THE EFFECT OF MONETARY AND EXCHANGE RATE INSTITUTIONS ON THE BOOM – BUST CYCLE IN STOCK MARKETS: 1922-2015

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Abstract

We draw evidence on a possible link between monetary and exchange rate institutions and the behavior of the stock market's boom-bust cycle. We run panel regressions of regime dummy sequences on innovative boom bust indicators (BBIs) for the stock market of six Western European countries and find there is a role for the monetary regime on the evolution of asset prices. The BBIs behave differently in mean according to the regime in place. We identify that a pegged exchange rate regime, is more prone to crises than any of the other regimes. Also, both the free float and the European Monetary Union (EMU) regimes are more prone to short-run booms, while long term effects only show differences between a prone-to-crises peg regime and a prone-to-booms free floating regime. Additionally, there is no statistical difference in the effect of the EMU and the gold exchange standard on the boom-bust cycle of the stock market.

Keywords: Boom-bust cycle, stock market, financial crises, non-parametric models, stock market history, monetary regimes, international monetary institutions.

JEL codes

C14, C23, E02, E32, E42, E44, F33, G01, N2

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Introduction

The period starting in 1922 has witnessed a wide array of monetary institutions which have set constraints on the way monetary authorities and regulators conduct macroeconomic policy and manage expectations from investors. Henceforth we will refer to a monetary regime as the set of arrangements on monetary policy, exchange rates and capital flows that determine the instruments the authorities have to influence the short and long-run behavior of macroeconomic aggregates and agents (Obstfeld, Shambaugh, & Taylor, 2005). The time period covered in this paper is also interesting since it has seen some of the worst stock market crashes and some of the largest, most long-lasting booms on record. We aim to expand on the literature on financial crises by drawing evidence on a possible link between the institutional framework and the behavior of asset prices, proxied by the behavior of wide stock market indices- We will do so by studying the way monetary institutions are set up and how the stock market's boom-bust cycle behaves. This study will be performed for six countries: France, Germany, Italy, the Netherlands, Sweden and the United Kingdom.

In theory, surges in asset prices, in order to be sustainable, should happen through an increase in expected income from those investments or through a reduction of their risk profile (Fama, 1970). Whenever asset prices increase disconnected from fundamentals —building financial imbalances— they are likely to correct this increase when the unsustainable trend is evidenced (Kindleberger & Aliber, 2005). This boom-bust process has become relevant for policy makers because it adds volatility to the behavior of asset prices, increases financial instability, affects consumption and real economic activity (Bernanke & Gertler, 1999). Recently the interaction between financial markets and macroeconomic fluctuations has become central to economic research (Airaudo, et. al., 2015). The financial instability generated by the boom-bust cycle in asset prices leads, in some cases to financial crises which not only threaten the financial market but the entire economy by impairing growth, increasing the duration of normal recessions (Assenmacher-Wesche & Gerlach, 2010) and increasing inequality (Atkinson & Morelli, 2011).

However, as Forero-Laverde (2016) indicated, not all booms and busts were created equal. Some booms or crises are more pervasive, while others are more explosive. Some crashes in the stock market occur after large booms while some happen "out of the blue". In that sense, understanding what may cause these differences becomes critical for designing policies that may reduce both the amplitude and frequency of the cycle. An intriguing line of research, which we follow to delve into this question, is proposed by Borio & White (2004), who indicate monetary regimes are characterized by their elasticity, understood as the "inherent potential to allow financial imbalances to build up over time, with endogenous forces failing to rein them in, until the imbalances eventually unwind, possibly resulting in financial instability" (pg. 1). Following this idea, we investigate the possibility that under different monetary regimes the behavior of the stock market cycle changes.

From our initial definition, the way through which monetary and exchange rate institutions may affect the asset price cycle operates through different channels: the amount of available money and level of interest rates, the commitment or not to a stable exchange rate and the presence or not of controls to international capital flows. These should impinge both on risk pricing and the

investment/consumption opportunity set for households, firms and the government which affect overall economic growth.

From a methodological perspective, we build on Forero-Laverde (2016) to construct three new dependent variables, each with a different time horizon, which serve as measures of the cycles in the stock market: the Boom Bust Indicators (BBIs). These time series, as discussed by Forero-Laverde (2016), are preferred above traditional dummy sequences for several reasons: they contain more variability; their informational content is closer to the original data; they indicate whether there is a boom or bust and provide a measure of intensity to establish qualitative differences between diverse types of expansions and contractions, and they focus on the structure of the tails rather than smoothing the series or performing statistical assumptions about the data generating process (DGP). Then, we construct regime-switching matrices based on dummy variable regressions on a strongly balanced panel to identify whether these indicators behave differently under certain monetary regimes, and whether some regimes are more prone to booms or busts.

We find there is a role for the monetary regime on the evolution of asset prices. This is clear from the joint significant coefficients for all specifications of the regressions with 90% confidence. We identify that a pegged exchange rate regime, by any definition, is more prone to crises than any of the other regimes. We can also state that both the free float and the European Monetary Union regimes are more prone to short-run booms, while long term effects only show differences between a prone-to-crises peg regime and a prone-to-booms free floating regime. Additionally, the short run effect of the regime on the boom-bust cycle of the stock market is statistically the same for the EMU and any definition of the gold exchange standard which confirms what Bordo & James (2015) propose.

The rest of the paper is structured as follows: Part 2 presents a theoretical framework based on the trilemma described by Mundell (1963) and James & Bordo (2015). Part 3 offers a literature review on the interaction between monetary regimes and financial crises. Part 4 motivates the choice of countries through the lens of the monetary and exchange rate institutions. Part 5 presents the database both in terms of stock market variables and of dummy sequences to be used as explanatory variables. The methodological issues are separated in two parts. Part 6 describes the methodology for constructing the Boom-Bust Indicators (BBIs) for the stock market and reflects on the important issue of stationarity. Part 7 describes the construction of regime-switching matrices where we pay particular attention to, and exploit, the "dummy trap" problem. Part 8 offers a discussion of results. Part 9 concludes and presents future lines of research.

Part 2. The trilemma and financial crises

Monetary regimes are institutional arrangements and thus determinant to the economic system's vulnerability to shocks caused by macroeconomic instability (Eichengreen & Portes, 1987). A monetary arrangement has three salient features which, according to Bordo & Schwartz (1997), are the following:

- *Nominal anchor*: Regimes may be based on convertible currencies where the nominal anchor is the price of the specie, or fiat currencies where the nominal anchor is some macroeconomic variable such as the price level.
- *Exchange rates*: Convertible regimes imply a fixed exchange rate between currencies of participants while fiat currency regimes allow for exchange rates to be fixed, floating or somewhere in between.
- *Foreign sector*: Monetary regimes may have different degrees of openness of the current and capital accounts and thus may allow or restrict imports and foreign flows to and from the country in order to protect their exchange rates or manage the volatility of foreign investment.

As stated in the introduction, policy makers are faced with a macroeconomic trilemma in which they have to choose two out of three desirable goals: free monetary policy, stable exchange rates and free capital mobility. Any combination of two of these goals means sacrificing the remaining one. Fortunately, the period 1922 – 2015 offers examples of all possible combinations of these choices as presented in the following Table.

Table 1: Monetary regimes and the trilemma

Monetary Regimes and the Trilemma			
Regime	*Free monetary policy*	*Stable exchange rates*	*Free capital flows*
Interwar gold exchange standard (1922 - 1936)	NO	**YES**	**YES**
Bretton Woods (1946 - 1971)	**YES**	**YES**	NO
Managed float (1971 - 2015)	**YES**	NO	**YES**
Sources: Bordo & Schwartz (1997), Obstfeld, Shambaugh & Taylor (2005), Bordo & James (2015). Author's design			

Of course this categorization is not clean cut, particularly around the dates of regime changes. For example during the 8 years prior to the start of the Second World War, starting with the failure of the Austrian Credit-Anstalt in 1931, several countries that partook in the gold exchange standard started imposing capital controls (Eichengreen & Portes, 1987). Similarly, one of the causes for the demise of Bretton Woods was increased capital mobility (Bordo & Schwartz, 1997). During the managed float regime, several European countries took up to 1988 to remove capital controls completely (OECD, 1993). Additionally, since 1999 several European countries have adopted the Euro and formed the European Monetary Union which, because of its characteristics is closer to the interwar gold exchange standard than to a managed float regime (Bordo & James, 2015). A final criticism to this characterization is brought forward by Rey (2015) who states that there is a transmission of monetary policy from core countries towards the periphery via cross border flows and the leverage of financial institutions. For said author, this renders the possibility of independent monetary policies moot, even in the presence of floating exchange rates.

Even though this paper exploits only the structure presented in Table 1, future lines of research, that will be presented in Part 9, arise when we further the analysis by trying to characterize each monetary regime according to its elasticity. More elastic regimes will allow for more ample boom-bust cycles while less elastic regimes will be characterized by more muted evolutions of asset prices. This requires that we analyze all possible channels of transmission from the monetary regime in place onto asset prices: monetary policy can be lax or tight; there can be a

commitment to a fixed exchange rate or not; and international capital mobility can be free or restricted. The summary of the five possible channels is presented in the following Table:

Table 2: Decomposition of the trilemma into transmission channels

Decomposition of the Trilemma into Transmission Channels			
Channel	*Independent variable*		*Stance*
1	Monetary policy		Lax / tight
2	Exchange rate	International capital	Free
3	commitment	flows	Restricted
4	No exchange rate	International capital	Free
5	commitment	flows	Restricted
Sources: Author's design			

Although expanding on this theoretical construct goes well beyond the scope of this paper, an example can be illustrative. During the gold exchange standard, participating countries resigned to their independent monetary policy and obtained the benefits of free capital flows and stable exchange rates. This means channel one (monetary policy) should have no statistical significance or explanatory power during that monetary regime. Conversely, channel 2 (free capital flows under an exchange rate commitment) should be the culprit of most of the variability in the boom-bust cycle. It is noteworthy that channel 5 is irrelevant because the trilemma implies monetary authorities pick at least 2 of the objectives. In channel five they have floating exchange rates and capital controls, meaning the choice is only for free monetary policy which, by itself, may be suboptimal as shown by Almunia, et. al., (2010).

Part 3. Monetary arrangements and financial crises: Implications for policy-making

Recent literature on the link between monetary arrangements and financial and economic crises is abundant. According to Dell'Ariccia, et. al., (2013), the monetary regime in place impinges on the cost of money and credit markets which, with their booms and busts, augment asset volatility increasing the probability of negative shocks that may affect long term stability and growth. Concurrently, monetary regimes affect policy space for the resolution of crises. On one hand, countries with flexible exchange rates can respond aggressively to shocks since their monetary policy options are unfettered by exchange rate obligations (Almunia, et. al., 2010). On the other hand, economies with fixed exchange rates are unable to respond adequately to the build-up of imbalances (Dell'Ariccia, et. al., 2013). Additionally, under fixed exchange rates it becomes easier for an economy to accumulate and service debts denominated in foreign currency (Eichengreen & Bordo, 2002).

According to Kindleberger & Aliber (2005), capital inflows are relevant variables since they increase the amplitude of the credit cycle[1] —by augmenting the availability of funds for banks and possibly reducing credit constraints—, and of the asset cycle —as they increase both the demand for

[1] Although this paper does not cover the behavior of credit aggregates, the analysis can be extended from the asset cycle to the financial cycle, described by Borio (2006) as the one that emerges from the interaction of credit and asset prices.

securities and the volatility of their prices in the recipient country (Claessens & Kose 2013). Additionally, capital flows may increase a country's vulnerability to external shocks from shifts in interest rates, growth rates or perceived risk (Taylor, 2013). Finally, open capital accounts expose countries to the risk of a sudden stop, defined as a large decline or a sharp reversal in aggregate capital flows to a country which can lead to deflation since it contracts credit, prices and the value of collateral assets (Claessens & Kose, 2013).

The role of stock prices, which in this paper proxy for general asset prices, deserves special mention since they are more volatile than housing prices and thus present many more booms and busts. For example, most countries had mayor booms and busts in the pre-Second World War period. Booms after the Second World War were related to recovery in Europe (France, Italy and Switzerland). The next series of booms and busts came in the 1980s and 1990s in the United Kingdom, Germany, Italy and Sweden among others (Bordo & Landon-Lane, 2013). However, boom and bust cycles in the equity market seem to represent lower risk for the economy than those in the housing market (Claessens & Kose, 2013). Barro & Ursúa (2009) find that stock market crashes go along with minor depressions on 10% of occasions and that depressions are usually accompanied by market crashes. Mishkin & White (2002) highlight that establishing causality going from stock market crashes towards financial stability is a challenge and hint that increased risk taking by investors may be a possible channel.

