	No
Myanmar	2000	2002	2001	Yes
Nicaragua	1979	1984	1982	Yes
Niger	1991	1994	1993	Yes
Norway	1985	1990	1987	Yes
Peru	1996	2000	1998	No
Qatar	1991	1992	1992	Yes
Saudi Arabia	1979	1985	1980	Yes
Sudan	2003	2010	2006	Yes
UAE	1976	1981	1977	Yes
Uruguay	1998	2003	2002	Yes
Venezuela	2006	2009	2007	Yes
Zambia	1996	2000	2000	No

1/ Commodity booms based on Cespedes's and Velasco's (2012) database.

APPENDIX 6: CREDIT BOOMS AND BANKING CRISES

Commodity exporters			
Country	**Start year**	**End year**	**Estimated output loss 1/**
Algeria	1990	1994	41.4
Argentina	2001	2003	71.0
Bolivia	1986	1986	49.2
Brazil	1990	1994	62.3
Cameroon	1987	1991	105.5
Chile	1981	1985	8.6
Colombia	1998	2000	43.4
Ecuador	1998	2002	25.4
Indonesia	1997	2001	69.0
Malaysia	1997	1999	31.4
Norway	1991	1993	5.1
Uruguay	2002	2005	27.4
Zambia	1995	1998	31.1

Non-commodity exporters			
Country	**Start year**	**End year**	**Estimated output loss 1/**
Bangladesh	1987	1987	n.a.
Burkina Fasso	1990	1994	n.a.
Dominican Republic	2003	2004	n.a.
Finland	1991	1995	69.6
Iceland	2008		43
Ireland	2008		106
Japan	1997	2001	45
Mexico	1994	1996	13.7
Nigeria	2009		n.a.
Philippines	1983	1986	91.7
Philippines	1997	2001	n.a.
Spain	2008		39
Sweden	1991	1995	32.9
Sweden	2008		25
Thailand	1997	2000	109.3
Turkey	2000	2001	35
United States	1988	1988	n.a.
United States	2007		31

1/ Estimated by Laveen and Valencia (2012).