Recently, researchers from the BIS and many others have highlighted that the fact that financial imbalances may accumulate under scenarios of stable inflation challenges the conventional wisdom that price stability, as guaranteed by inflation targeting regimes, is tantamount to financial stability (Borio, 2014). If the choice of a monetary regime has an effect on the accumulation and unwinding of imbalances then, necessarily it has implications for policymaking, crises prevention and crises resolution. The contribution of this paper to the literature is precisely to shed light on this relationship in order to include it in a broader debate on the role that the monetary policy reaction functions should give to asset prices and their cycle.

Currently, one side of the debate, the "Jackson Hole Consensus" (Jones, 2015, p. 8) proposes a view of benign neglect arguing that increases in asset prices should be taken into account if and only if they affect expected inflation; that it is impossible to determine whether a boom is tied or not to fundamentals making equivocal reactions in monetary policy costly in terms of output and inflation; and that there is no theoretical justification for singling out the stock market as an additional variable for monetary policy (Bernanke & Gertler, 1999, 2001). Additionally, Dell'Ariccia, et. al. (2013) indicate that tightening monetary policy will lower unobservable risk but will increase observable unemployment, the present debt burden and reduce asset prices, making policy decisions harder to take.

At the other side of the debate, the "Basel consensus" (Jones, 2015, p. 8) lead by the BIS, proposes policymakers should follow a leaning against the wind policy —monetary tightening in the face of imbalances—, as a sort of insurance against crises in order to prevent busts that may be followed by a credit crunch and a fall in output (Bordo & Jeanne, 2002). Borio & Lowe (2002) find that under a fiat currency the only constrain for the expansion of credit is the policy rule of monetary authorities. Thus, there cannot be a real anchor to the value of currency unless the

monetary rule responds to the buildup of financial imbalances. Additionally, Jordà, et. al., (2010) do not find that inflation trends serve to detect growing financial vulnerability, a strong criticism to the inflation targeting regime. They state that it is possible central banks misread the absence of inflation and kept interest rates too low for too long prior to the recent financial crises. Concurrently, Bordo & Landon-Lane (2013) find loose monetary policy is a good indicator of booms in asset prices.

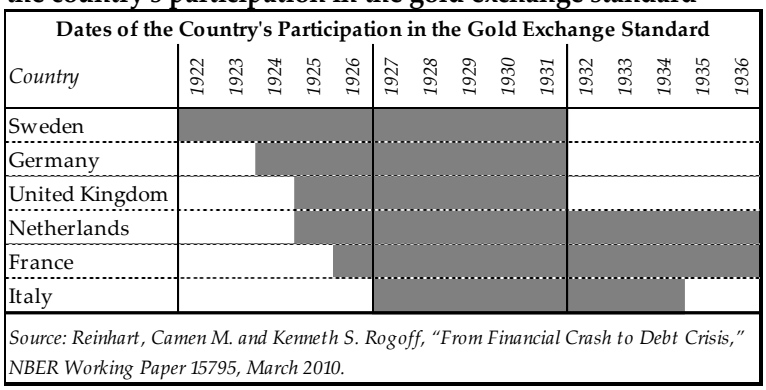
In our case, results in the direction that the accumulation and unwinding of imbalances is not contingent on the different monetary regimes may be seen as an argument in favor of a benign neglect policy and of the irrelevance of foreign sector controls. However, if the boom-bust cycle in asset prices is contingent on the monetary regime, then under regimes that are more prone to the accumulation and unwinding of imbalances there should be both a leaning against the wind policy and regulation of the foreign sector. This argument would alter the benign neglect claim and suggest that an optimal monetary order is not only that where prices are stable but where other conditions are present so as to avoid imbalances from accumulating. Additionally, it would imply that not only monetary authorities but regulators are responsible for financial stability in an environment of international cooperation, a relevant argument in favor of macroprudential regulation (Freixas, et al., 2015).

Part 4. Choice of countries

This study will be limited to Western European countries —France, Germany, Italy, the Netherlands, Sweden and the United Kingdom— instead of continuing on the tradition of long-run panel data with all available countries as in the works of Jordà, et. al., (2010, 2011, 2013, 2014), Schularick & Taylor (2012), or Reinhart & Rogoff (2009a, 2009b, 2010, 2013). The main reason to avoid a large set of countries is that it complicates disentangling specific events in each of them, and it increases the margin of error in complicated issues such as arriving to policy recommendations. Large panels of data presume comparability between countries assuming that whatever country-specific characteristics remain within the estimators for country fixed effects. A usual caveat to reducing the length of the panel has to do with the fact that since booms and busts are rare events, the variability of the independent variables may be nuanced (Jordà, et. al., 2013). We aim at resolving this issue by substituting the traditional dummy sequence for booms and busts with a more sophisticated variable that will be presented in the following section.

The choice of countries is related to the fact that they all participated in the three monetary regimes discussed. First, the following Table shows the participation of the countries in the database in the interwar gold exchange standard.

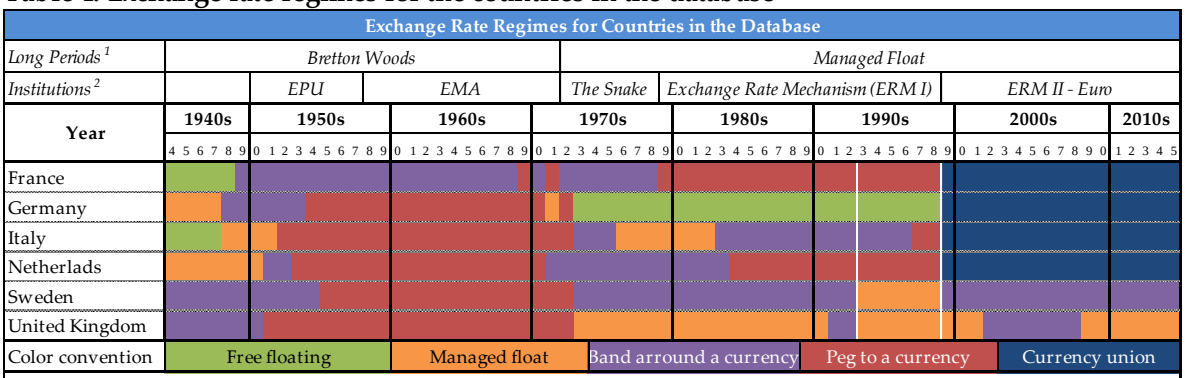
Table 3: Dates of the country's participation in the gold exchange standard



Source: Reinhart, Camen M. and Kenneth S. Rogoff, "From Financial Crash to Debt Crisis," NBER Working Paper 15795, March 2010.

Second, following Eichengreen (2008) we know that all six countries in the database were founding members of the European Payments Union (1950), and the European Monetary Agreement which came into force in 1958. These institutions were all aimed at attaining currency convertibility for Europe at fixed rates of exchange complying with the Bretton Woods agreement signed in 1944. By 1973 all countries except Sweden were members of the European Economic Community, and all participated in the "snake" (1972), an agreement where signatories would not let their pairwise currencies fluctuate more than 4.5%. In 1979 the European Monetary System and the Exchange Rate Mechanism were put in place and all countries in the database except the United Kingdom participated either explicitly or *de facto*. Exchange rates were not to be allowed to fluctuate more than 2.25%. This margin was expanded to 15% by 1993, a fact that we will exploit as a free floating regime. After 1999 all countries in the database except for Sweden and the United Kingdom adopted the Euro and lost control of their independent monetary policies. This brief recount of the exchange rate history, summarized in the following Table, serves to prove that the choice of countries will allow us to have representatives of all monetary regimes.

Table 4: Exchange rate regimes for the countries in the database



[1] *Corresponds to the periods as established in Bordo & Schwartz (1997)*
[2] *EPU - European Payments Union. EMA - European Monetary Arrangement. This institutional timing follows Eichengreen (2008)*
The white vertical lines that signal the 1993-1998 period show when the ERM band was widened to 15%
Regime changes and periods from Ilzetzki, Reinhart and Rogoff (2011)

Part 5. Database and descriptive statistics

In this section we will discuss first the construction of the stock market database and then the construction of dummy sequences that will represent each country's participation in a given

monetary and exchange rate regime at any given month in the period ranging from January 1922 to September 2015.

Stock market information

We will use monthly market-wide value-weighted stock indices expressed in real terms for the six countries starting in January 1922 and ending in September 2015. All time series were downloaded from the Global Financial Database[2] and were normalized to a value of 100 in January, 1950. When data had a daily frequency we chose as the monthly datum the last trading day of each month. Missing data were filled by using the last known value of the index. Specifics for each time series are presented next:

- *France*: The leading time series is *France CAC All-Tradable Total Return Index* which has a monthly frequency from January 1885 until January 1991 and daily frequency from January 1991 until March 2015. The data was obtained in real terms with CPI index = 100 for December 1998. There was no missing data but this series ends six months before all others.
- *Germany*: The leading time series is the *CDAX Total Return Index* which has a monthly frequency from December 1869 until December 1969 and daily frequency from January 1970 until September 2015. There is an issue with hyperinflation (1922-1923) which makes including stock prices prior to 1924 for Germany nonsensical due to an increase in measurement error. Thus we decide to cut the series and only use values starting in November 1923, the month in which Germany returned to the Gold Exchange Standard and where it remained until 1931. The data was obtained in real terms with CPI index = 100 for April 2010. There were 66 missing observations.
- *Italy*: The leading time series is the *Banca Commerciale Italiana (BCI) Index* which has a monthly frequency from September 1905 until December 1956 and daily frequency from December 1956 until September 2015. The data was obtained in real terms with CPI index = 100 for year 2010. There were 29 missing observations.
- *Netherlands*: The leading time series is the *All-Share Price Index* which has a monthly frequency from January 1919 until December 1979 and daily frequency from January 1980 until September 2015. The data was obtained in real terms with CPI index = 100 for year 2010. There were 31 missing observations.
- *Sweden*: The leading time series for Sweden is the *OMX Affärsvärldens General Index* which has a monthly frequency from January 1906 until December 1979 and daily frequency from January 1980 until September 2015. The data was obtained in real terms with CPI index = 100 for year 1980. There was no missing data.
- *United Kingdom*: The leading time series is the *UK FTSE All-Share Return Index* which has a monthly frequency from August 1694 until December 1964 and daily frequency from December 1964 until September 2015. The data was obtained in real terms with CPI index = 100 for January 1987. There was no missing data.

[2] A particular issue with the use of stock market indices for such long periods of time since their composition is not constant. This issue is partially solved by using broad market indices so that the particular weight of any single stock decreases.

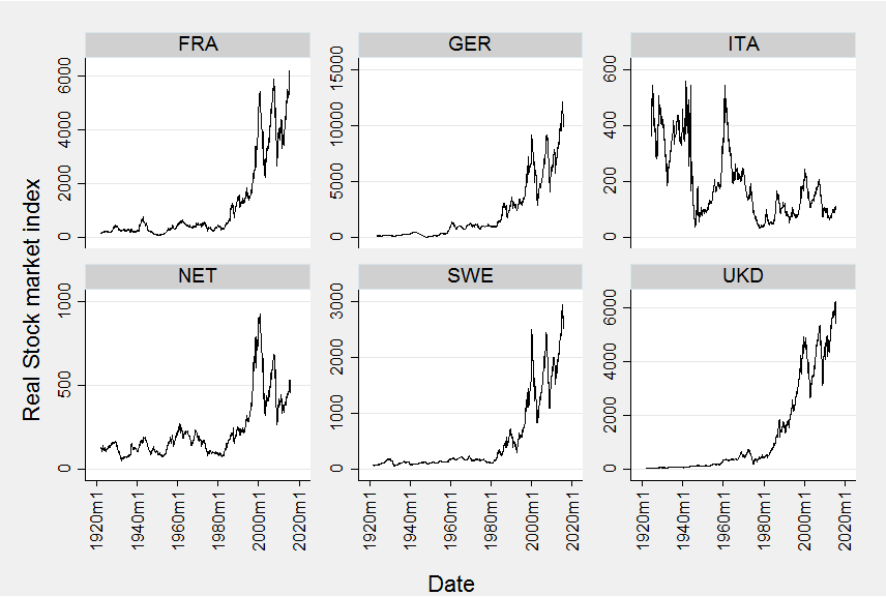
We present descriptive statistics for the series in levels in the following Table:

Table 5: Descriptive statistics for the stock market indices in levels

Descriptive statistics on stock market index levels						
	France	*Germany*	*Italy*	*Netherlands*	*Sweden*	*United Kingdom*
Observations	1119	1103	1125	1125	1125	1125
Mean	1166.44	2130.40	195.22	227.08	492.16	1259.93
Standard deviation	1485.47	2614.88	128.01	174.40	649.47	1701.99
Min	82.26	41.69	33.82	46.74	47.42	31.24
Max	6221.24	12149.17	558.90	923.51	2932.57	6252.60

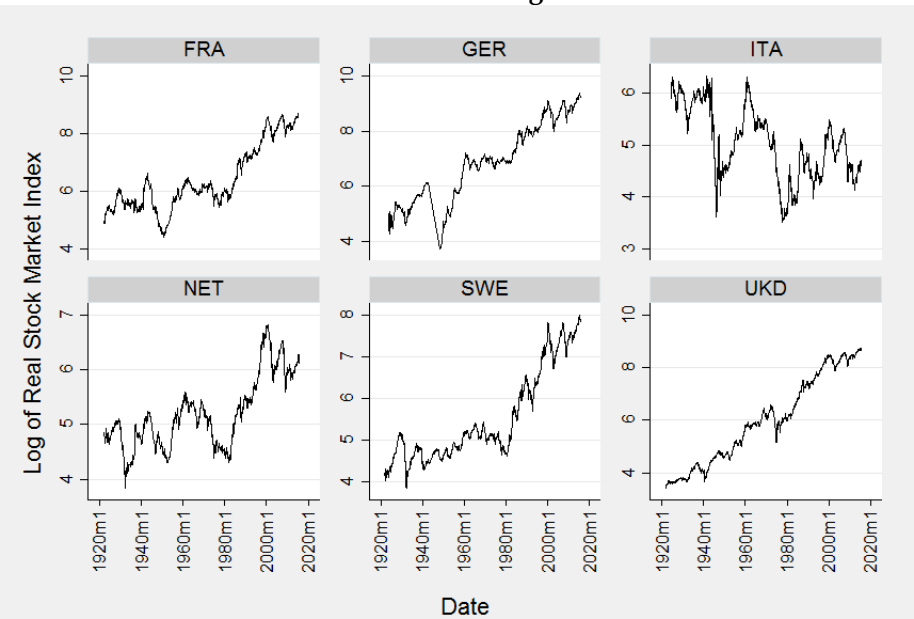
These descriptive statistics provide little information about the behavior of the stock market in each country as we are dealing with very long-run indices. Thus stating that the minimum value of the index for Italy is 33.82 or that the maximum for Sweden is 2932.57 tells us very little about the evolution of each index across time. In order to better understand our behavior we present the evolution of each index through time in the following Figure.

Figure 1: Evolution of the real stock market index in levels



Interestingly, the first half of each series appears to be much more stable than the second portion (except for Italy). This is not necessarily due to the fact that crises are become more frequent or to an increase in volatility after the 1980s but because we are presenting the series in levels. In order to correct for this bias, we present the logarithmic transformation of the indices in the following Figure.

Figure 2: Evolution of the real stock market index in logarithms



Presenting the series in this fashion allows for a clearer understanding of the overall evolution of the indices across time. Peaks, troughs and changes in volatility appear to be clearer with a simple inspection. We see, for example, all the stock markets present a crash during the 1940s, possibly due to the Second World War. A problem with this way of presenting the data is that it does not allow for side-to-side comparisons of the series since the scales on the Y axis are different. In order to compare summary statistics we calculated a linear growth rate (simple return) of the form $R_{it} = (P_{it}/P_{it-1}) - 1$ for each series. We present the summary statistics on the following Table.

Table 6: Descriptive statistics for the simple one month return on the stock market indices

Descriptive statistics on stock market index simple returns						
	France	*Germany*	*Italy*	*Netherlands*	*Sweden*	*United Kingdom*
Observations	1118	1102	1124	1124	1124	1124
Mean	0.53%	0.71%	0.20%	0.23%	0.45%	0.57%
Standard deviation	6.22%	6.01%	7.78%	4.89%	5.00%	4.66%
Min	-22.01%	-91.10%	-60.05%	-36.06%	-32.12%	-26.87%
Max	86.76%	47.82%	59.70%	23.92%	27.95%	50.05%

This summary statistics are interesting as they allow for comparisons across countries. For example, although the average monthly return is positive for all countries, Germany's average monthly growth is more than three times that of the Italian stock market. The riskiest stock market is Italy, since it has the largest sample standard deviation while the United Kingdom seems to have the safest stock market in the sample. The worst month on the whole sample saw investors lose 91.1% of their wealth (in Germany) while the worst month in France signified a loss of "only" 22.01%.

Dummy sequences for the monetary regimes

In order to study the effect the monetary regime may have on the stock market boom bust cycle it is imperative that we construct "regime dummies" that will serve as independent variables in the panel regressions. We construct eight different dummies under the following definitions:

A. DGESL: Dummy for the lax gold exchange standard. Taken from Bernanke & James (1991). It is lax because it includes both the *de facto* and the *de jure* gold exchange standard. It does not take into account periods in which convertibility was not supported or the regime was not credible.
B. DGESS: Dummy for the strict gold exchange standard. Taken from Bernanke & James (1991). It is strict because it does not include the *de jure* gold exchange standard if it did not function appropriately. Except for France and Italy it is the same as the lax dummy for all countries.
C. DPEGL: Dummy for lax pegged exchange rates. Taken from Ilzetzki, Reinhart & Rogoff (2008). It includes hard peg, crawling peg, band around a currency (any band), crawling band and managed float. It takes a value of 1 when either DPEGS or DMF take a value of 1.
D. DPEGS: Dummy for the strict pegged exchange rate regime. Taken from Ilzetzki, Reinhart & Rogoff (2008). It includes hard peg, crawling peg, band around a currency (narrower and up to 6% included) and the crawling band. If there is a double exchange rate and deviations from the peg are in double digits it takes the value of 0.
E. DMF: Dummy for managed float. Taken from Ilzetzki, Reinhart & Rogoff (2008). It includes anything that is a non-strict peg. Bands broader than 6%, managed floats, and situations in which deviations from the de jure peg exceed 10%.
F. DFFS: Dummy for the strict free floating regime. Taken from Ilzetzki, Reinhart & Rogoff (2008). Only when the authors indicate free floating regime is present.
G. DFFL: Dummy for the lax free floating regime. Taken from Ilzetzki, Reinhart & Rogoff (2008). When the authors indicate a free floating regime or when the *de jure* gold exchange standard is unbelievable.
H. DEMU: Dummy for European Monetary Union. Taken from Ilzetzki, Reinhart & Rogoff (2008). Takes a value of 1 for countries in the Euro.

Certain identities are important and they must hold.

Identity 1. $A_{t,i}+C_{t,i}+F_{t,i}+H_{t,i}=1$ for all time t and every country i. This means that every country at any point in time was in either the lax gold standard (A), the lax pegged system (C), the strict free floating (F) or the economic and monetary union (H).

Identity 2. $A_{t,i}+D_{t,i}+E_{t,i}+F_{t,i}+H_{t,i}=1$ for all time t and every country i. This identity breaks down the lax pegged system (C) in the identity 1 into a strict peg (D) or a managed float system (E).

Identity 3. $B_{t,i}+C_{t,i}+G_{t,i}+H_{t,i}=1$ for all time t and every country i. This means that every country at any point in time was in either the strict gold standard (B), the lax pegged system (C), the lax free floating (G) or the economic and monetary union (H).

Identity 4. $B_{t,i}+D_{t,i}+E_{t,i}+G_{t,i}+H_{t,i}=1$ for all time *t* and every country *i*. This identity breaks down the lax pegged system (C) in the previous identity into a strict peg (D) or a managed float system (E).

After constructing the regime dummies, we can count the number of ones per country to identify how the number of months each country spent per monetary arrangement out of the 1,125 months that span the time period January 1922 - September 2015. The following Table presents these statistics as well as the verification of the four identities for each country. The last row contains the number of observations of each stock market index.

Table 7: Descriptive statistics for regime dummies

Panel A: Number of Months in each Regime										
Monetary Regime				*France*	*Germany*	*Italy*	*Netherlands*	*Sweden*	*United Kingdom*	***Total***
Description		**Variable name**								
Gold Exchange Standard	**Lax**	*A*	*DGESL*	123	83	107	139	90	77	**619**
	Strict	*B*	*DGESS*	101	83	78	139	90	77	**568**
Pegged Rates	**Lax**	*C*	*DPEGL*	592	332	626	704	993	1,008	**4,255**
	Strict	*D*	*DPEGS*	439	252	467	616	842	438	**3,054**
Managed Float		*E*	*DMF*	153	80	159	88	151	570	**1,201**
Free Floating	**Strict**	*F*	*DFFS*	209	509	191	81	42	40	**1,072**
	Lax	*G*	*DFFL*	231	509	220	81	42	40	**1,123**
European Monetary Union		*H*	*DEMU*	201	201	201	201	0	0	**804**
Panel B: Identities										
Identity 1	$A_{t,i}+C_{t,i}+F_{t,i}+H_{t,i}=1,125$			1,125	1,125	1,125	1,125	1,125	1,125	**6,750**
Identity 2	$A_{t,i}+D_{t,i}+E_{t,i}+F_{t,i}+H_{t,i}=1,125$			1,125	1,125	1,125	1,125	1,125	1,125	**6,750**
Identity 3	$B_{t,i}+C_{t,i}+G_{t,i}+H_{t,i}=1,125$			1,125	1,125	1,125	1,125	1,125	1,125	**6,750**
Identity 4	$B_{t,i}+D_{t,i}+E_{t,i}+G_{t,i}+H_{t,i}=1,125$			1,125	1,125	1,125	1,125	1,125	1,125	**6,750**
Observations in the stock market index				1,119	1,103	1,125	1,125	1,125	1,125	**6,722**

The number of observations for each country, both for the dependent and independent variables indicates that we are dealing with a strongly balanced panel. It is important to know that the four identities for all countries are fulfilled. This will be important as there will be a regime switching matrix for each identity.

Part 6. The Boom-Bust Indicator (BBI)

For the last two decades, a rich set of literature has evolved with the aim of understanding the determinants of the behavior of the asset cycle, understanding the role monetary policy and capital flows may play in their evolution and deriving implications for both crisis management and prevention. To do so, researchers use diverse definitions of what constitutes "excessive growth" for asset prices which can be broadly categorized in two distinct groups. One group of researchers, borrows from business cycle theory and the works of Bry & Boschan (1971) and Pagan & Sossounov (2003), and uses a non-parametric algorithm, the turning point analysis, in order to find peaks and troughs in asset prices and growth time series. Other researchers use parametric filtering techniques such as the Hodrick & Prescott (1997) filter or the Band Pass filter as in Christiano & Fitzgerald (2003) to determine periods of above trend growth in those variables. Most of these analyses produce a dummy sequence that takes a value of one for crises or busts and a value of zero for calm periods or booms depending on the research question.

These dummy sequences are subject to criticism for several reasons. First, results vary from study to study as there is a lack of consensus on the way of constructing the indicators and on the conditions a variable has to fulfill in order to determine whether there is a boom or a bust (Schüler, Hiebert, & Peltonen, 2015). Second, since these sequences are distilled from data with large variability and other statistical properties such as serial correlations, many times the resulting sequence does not reflect the breadth and informational content of the underlying series (Pagan & Sossounov, 2003). Finally, Romer & Romer (2015) highlight that a dummy sequence does not allow drawing distinctions between different kinds of booms and busts but treats all booms (or busts) as formally similar events. Additionally, the fact that crises are rare events forces researchers to pool data in order to perform more robust statistical inference. That explains why most of the studies perform analysis of long and wide panels, including several tens of countries, in order to find the commonalities in the evolution of credit and asset cycles.

In order to tend to these issues, we will follow Forero-Laverde (2016) to construct a boom bust indicator that better reflects the underlying data and contains more variability than a comparable crisis dummy. To do so, we will construct an N-month linear return matrix **R** in which rows will represent time and columns will hold the return from month *t-n* until *t*. N will only take successive integer values from 1 to 12 months and then values of 18, 24, 30, 36, 42, 48, 54 and 60. When *n*=3, for example, the return refers to a quarterly measure, if *n*=24 it is the return for the two year period. The following Table depicts graphically the resulting matrix:

Table 8: Graphical representation of matrix R

Graphical representation of an N-monthly return matrix																				
Year	N-monthly return - UK stock market																			
	Short run												Medium run				Long run			
	1	2	3	4	5	6	7	8	9	10	11	12	18	24	30	36	42	48	54	60
1																				
2																				
3																				
4		A																		
…						…								…				…		
T-1																			C	
T														B						

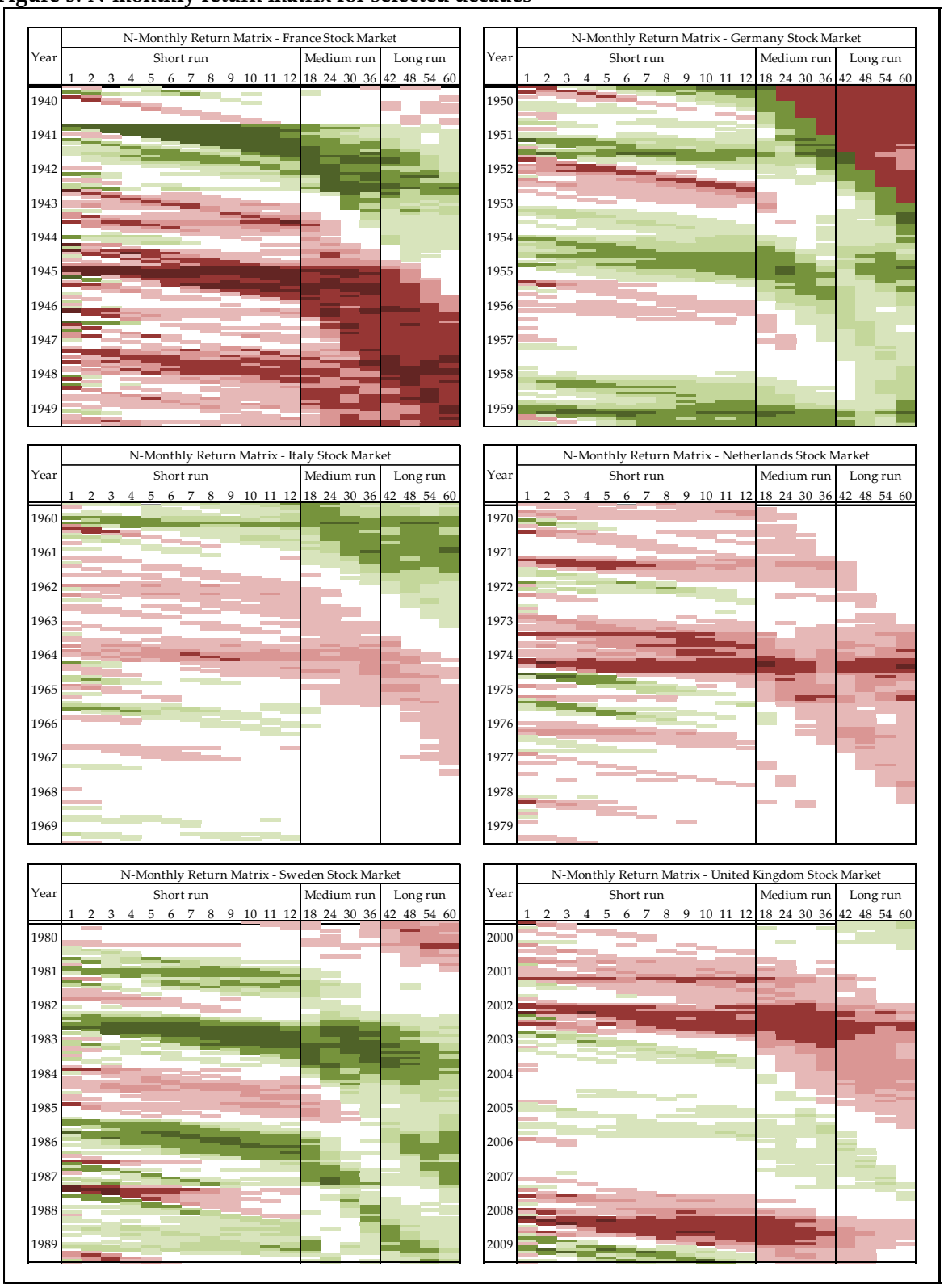
Observation A represents the two month simple return between *t*=2 and *t*=4. Observation B represents the two year return between month *T*-24 and *T*. Observation C represents the 4.5 year return between month *T*-55 and *T*-1. We have separated the returns for the first twelve values of N as short-run returns, those between 1.5 and 3 years as medium run returns and the rest as long-run returns. We use matrix **R** as input to build a heat map following a simple coloring rule on a column-by-column basis. The rule is such that returns farther away in the tails are colored darker, while if closer to the median of the distribution their color is lighter, but any return falling between

the 25th and 75th percentiles (both ends excluded) will not be colored. Left tail (first quartile) events will be colored in shades of red and right tail (fourth quartile) events will be colored in shades of green.

The following Figure presents the heat map described above for a selected decade for each country. A first issue that becomes evident is the clustering of both positive and negative returns. Second, since the heat map is based on the empirical distribution of the whole sample, darker shades of red (green) can be interpreted as the worst (best) returns in the full sample, thus allowing for comparisons between different booms and busts. An additional feature of this heat map is that colors that move farther to the right of each graph indicate more pervasive booms or busts.

Finally, the darkest shade of red (green) represents data below (above) percentile 1 (99), the next lighter shade of red (green) represents data below (above) percentile 5 (95), the third, even lighter shade of red (green) represents data below (above) percentile 10 (90). The lightest shade of red (green) represents data below (above) percentile 25 (75). The fact that data in the interquartile range is not colored attests to the fact that we are placing our emphasis on the tails of the empirical distribution.

Figure 3: N-monthly return matrix for selected decades



Providing a reading of each of the panels in Figure 3 exceeds the scope of this paper. However, the interested reader will find a post- Second World War crash in the French stock

market, strong volatility in the German market of the 1950s, a soft recovery in Italy's market of the 1960s, the effects of the 1970s'oil shocks on the Dutch stock market, a long lasting and very pervasive boom in Sweden at the beginning of the 1980s, and the "Dot.com" bubble and the recent financial crises in the UK stock market.

The BBI methodology consists of building a variable that aggregates as many of the underlying characteristics in the data as possible, including the percentile clustering discussed above. In order to do so, recall matrix **R**, where observation $r_{t,n} = [(P_t/P_{t-n}) - 1]$ for $t<n$, refers to the n-monthly return for month t. Each column vector in **R** is a time series of returns $\boldsymbol{r_n}$ with no time subscript. Let $\text{Per}_x(\boldsymbol{r_n})$ refer to the xth percentile in vector $\boldsymbol{r_n}$. Let the distance from a given percentile to the mean be measured as,

$$z_x = \frac{Per_x(\boldsymbol{r_n}) - \mu_n}{\sigma_n} \qquad (1)$$

Where μ_n is the mean and σ_n is the sample standard deviation for vector $\boldsymbol{r_n}$. Note that if $|z_1| > |z_{99}|$, the distribution is skewed to the left as it has a longer left tail, while if $|z_1| < |z_{99}|$, the distribution is skewed to the right. Then, define a grading matrix **G** with the same dimensions as **R** such that each observation $g_{t,n}$ contains a grade which is contingent on how distant observation $r_{t,n}$ is from the mean of vector $\boldsymbol{r_n}$. For distributions skewed to the left, the grade for $r_{t,n} < Per_1(\boldsymbol{r_n}) | Per_1(\boldsymbol{r_n}) < 0$ will be -10. The rest of the grading for the different bins will be built following a recursive process that uses proportions of z. For example, the grade for $Per_1(\boldsymbol{r_n}) < r_{t,n} < Per_5(\boldsymbol{r_n}) | Per_5(\boldsymbol{r_n}) < 0$ will be $-10(z_5/z_1)$. The formulae for the different grades in this recursive process are contained in the following Table.

Table 9: Recursive process for grades when r_n is skewed to the left

Recursive process for grades when r_n is skewed to the left								
Percentile	$r_{n,t}<\text{Per}_x(\mathbf{r_n}) \mid r_{n,t}<0$				$r_{nt}>\text{Per}_x(\mathbf{r_n})$			
	1	5	10	25	75	90	95	99
Grade g_x	-10	g_5=-10(z_5/z_1)	g_{10}=-10(z_{10}/z_1)	g_{25}=-10(z_{25}/z_1)	g_{75}=-10(z_{75}/z_1)	g_{90}=-10(z_{90}/z_1)	g_{95}=-10(z_{95}/z_1)	g_{99}=-10(z_{99}/z_1)

For distributions that are skewed to the right, the grade for $r_{t,n} > Per_{99}(\boldsymbol{r_n})$ will be 10. The rest of the grading for the different bins will be built following a recursive process similar to the one used in the case of distributions skewed to the left. For example, the grade for $Per_{95}(\boldsymbol{r_n}) < r_{t,n} < Per_{99}(\boldsymbol{r_n})$ will be $10(z_{95}/z_{99})$. The formulae for the different grades in this recursive process are contained in the following Table.

Table 10: Recursive process for grades when r_n is skewed to the right

Recursive process for grades when r_n is skewed to the right								
Percentile	$mt<\text{Per}x$ (**rn**)				$mt>\text{Per}x$ (**rn**)			
	1	5	10	25	75	90	95	99
Grade gx	g_1=10(z_1/z_{99})	g_5=10(z_5/z_{99})	g_{10}=10(z_{10}/z_{99})	g_{25}=10(z_{25}/z_{99})	g_{75}=10(z_{75}/z_{99})	g_{90}=10(z_{90}/z_{99})	g_{95}=10(z_{95}/z_{99})	10

Note that this process gives the largest grade (positive or negative) to the datum which is farthest away, to the right or to the left, of the center of the empirical distribution. Let the boom-bust indicator (BBI) be defined as a column vector of the form:

$$\text{BBI}=\mathbf{G}\boldsymbol{\omega}' \qquad (2a)$$

Or, in algebraic notation,

$$BBI_t = \sum_{n=1}^{N} G_{t,n}\omega_n \qquad (2b)$$

Where $\boldsymbol{\omega}$ is a column vector of weights. For ease of interpretation $\omega_n \geq 0$ and $\sum_{n=1}^{N} \omega_n = 1$. Note that by construction BBI is bounded in the interval [-10, 10]. Let us define three possible $\boldsymbol{\omega}$ to obtain an equal number of BBIs, for the short-run, for the long-run and an equally-weighted one. The weight vectors are presented in the following Table.

Table 11: Weighing vectors for different specifications of BBIs

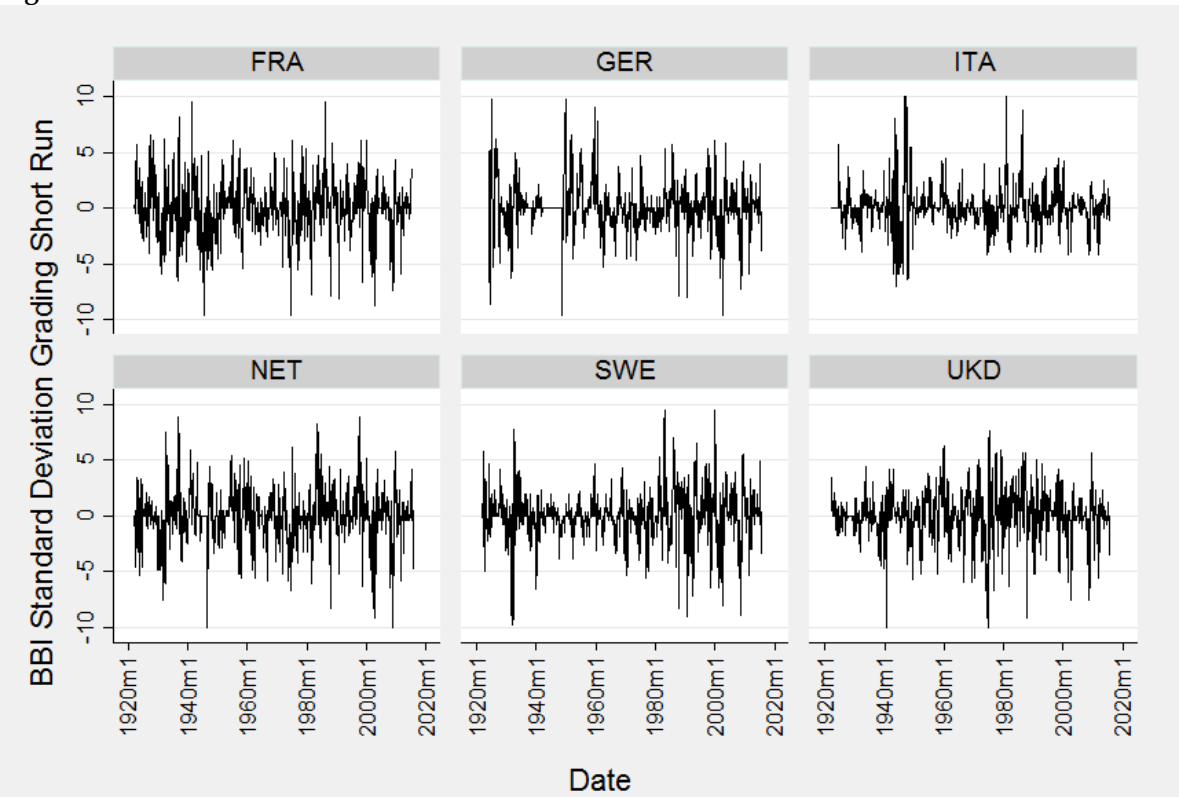
Weighing vectors for different specifications of BBIs																				
Months	Short run												Medium run				Long run			
	1	*2*	*3*	*4*	*5*	*6*	*7*	*8*	*9*	*10*	*11*	*12*	*18*	*24*	*30*	*36*	*42*	*48*	*54*	*60*
Short run (ω_s')	0.20	0.20	0.20	0.20	0.20	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Long run (ω_l')	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.00	0.20	0.20	0.20	0.20	0.20
Equally weighted (ω_e')	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05	0.05
N	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20

We expect the short-run vector to privilege non pervasive or explosive booms and busts while the long-run BBI should show reflect the more economically significant and pervasive booms or crashes, as it represents more permanent shocks. The equally-weighted specification should serve to control for the intensity of booms without discriminating for their pervasiveness. In the following subsections we present an application of the BBI methodology to the data and a discussion of stationarity of BBIs and its relevance for performing statistical inference and hypothesis testing.

BBIs for the different stock markets

We applied the BBI methodology to the stock market data for each country and obtained three different time series for each country: a short-run indicator, a long-run indicator and an equally-weighted indicator. The following Figures present the results grouped by time horizon with a brief discussion of the findings.

Figure 4: Short-run Boom Bust Indicator

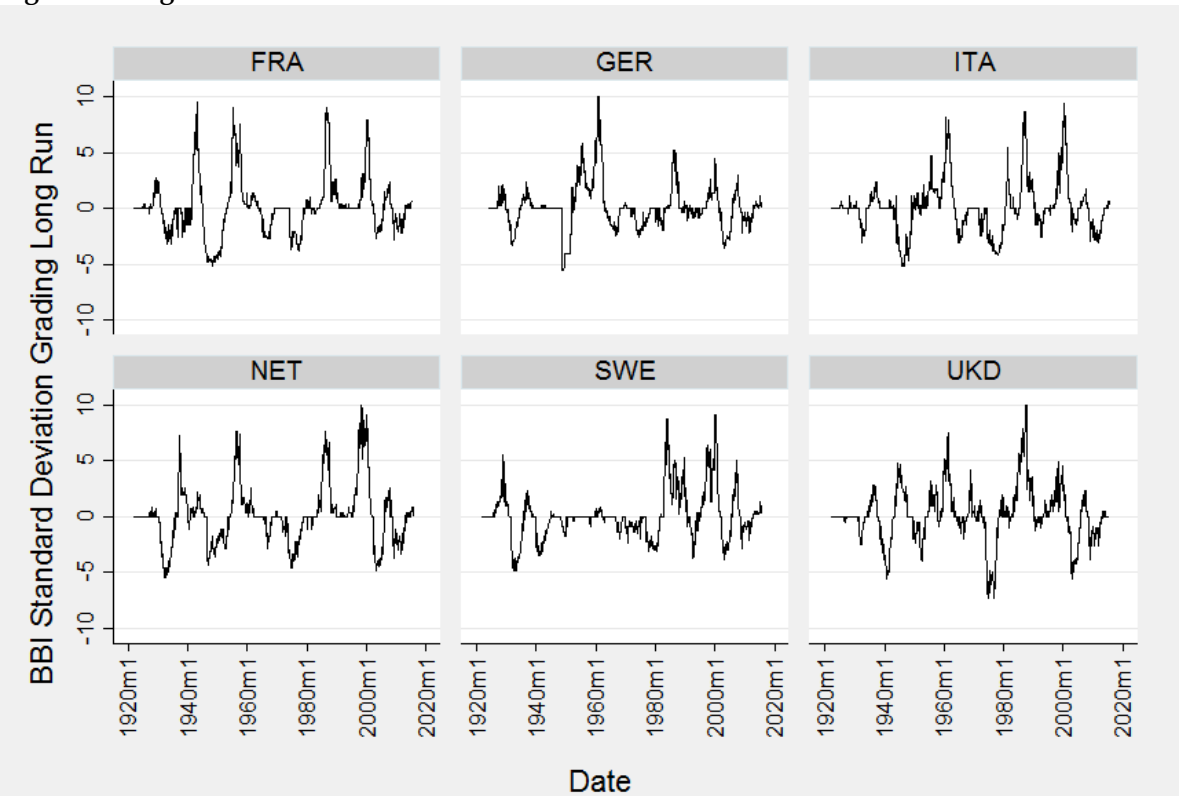


A first element that is critical to interpret these results is that they are comparable both within time series (compare for example two booms for the same country) and across time series (compare a given decade for two countries). The short-run BBI has a lot of variability, it is actually very similar to the standard graph of a return series, characterized by noise and volatility clustering (Campbell, Lo & MacKinlay, 1997).

In a country by country analysis we observe the following stylized facts. France, Germany and Sweden have booms that reach the value of 10 and busts that reach the value of -10. Meanwhile, the Netherlands and the United Kingdom have busts that reach the minimum value but booms are weaker, particularly for the UK. The case of Italy is different in the sense that busts are not as critical as in other countries, while booms tend to reach higher values.

The presence of volatility clustering is important, since we find periods where very strong booms are followed by very strong busts, and other where both booms and busts are rather muted. For example look at Sweden between 1940 and 1980 (low volatility, weak booms and busts) vis-à-vis the period ranging from 1980 until today (high volatility, strong and explosive booms and busts). This graph, however, does not allow us to derive any kind of conclusion about the pervasiveness of a boom or a bust process. This will be better evidenced in the following Figure.

Figure 5: Long-run Boom Bust Indicator



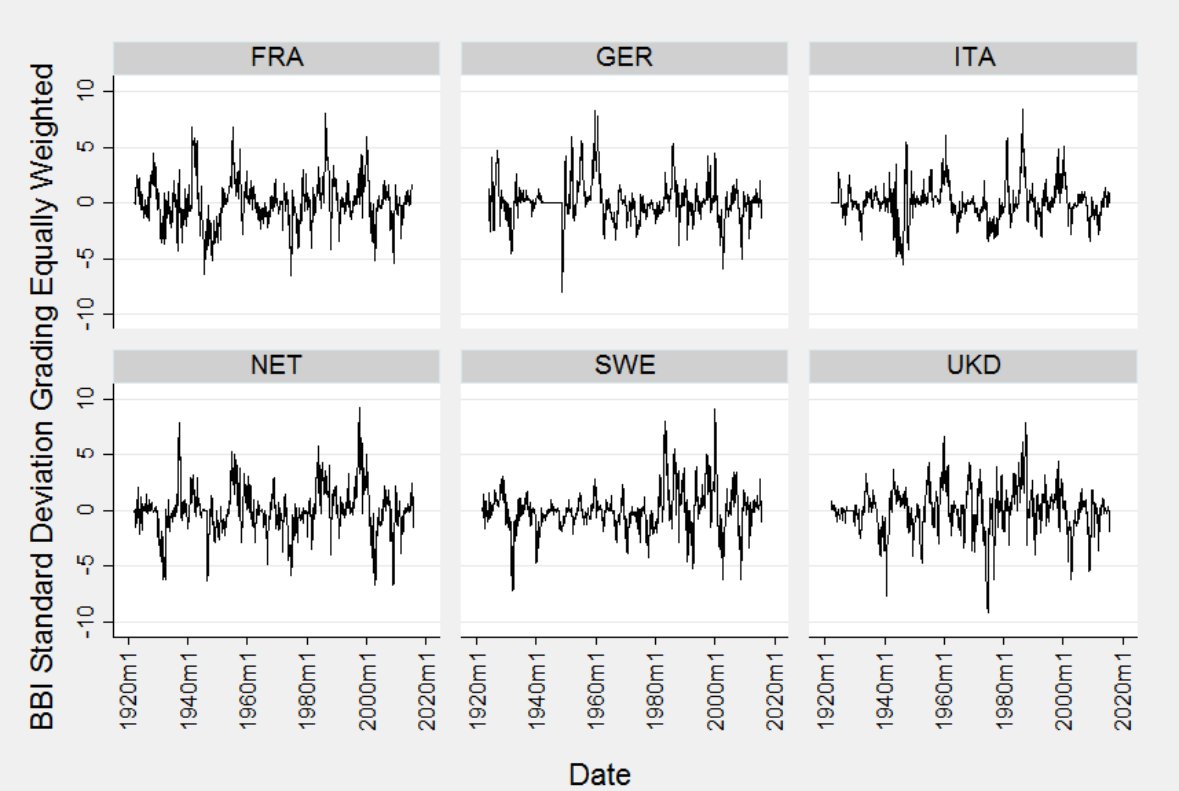
The long-run indicator is far less noisy than the BBI for the short-run specification. However, it still maintains an important level of variability that we will exploit in the following section. This indicator, as shown by Forero-Laverde (2016), measures the pervasiveness of any given boom or bust. Intuitively, it shows whether a boom or a bust affects very long-run returns in the R matrix (when N>36 months).

A first glance shows that booms are more pervasive than busts for all countries. This is true since booms in every country reach higher absolute values of the indicator than busts, which is in stark contrast with what we evidenced for the short-run BBIs. The French, German and Swedish short-run BBIs cover the full [-10, 10] interval while, in terms of the pervasiveness evidenced by this indicator, not a single country covers the full range. A possible reason for the long-run pervasiveness of booms has to do with the fact that no policymaker wants to be responsible for "bursting the bubble" and causing a reduction in asset prices. Since the distance between the fundamental price of an asset and its market value cannot be adequately measured, very long lasting booms can be seen as positive events and not necessarily as excessive accumulation of financial imbalances thus delaying or even deterring policy action. Busts, on the other hand, are clearly negative events and policymakers, regulators and agents tend to act in order to avoid their negative effects. Effective action should effectively reduce their pervasiveness.

We can see busts that are common to all countries, such as the 1940s, the 1970s, and the recent 2008 crisis. Common booms can be found in the late 1950s and early 1960s (except for Sweden) and in the early 2000s. This is interesting as it hints about the possibility of contagion. Additionally, In most series, except for France and Germany, recent booms are more intense than

earlier booms. Contrarily, for all series the more extreme busts tend to maintain their level of pervasiveness. In the next Figure we present the equally-weighted indicator which looks at overall booms and busts without weighing them for pervasiveness (long-run BBI) or explosiveness (short-run BBI).

Figure 6: Equally-weighted Boom Bust Indicator



The equally-weighted indicator offers a combination of the previous results. First, it is less noisy than the short-run indicator but allows to observe volatility clustering through time. It is more flexible so that smaller less pervasive booms and busts can be identified in the time series. This indicator is useful if a researcher wants to delve in deeper into the story of specific short-run market events that are smoothed away in the long-run indicator. The fact that the three indicators show different things is an indication that the three of them should be used as dependent variables in the panel data analysis.

Time series analysis of BBIs: Trend and stationarity

Two relevant issues arise when preparing time series for regression analysis. First, it is important to identify whether there is a trend in the series as to a void spurious results that are due more to the trend than to the effect represented by the independent variables. In that sense, we performed a regression of each BBI for each country on a single time dependent variable, a counter of sorts that covered all positive integers from 1 to 1,125 with a delta of 1 per month. Results are presented in the following Table.

Table 12: Trend analysis for BBIs

Regression of BBIs on time trend				
		BBI_{Short}	BBI_{Long}	BBI_{Equal}
France	*Coefficient*	0.0001127	0.0007104***	0.0002761
	S.E.	0.0002318	0.0002356	0.0001868
	T-statistic	0.49	3.01	1.48
Germany	*Coefficient*	-0.0004335**	-0.0002032	-0.0004634***
	S.E.	0.0002104	0.0001917	0.0001633
	T-statistic	-2.06	-1.06	-2.84
Italy	*Coefficient*	-0.0000599	0.0005579***	0.0001396
	S.E.	0.0001668	0.0002146	0.0001471
	T-statistic	-0.36	2.6	0.95
Netherlands	*Coefficient*	0.0001789	.0009993***	.0004685**
	S.E.	0.0002142	0.000244	0.0001901
	T-statistic	0.84	4.1	2.46
Sweden	*Coefficient*	.0004006*	0.001486***	0.0009023***
	S.E.	0.0002059	0.0001972	0.0001687
	T-statistic	1.95	7.54	5.35
United Kingdom	*Coefficient*	-0.0000118	0.000179	0.0000753
	S.E.	0.0002028	0.0002259	0.0001847
	T-statistic	-0.06	0.79	0.41
*Two sided test significance levels: ***=99%, **95%, *=90%*				

We identify trends at any significance level for half the sample. Trends are most frequently found for the Swedish BBIs and they do not appear for the United Kingdom. All other countries have some sort of trend in at least one of the BBI specifications. Analyzing only the significant trends, we find that all trends for France, Italy, Sweden and the Netherlands are positive while all trends for Germany are negative. This is consistent with the stronger presence of pervasive booms reflected on in the previous section

Even if the value of the coefficient is statistically significant, a first glance at the table shows that their economic significance can be question. Recall that the boom bust indicator is a random variable that is bounded in the [-10, 10] interval. This means that the highest absolute value of the trend coefficient (for Sweden's long-run BBI) is on 0.01486% of the maximum value of the indicator. This raises questions about the economic significance of the trend component which are even more profound after inspecting the Figures presented in the previous subsection, and will come in stark contrast with the value of the coefficients of the panel regressions in Part 7. Detrended variables could be used in the following section, but this will be performed for a future version of this paper as a robustness check.

A more relevant issue that has to be analyzed before performing any sort of regression variable has to do with stationarity. Following Wooldridge (2002), the ideal scenario is one in which the dependent variable is stationary so as to ensure that the variability explained in the regressions is due to the independent variables and not to changes in the DGP for the dependent variables. Additionally, stationary I(0) variables are not subject to issues of cointegration and mitigate the spurious regression problem. For monthly variables, such as BBIs we ran an Augmented Dickey

Fuller (ADF) test for up to twelve lags. For variables that have a trend component, albeit small but statistically significant, we ran the ADF test both for the variable with and without a trend component. Results are presented in the following Tables. Recall that if the test statistic is larger than the critical value there is no evidence of unit root, in other words, we can treat the process as stationary.

Table 13: ADF test for short-run BBI

T statistic for the Augmented Dickey Fuller test on BBI_{Short}								
Lags	**France**	**Germany**		**Italy**	**Netherlands**	**Sweden**		**United Kingdom**
		No trend	*Trend*			*No trend*	*Trend*	
0	-14.063	-12.269	-12.293	-14.598	-13.863	-13.683	-13.700	-14.523
1	-14.335	-13.589	-13.613	-15.315	-14.301	-13.968	-13.986	-14.763
2	-13.039	-12.682	-12.704	-14.386	-13.525	-12.707	-12.722	-13.250
3	-12.794	-12.148	-12.180	-12.919	-13.441	-12.708	-12.740	-13.059
4	-11.607	-12.117	-12.172	-11.738	-12.002	-11.384	-11.429	-12.734
5	-10.492	-10.650	-10.715	-10.781	-10.948	-9.880	-9.922	-10.697
6	-10.226	-10.759	-10.842	-10.253	-10.346	-9.472	-9.515	-9.834
7	-9.128	-9.787	-9.866	-9.696	-9.256	-8.822	-8.862	-9.238
8	-8.790	-9.623	-9.679	-8.954	-8.643	-8.545	-8.580	-8.787
9	-8.365	-8.844	-8.896	-8.314	-8.276	-8.455	-8.492	-8.740
10	-8.030	-8.295	-8.357	-8.250	-7.932	-8.080	-8.104	-8.588
11	-7.764	-8.284	-8.344	-7.665	-7.520	-8.495	-8.537	-8.419
12	-7.939	-8.823	-8.868	-8.678	-7.864	-8.612	-8.650	-8.669

If T-statistic > than critical value there is no evidence of a unit root.
Critical values without trend: 1% = -3.430, 5% = -2.860, 10% = -2.570
Critical values with trend: 1% = -3.960, 5% = -3.410, 10% = -3.120

Table 14: ADF test for long-run BBI

T statistic for the Augmented Dickey Fuller test on BBI_{Long}										
Lags	**France**		**Germany**	**Italy**		**Netherlands**		**Sweden**		**United Kingdom**
	No trend	*Trend*		*No trend*	*Trend*	*No trend*	*Trend*	*No trend*	*Trend*	
0	-3.292	-3.309	-3.816	-3.830	-3.841	-3.347	-3.368	-3.922	-4.021	-4.153
1	-3.309	-3.326	-3.716	-3.591	-3.602	-3.186	-3.207	-3.656	-3.750	-3.713
2	-3.303	-3.320	-3.615	-3.503	-3.514	-3.272	-3.293	-3.448	-3.539	-3.622
3	-3.298	-3.316	-3.760	-3.399	-3.409	-3.255	-3.276	-3.930	-4.033	-3.502
4	-3.732	-3.751	-3.577	-3.462	-3.473	-3.508	-3.531	-3.877	-3.980	-3.625
5	-4.008	-4.028	-3.449	-3.459	-3.469	-3.618	-3.642	-3.917	-4.023	-3.481
6	-4.362	-4.384	-3.981	-3.923	-3.935	-3.585	-3.609	-4.627	-4.749	-3.672
7	-4.163	-4.185	-3.942	-3.884	-3.895	-3.282	-3.304	-4.862	-4.993	-3.863
8	-4.563	-4.588	-4.046	-4.115	-4.127	-3.535	-3.560	-4.774	-4.905	-3.811
9	-4.398	-4.422	-4.048	-4.170	-4.183	-3.557	-3.583	-4.763	-4.898	-3.668
10	-4.298	-4.322	-4.010	-4.122	-4.135	-3.646	-3.673	-4.643	-4.777	-3.784
11	-4.393	-4.417	-4.169	-4.412	-4.427	-3.776	-3.805	-4.893	-5.038	-3.920
12	-4.846	-4.874	-4.798	-4.902	-4.919	-4.238	-4.270	-4.887	-5.036	-4.103

If T-statistic > than critical value there is no evidence of a unit root.
Critical values without trend: 1% = -3.430, 5% = -2.860, 10% = -2.570
Critical values with trend: 1% = -3.960, 5% = -3.410, 10% = -3.120

Table 15: ADF test for equally-weighted BBI

T statistic for the Augmented Dickey Fuller test on $BBI_{Equally}$									
Lags	**France**	**Germany**		**Italy**	**Netherlands**		**Sweden**		**United Kingdom**
		No trend	*Trend*		*No trend*	*Trend*	*No trend*	*Trend*	
0	-7.436	-7.242	-7.273	-7.829	-7.259	-7.269	-7.332	-7.418	-7.87
1	-7.558	-7.766	-7.796	-7.826	-7.321	-7.332	-7.318	-7.402	-7.848
2	-6.724	-7.54	-7.569	-7.172	-6.867	-6.877	-6.797	-6.873	-7.168
3	-6.535	-7.6	-7.636	-6.598	-6.796	-6.808	-6.992	-7.089	-7.018
4	-6.397	-7.932	-7.985	-6.453	-6.491	-6.499	-6.754	-6.864	-7.344
5	-6.491	-7.569	-7.627	-6.41	-6.548	-6.553	-6.515	-6.624	-6.872
6	-6.284	-7.569	-7.637	-6.448	-6.175	-6.179	-6.723	-6.836	-6.623
7	-5.774	-7.133	-7.197	-6.245	-5.746	-5.752	-6.513	-6.623	-6.65
8	-5.941	-7.226	-7.276	-6.115	-5.561	-5.567	-6.575	-6.682	-6.356
9	-5.707	-6.715	-6.763	-5.933	-5.507	-5.521	-6.645	-6.757	-6.386
10	-5.58	-6.572	-6.629	-6.035	-5.457	-5.471	-6.547	-6.644	-6.318
11	-5.465	-6.299	-6.35	-5.684	-5.157	-5.168	-6.769	-6.895	-6.157
12	-5.591	-6.536	-6.574	-6.316	-5.325	-5.342	-6.55	-6.669	-6.022

If T-statistic > than critical value there is no evidence of a unit root.
Critical values without trend: 1% = -3.430, 5% = -2.860, 10% = -2.570
Critical values with trend: 1% = -3.960, 5% = -3.410, 10% = -3.120

The results from the previous three Tables point in the same direction. All BBIs, for each country and for any given number of lags up to twelve, are stationary with 95% confidence. For the short-run and equally-weighted BBIs this holds true with a confidence level of 99%. After these tests we can confidently run panel regressions, the results of which are presented in the next section.

Part 7. Regime-switching matrices and dummy identities

Using the BBIs described in the previous section as dependent variables, we will investigate the question of whether the monetary and exchange rate institutions that occurred during the twentieth century impinge on the evolution of the stock market's boom bust cycle. We will do so by running regime dummy regressions on the strongly balance panel described in Part 5. We will run four different sets of regressions, one for each identity presented in the second subsection of Part 5, with country fixed effects.

In the specification we need to avoid the "dummy variable trap" which appears when all dummy variables are included as regressors, since a linear transformation of them may cause perfect collinearity[3]. In a traditional dummy regression, for example when the dummy represents gender (male=1 and female=0) the effect of being female is captured by the intercept in the regression and the effect of being male is the sum of the intercept and the coefficient for the dummy

[3] Recall that the identities presented in Part 5 indicate that the sum of each set of dummy variables for all *i* and for each *t* are equal to 1 by definition.

variable. However, when using more than one dummy variable for the same phenomenon, the monetary regime, the value of the intercept cannot be interpreted as the coefficient for the base case (the omitted dummy) (Wooldridge, 2002). Hence, we must change the identification strategy in order to obtain interpretable coefficients that allow for hypothesis testing.

Thus we define a regime switching matrix as an array that contains all possible regressions under a given set of regime dummy variables. For example, the specification for the regression of the dummies in Identity 1 on the short-run BBI would take the following form:

$$\mathrm{BBIs}_{i,t} = f\left(DGESL_{i,t}, DPEGL_{i,t}, DFFS_{i,t}, DEMU_{i,t}\right) \qquad (3)$$

Where the index i refers to the country and t to the time series component. The specific regressions would be the following:

$$\mathrm{BBIs}_{i,t} = \beta_0 + \beta_1 \mathrm{DPEGL}_{i,t} + \beta_2 \mathrm{DFFS}_{i,t} + \beta_3 \mathrm{DEMU}_{i,t} + \alpha_i + u_{i,t} \qquad (4a)$$

$$\mathrm{BBIs}_{i,t} = \beta_0 + \beta_1 \mathrm{DGESL}_{i,t} + \beta_2 \mathrm{DFFS}_{i,t} + \beta_3 \mathrm{DEMU}_{i,t} + \alpha_i + u_{i,t} \qquad (4b)$$

$$\mathrm{BBIs}_{i,t} = \beta_0 + \beta_1 \mathrm{DGESL}_{i,t} + \beta_2 \mathrm{DPEGL}_{i,t} + \beta_3 \mathrm{DEMU}_{i,t} + \alpha_i + u_{i,t} \qquad (4c)$$

$$\mathrm{BBIs}_{i,t} = \beta_0 + \beta_1 \mathrm{DGESL}_{i,t} + \beta_2 \mathrm{DPEGL}_{i,t} + \beta_3 \mathrm{DFFS}_{i,t} + \alpha_i + u_{i,t} \qquad (4d)$$

Where α_i refers to the country fixed effects- Note that the omitted dummy in each of the regression establishes the base case and the coefficients can be interpreted as the change in the dependent variable due to a change from the base case regime to the regime represented by the dummy of interest. Thus, for example in equation 4b, β_2 can be interpreted as the change in the short-run BBI when there is a regime switch form the lax peg regime (the omitted dummy) to the strict free floating regime. This regression structure and interpretation of coefficients is similar for all 4 identities.

Interestingly, in equation 4a, β_3 can be interpreted as the change in the short-run BBI when there is a regime switch form the lax gold exchange standard (the omitted dummy) to the European Monetary Union. Even if this case does not make historical sense, the coefficient identifies whether the BBI is statistically different under both regimes. This is comparable to a differences-in-means analysis that covers several means at the same time. It is in this sense that we provide the interpretation of results.

It is important to recall that identities 1 and 3 contain 4 dummy variables since they have a broader definition of a peg system (DPEGL). Identities 2 and 4 break this broad definition of the peg into two more granular variables: one for strict pegs (DPEGS) and the other for the managed float (DMF). On the other hand, identities 1 and 2 have strict definitions of the gold exchange standard (DGESS) and the free floating regime (DFFS) while identities 3 and 4 have more lax definitions for both variables (DGESL and DFFL respectively). The dummy for the European Monetary Union (DEMU) is the same for all especifications.

The resulting matrix has an empty diagonal and the upper triangle is similar the lower triangle only that coefficients have changed signs. In the following subsections we interpret only the upper triangles (data above the diagonal). In all tables, data that is statistically significant with a 95% confidence is highlighted in bold and it contains the only results we analyze. All regressions contain the F-statistic and p-value for a test of joint significance of the coefficients. As stated before, even if the intercept is statistically significant we do not analyze it as it has no relevance for the analysis.

Identity 1

This identity analyses the lax gold exchange standard (DGESL), the lax pegged rate (DPEGL), the strict free floating (DFFS), and the European Monetary Union (DEMU) regimes.

Table 16: Regime switching matrix for Identity 1

	Dependent variable		BBI_{Short}				BBI_{Long}				$BBI_{Equally}$			
	Moving to…		*DGESL*	*DPEGL*	*DFFS*	*DEMU*	*DGESL*	*DPEGL*	*DFFS*	*DEMU*	*DGESL*	*DPEGL*	*DFFS*	*DEMU*
Moving from…	DGESL	*Coefficient*		**-0.207**	0.101	0.167		-0.601	0.023	-0.235		-0.392	0.125	0.125
		RSE		**0.059**	0.075	0.072		0.395	0.531	0.390		0.217	0.318	0.212
		T-statistic		**-3.530**	1.340	2.310		-1.520	0.040	-0.600		-1.800	0.390	0.590
		P Value		**0.017**	0.239	0.069		0.189	0.967	0.573		0.131	0.710	0.581
	DPEGL	*Coefficient*	**0.207**		**0.307**	**0.374**	0.601		**0.624**	0.366	0.392		**0.517**	**0.517**
		RSE	**0.059**		**0.047**	**0.045**	0.395		**0.236**	0.203	0.217		**0.142**	**0.114**
		T-statistic	**3.530**		**6.540**	**8.220**	1.520		**2.640**	1.800	1.800		**3.650**	**4.540**
		P Value	**0.017**		**0.001**	**0.000**	0.189		**0.046**	0.131	0.131		**0.015**	**0.006**
	DFFS	*Coefficient*	-0.101	**-0.307**		0.067	-0.023	**-0.624**		-0.258	-0.125	**-0.517**		0.000
		RSE	0.075	**0.047**		0.077	0.531	**0.236**		0.374	0.318	**0.142**		0.237
		T-statistic	-1.340	**-6.540**		0.870	-0.040	**-2.640**		-0.690	-0.390	**-3.650**		0.000
		P Value	0.239	**0.001**		0.425	0.967	**0.046**		0.521	0.710	**0.015**		0.999
	DEMU	*Coefficient*	-0.167	**-0.374**	-0.067		0.235	-0.366	0.258		-0.125	**-0.517**	0.000	
		RSE	0.072	**0.045**	0.077		0.390	0.203	0.374		0.212	**0.114**	0.237	
		T-statistic	-2.310	**-8.220**	-0.870		0.600	-1.800	0.690		-0.590	**-4.540**	0.000	
		P Value	0.069	**0.000**	0.425		0.573	0.131	0.521		0.581	**0.006**	0.999	
	Intercept	*Coefficient*	-0.105	0.101	-0.206	-0.273	-0.306	0.296	-0.328	-0.071	-0.181	0.210	-0.307	-0.307
		RSE	0.053	0.009	0.042	0.044	0.367	0.044	0.228	0.189	0.206	0.018	0.141	0.111
		T-statistic	-1.970	11.050	-4.860	-6.270	-0.830	6.650	-1.440	-0.370	-0.880	11.600	-2.170	-2.750
		P Value	0.106	0.000	0.005	0.002	0.443	0.001	0.209	0.725	0.418	0.000	0.082	0.040
	R2 (Between)		0.444				0.174				0.685			
	Observations		6721				6721				6721			
	F-test	*Statistic*	**61.930**				**7.690**				**50.670**			
		P Value	**0.000**				**0.026**				**0.000**			

Moving from the lax gold exchange standard to the lax pegged rate system translates in a decrease in the short-run BBI, which may be indicative of a stronger propensity of the peg regime to crises or, conversely a stronger presence of short-run booms in the gold exchange standard.

Moving from the lax pegged rate to any other regime causes increases in the short-run BBI. This may be interpreted as the peg regime being the most prone to low values of the short-run indicator (more presence of crises and less presence of booms). This effect remains for changes towards the free floating regime and the EMU in the equally-weighted BBI, probably indicating a longer effect for these two. There appears to be an important long-run effect on the BBI when there is a change from a peg regime towards a strict free floating regime as evidence by an increase of 0.64 units in the indicator which indicates propensity to more booms (or at least less crises) in the strict free float regime rather than in the peg regime. It is important to indicate that the size of the statistically significant coefficients in these regressions seem to also bear economic significance.

Moving from the strict free floating towards the EMU has no statistically significant effect for any of the specifications of the BBIs. Since this is the change that occurred for 4 out of six countries in the database in 1999, it might be interesting to delve deeper into the argument that a single

currency reduces financial fragility. Interestingly the F-test indicates that coefficients are jointly significant under all specifications of the regressions.

Identity 2

This identity is similar to Identity 1, but the lax pegged rate regime dummy (DPEGL) is broken down into a strict peg (DPEGS) and a managed float (DMF). All other variables remain the same.

Table 17: Regime switching matrix for Identity 2

	Dependent variable		BBI_{Short}					BBI_{Long}					$BBI_{Equally}$				
	Moving to…		*DGESL*	*DPEGS*	*DMF*	*DFFS*	*DEMU*	*DGESL*	*DPEGS*	*DMF*	*DFFS*	*DEMU*	*DGESL*	*DPEGS*	*DMF*	*DFFS*	*DEMU*
Moving from…	DGESL	*Coefficient*		-0.221	**-0.164**	0.100	0.166		-0.778	-0.079	0.019	-0.253		-0.474	-0.147	0.123	0.117
		RSE		0.089	**0.049**	0.076	0.075		0.485	0.440	0.530	0.399		0.271	0.169	0.318	0.219
		T-statistic		-2.470	**-3.370**	1.320	2.210		-1.600	-0.180	0.040	-0.630		-1.750	-0.870	0.390	0.530
		P Value		0.056	**0.020**	0.244	0.078		0.170	0.865	0.973	0.554		0.141	0.426	0.714	0.617
	DPEGS	*Coefficient*	0.221		0.057	**0.321**	**0.387**	0.778		0.699	**0.796**	0.525	0.474		0.328	**0.598**	**0.591**
		RSE	0.089		0.132	**0.061**	**0.058**	0.485		0.639	**0.250**	0.262	0.271		0.303	**0.135**	**0.143**
		T-statistic	2.470		0.430	**5.310**	**6.690**	1.600		1.090	**3.180**	2.000	1.750		1.080	**4.440**	**4.130**
		P Value	0.056		0.683	**0.003**	**0.001**	0.170		0.324	**0.024**	0.102	0.141		0.329	**0.007**	**0.009**
	DMF	*Coefficient*	**0.164**	-0.057		0.264	**0.330**	0.079	-0.699		0.097	-0.175	0.147	-0.328		0.270	0.263
		RSE	**0.049**	0.132		0.104	**0.104**	0.440	0.639		0.599	0.499	0.169	0.303		0.314	0.231
		T-statistic	**3.370**	-0.430		2.550	**3.160**	0.180	-1.090		0.160	-0.350	0.870	-1.080		0.860	1.140
		P Value	**0.020**	0.683		0.051	**0.025**	0.865	0.324		0.877	0.741	0.426	0.329		0.428	0.307
	DFFS	*Coefficient*	-0.100	**-0.321**	-0.264		0.065	-0.019	**-0.796**	-0.097		-0.272	-0.123	**-0.598**	-0.270		-0.007
		RSE	0.076	**0.061**	0.104		0.076	0.530	**0.250**	0.599		0.365	0.318	**0.135**	0.314		0.232
		T-statistic	-1.320	**-5.310**	-2.550		0.860	-0.040	**-3.180**	-0.160		-0.740	-0.390	**-4.440**	-0.860		-0.030
		P Value	0.244	**0.003**	0.051		0.431	0.973	**0.024**	0.877		0.490	0.714	**0.007**	0.428		0.978
	DEMU	*Coefficient*	-0.166	**-0.387**	**-0.330**	-0.065		0.253	-0.525	0.175	0.272		-0.117	**-0.591**	-0.263	0.007	
		RSE	0.075	**0.058**	**0.104**	0.076		0.399	0.262	0.499	0.365		0.219	**0.143**	0.231	0.232	
		T-statistic	-2.210	**-6.690**	**-3.160**	-0.860		0.630	-2.000	0.350	0.740		-0.530	**-4.130**	-1.140	0.030	
		P Value	0.078	**0.001**	**0.025**	0.431		0.554	0.102	0.741	0.490		0.617	**0.009**	0.307	0.978	
	Intercept	*Coefficient*	-0.105	0.117	0.060	-0.205	-0.270	-0.295	0.483	-0.217	-0.314	-0.042	-0.177	0.298	-0.030	-0.300	-0.293
		RSE	0.051	0.042	0.090	0.043	0.044	0.356	0.186	0.459	0.237	0.183	0.200	0.090	0.214	0.146	0.107
		T-statistic	-2.040	2.750	0.660	-4.820	-6.200	-0.830	2.590	-0.470	-1.320	-0.230	-0.880	3.290	-0.140	-2.060	-2.750
		P Value	0.097	0.040	0.536	0.005	0.002	0.444	0.049	0.657	0.243	0.827	0.417	0.022	0.894	0.095	0.040
	R2 (Between)		0.433					0.029					0.770				
	Observations		6721					6721					6721				
	F-test	*Statistic*	**360.390**					**5.780**					**45.060**				
		P Value	**0.000**					**0.041**					**0.000**				

Moving from the lax gold exchange standard to the strict pegged rate system translates in a decrease in the short-run BBI, which may confirm the findings in identity 1. The value of the coefficient remain significant at the 98% confidence, but slightly reduce its value after removing the managed float regime from the lax peg dummy.

Moving from the strict pegged rate to the managed float regime has no effect on any BBI specification. However, moving towards the free float regime has a positive and significant effect on all specifications of the BBI, indicating that the free float regime is more prone to booms, or less prone to crises than the peg rate system. This is consistent with what was found in Identity 1. Changing towards the EMU affects positively the equally-weighted definition of the BBI, and changes the long-run BBI in a positive direction, being almost significant to the 90% confidence level.

Moving from the managed floating regime towards the EMU has a positive and statistically significant effect for the short-run specification of the BBI but on no other specification. Changes from the managed floating regime towards the EMU are irrelevant. Interestingly the F-test indicates that coefficients are jointly significant under all specifications of the regressions.

Identity 3

This identity analyses the strict gold exchange standard (DGESS), the lax pegged rate (DPEGL), the lax free floating (DFFL) and the European Monetary Union (DEMU) regimes.

Table 18: Regime switching matrix for Identity 3

	Dependent variable		BBI_{Short}				BBI_{Long}				$BBI_{Equally}$			
	Moving to…		*DGESS*	*DPEGL*	*DFFL*	*DEMU*	*DGESS*	*DPEGL*	*DFFL*	*DEMU*	*DGESS*	*DPEGL*	*DFFL*	*DEMU*
Moving from…	DGESS	*Coefficient*		**-0.293**	-0.045	0.075		-0.669	-0.089	-0.307		-0.480	-0.026	0.031
		RSE		**0.102**	0.114	0.121		0.425	0.546	0.436		0.238	0.307	0.251
		T-statistic		**-2.860**	-0.400	0.620		-1.570	-0.160	-0.700		-2.020	-0.080	0.120
		P Value		**0.035**	0.707	0.561		0.177	0.877	0.513		0.100	0.936	0.907
	DPEGL	*Coefficient*	**0.293**		**0.247**	**0.368**	0.669		**0.580**	0.362	0.480		**0.454**	**0.511**
		RSE	**0.102**		**0.028**	**0.046**	0.425		**0.224**	0.205	0.238		**0.108**	**0.115**
		T-statistic	**2.860**		**8.740**	**7.980**	1.570		**2.580**	1.760	2.020		**4.200**	**4.420**
		P Value	**0.035**		**0.000**	**0.000**	0.177		**0.049**	0.138	0.100		**0.008**	**0.007**
	DFFL	*Coefficient*	0.045	**-0.247**		**0.121**	0.089	**-0.580**		-0.218	0.026	**-0.454**		0.057
		RSE	0.114	**0.028**		**0.047**	0.546	**0.224**		0.347	0.307	**0.108**		0.199
		T-statistic	0.400	**-8.740**		**2.580**	0.160	**-2.580**		-0.630	0.080	**-4.200**		0.280
		P Value	0.707	**0.000**		**0.050**	0.877	**0.049**		0.557	0.936	**0.008**		0.788
	DEMU	*Coefficient*	-0.075	**-0.368**	**-0.121**		0.307	-0.362	0.218		-0.031	**-0.511**	-0.057	
		RSE	0.121	**0.046**	**0.047**		0.436	0.205	0.347		0.251	**0.115**	0.199	
		T-statistic	-0.620	**-7.980**	**-2.580**		0.700	-1.760	0.630		-0.120	**-4.420**	-0.280	
		P Value	0.561	**0.000**	**0.050**		0.513	0.138	0.557		0.907	**0.007**	0.788	
	Intercept	*Coefficient*	-0.194	0.099	-0.148	-0.269	-0.375	0.294	-0.286	-0.068	-0.272	0.207	-0.246	-0.303
		RSE	0.096	0.010	0.026	0.042	0.399	0.046	0.212	0.189	0.225	0.018	0.110	0.111
		T-statistic	-2.010	10.130	-5.640	-6.390	-0.940	6.410	-1.350	-0.360	-1.210	11.410	-2.240	-2.730
		P Value	0.101	0.000	0.002	0.001	0.391	0.001	0.235	0.735	0.281	0.000	0.075	0.041
	R2 (Between)		0.397				0.183				0.643			
	Observations		6721				6721				6721			
	F-test	*Statistic*	**51.540**				**6.530**				**47.180**			
		P Value	**0.000**				**0.035**				**0.000**			

Moving from the strict gold exchange standard to the lax pegged rate system translates in a decrease in the short-run BBI, which may be indicative of a stronger propensity of the peg regime to crises or, conversely a stronger presence of short-run booms in the gold exchange standard. It has no effect on any other specifications of the indicator. This is the same result found for Identity 1.

Moving from the lax pegged rate to any other regime causes increases in the short-run BBI. This effect remains for changes towards the free floating regime and the EMU in the equally-weighted BBI, probably indicating a longer effect for these two. There appears to be an important long-run effect on the BBI when there is a change from a peg regime towards a strict free floating regime as evidence by an increase of 0.58 units in the indicator which indicates propensity to more

booms (or at least less crises) in the strict free float regime rather than in the peg regime. These results provide the exact same indications as the results found for Identity 1.

Moving from the lax free floating towards the EMU has a small and almost insignificant effect on the short-run BBI, while no effect in any other specification. This may nuance the results found in the analysis of Identity 1. Interestingly the F-test indicates that coefficients are jointly significant under all specifications of the regressions.

Identity 4

This identity is similar to Identity 3, but the lax pegged rate regime dummy (DPEGL) is broken down into a strict peg (DPEGS) and a managed float (DMF) as was done in Identity 2. All other variables remain the same.

Table 19: Regime switching matrix for Identity 4

	Dependent variable		BBI_{Short}					BBI_{Long}					$BBI_{Equally}$				
	Moving to…		*DGESS*	*DPEGS*	*DMF*	*DFFL*	*DEMU*	*DGESS*	*DPEGS*	*DMF*	*DFFL*	*DEMU*	*DGESS*	*DPEGS*	*DMF*	*DFFL*	*DEMU*
Moving from…	DGESS	*Coefficient*		-0.307	**-0.250**	-0.046	0.074		-0.846	-0.146	-0.093	-0.325		-0.563	-0.235	-0.028	0.022
		RSE		0.130	**0.065**	0.115	0.123		0.522	0.424	0.544	0.446		0.294	0.167	0.307	0.256
		T-statistic		-2.370	**-3.860**	-0.400	0.600		-1.620	-0.340	-0.170	-0.730		-1.910	-1.400	-0.090	0.090
		P Value		0.064	**0.012**	0.706	0.575		0.166	0.745	0.871	0.498		0.114	0.220	0.931	0.934
	DPEGS	*Coefficient*	0.307		0.057	**0.261**	**0.381**	0.846		0.700	**0.752**	0.520	0.563		0.328	**0.535**	**0.585**
		RSE	0.130		0.131	**0.036**	**0.059**	0.522		0.638	**0.237**	0.263	0.294		0.302	**0.102**	**0.145**
		T-statistic	2.370		0.440	**7.260**	**6.490**	1.620		1.100	**3.180**	1.980	1.910		1.090	**5.250**	**4.040**
		P Value	0.064		0.680	**0.001**	**0.001**	0.166		0.323	**0.025**	0.105	0.114		0.327	**0.003**	**0.010**
	DMF	*Coefficient*	**0.250**	-0.057		0.204	**0.324**	0.146	-0.700		0.053	-0.179	0.235	-0.328		0.207	0.257
		RSE	**0.065**	0.131		0.110	**0.104**	0.424	0.638		0.595	0.500	0.167	0.302		0.294	0.229
		T-statistic	**3.860**	-0.440		1.850	**3.120**	0.340	-1.100		0.090	-0.360	1.400	-1.090		0.700	1.120
		P Value	**0.012**	0.680		0.123	**0.026**	0.745	0.323		0.933	0.734	0.220	0.327		0.514	0.314
	DFFL	*Coefficient*	0.046	**-0.261**	-0.204		**0.120**	0.093	**-0.752**	-0.053		-0.232	0.028	**-0.535**	-0.207		0.050
		RSE	0.115	**0.036**	0.110		**0.046**	0.544	**0.237**	0.595		0.337	0.307	**0.102**	0.294		0.194
		T-statistic	0.400	**-7.260**	-1.850		**2.630**	0.170	**-3.180**	-0.090		-0.690	0.090	**-5.250**	-0.700		0.260
		P Value	0.706	**0.001**	0.123		**0.047**	0.871	**0.025**	0.933		0.522	0.931	**0.003**	0.514		0.807
	DEMU	*Coefficient*	-0.074	**-0.381**	**-0.324**	**-0.120**		0.325	-0.520	0.179	0.232		-0.022	**-0.585**	-0.257	-0.050	
		RSE	0.123	**0.059**	**0.104**	**0.046**		0.446	0.263	0.500	0.337		0.256	**0.145**	0.229	0.194	
		T-statistic	-0.600	**-6.490**	**-3.120**	**-2.630**		0.730	-1.980	0.360	0.690		-0.090	**-4.040**	-1.120	-0.260	
		P Value	0.575	**0.001**	**0.026**	**0.047**		0.498	0.105	0.734	0.522		0.934	**0.010**	0.314	0.807	
	Intercept	*Coefficient*	-0.193	0.114	0.057	-0.147	-0.267	-0.365	0.481	-0.219	-0.272	-0.039	-0.268	0.295	-0.033	-0.240	-0.290
		RSE	0.095	0.042	0.090	0.028	0.042	0.387	0.187	0.458	0.222	0.183	0.219	0.092	0.212	0.115	0.106
		T-statistic	-2.030	2.710	0.630	-5.340	-6.370	-0.940	2.560	-0.480	-1.230	-0.220	-1.220	3.220	-0.160	-2.080	-2.730
		P Value	0.098	0.042	0.557	0.003	0.001	0.389	0.050	0.653	0.275	0.838	0.277	0.023	0.883	0.092	0.041
	R2 (Between)		0.386					0.037					0.733				
	Observations		6721					6721					6721				
	F-test	*Statistic*	**63.190**					4.960					**43.290**				
		P Value	**0.000**					0.054					**0.001**				

Moving from the strict gold exchange standard to the strict pegged rate system has no effect on any of the specifications of the BBIs. Although the coefficients are negative, as in Identity 3, they are statistically insignificant. However, moving from the strict gold exchange standard towards the manage float regime does have a negative and statistically significant effect on the short-run BBIs.

Moving from the strict pegged rate to the managed float regime has no effect on any BBI specification. However, moving towards the free float regime has a positive and significant effect on all specifications of the BBI, indicating that the free float regime is more prone to booms, or less prone to crises than the peg rate system. This is consistent with what was found in Identity 3.

Changing towards the EMU affects positively the short-run and equally-weighted definitions of the BBI, and changes the long-run BBI in a positive direction, being almost significant to the 90% confidence level which is also consistent with previous results.

Moving from the managed floating regime towards the EMU has a positive and statistically significant effect for the short-run specification of the BBI but on no other specification. Changes from the managed floating regime towards the free floating regime are irrelevant. Changes from the free floating regime towards the EMU regime are positive and statistically significant only for the short-run BBI while all others denote no effect. Interestingly the F-test indicates that coefficients are jointly significant with 95% confidence only for the regressions ran against the short-run and equally-weighted BBIs. The fact that the long-run effect is insignificant at 95% but significant at 90% confidence is not worrisome since these results are only preliminary and we need to add several independent variables in the future. This issue will be dealt with in the conclusions and future lines of research.

Part 8. Results and discussion

The contributions of this paper can be analyzed from two different perspectives: on the one hand, the addition of new time series to the literature and, on the other hand, the analysis of the panel regressions.

New time series: Contributions of the BBIs

The literature on financial crises has broadened our understanding of these phenomena for over thirty years, and it has done so using mostly dummy sequences as dependent variables. These series are not free from criticism, as they reflect rather poorly on the statistical characteristics of underlying data, depend strongly on choices performed by the researcher, and contain very little variability thus affecting the interpretability of results, increasing regression standard errors and thus affecting statistical significance of coefficients.

These criticisms, which we have made relevant in part 6, are partially resolved by the use of the Boom-Bust Indicator (Forero-Laverde, 2016) which has more desirable characteristics than its counterpart. First, it provides not only a measure of direction but also of intensity of the asset price cycle. Secondly, it reflects on different time horizons thus allowing for analysis of booms and busts as processes that may be both explosive and pervasive and it allows differencing these two characteristics. Third, by definition it contains more variability and thus will allow for the testing of new hypothesis. As an example, the tests ran in this paper would have been impossible using a *probit* model since it would be a dummy on dummy regression. Fourth, these time series resolve the identification problem that many researchers face when defining what a boom or a bust is. Rather, the researcher can observe both booms and busts arise in the time series, and this happens because of the non-parametric nature of its construction. Finally, and very importantly, at least for this database, all BBIs are stationary up to 12 lags, which is a characteristic of stability that guaranties that the variability found in the regressions is brought to the table by the independent variables and not by the data generating process.

Panel data regressions: Ranking monetary regimes by their propensity to booms and busts

Grapping the full reach of the findings presented in Part 7 might be a daunting task: there are four different identities, a myriad of regressions and three distinct dependent variables. The task at hand is simplified by using summary tables that contain a ranking of monetary regimes based only on the statistically significant coefficients of the regressions. Recall, for example from identity 1:

Table 20: Extract from regressions for identity 1

Dependent variable		**BBI_{Short}**			
Moving to…		*DGESL*	*DPEGL*	*DFFS*	*DEMU*
DGESL	*Coefficient*		**-0.207**	0.101	0.167
	RSE		**0.059**	0.075	0.072
	T-statistic		**-3.530**	1.340	2.310
	P Value		**0.017**	0.239	0.069

In Table 20 we identify that a change from de lax gold exchange standard to the lax peg regime has a negative effect on the value of the short-run BBI. This implies that DGESL has a higher propensity to booms than DPEGL or, conversely, DPEGL is more prone to crises. It is important to understand that we are not presenting probabilities but a something similar to a difference in means analysis. Even though the value of the short-run BBI is higher for the gold exchange standard than for the peg regime for the panel, this does not represent causality. The two phenomena are happening simultaneously (there are no leads or lags).

By performing this process for all identities we can build full rankings of the regimes. These are presented in the following tables broken down by identity and by BBI specification. We build two tables, one with the results from the more general identities (1 & 3) and another one with the results of the more granular identities (2 & 4).

Table 21: Ranking of institutional regime by value of the BBI using general identities

	Ranking of institutional regimes by statistical significant coefficients - General identities							
	Value of BBI	**Short-Run BBI**			**Long-Run BBI**		**Equally-Weighted BBI**	
		Lower	*Higher*	*Highest*	*Lower*	*Highest*	*Lower*	*Highest*
Identity 1	*Ranking*	DPEGL	DGESL DFFS DEMU		DPEGL	DFFS	DPEGL	DFFS DEMU
	Joint significance	YES			YES		YES	
Identity 3	*Ranking*	DPEGL	DGESS		DPEGL	DFFL	DPEGL	DFFL DEMU
			DFFL	DEMU				
	Joint significance	YES			YES		YES	

A first result we can highlight form both tables is that we have more to say about short run effects obtained by using the short-run BBI than about the pervasiveness or long-run effects contained in the results from the regressions of the dummies on long-run or equally-weighted BBIs. This may indicate that the long run effect of the monetary regime is lost or that, as we will discuss

in the following section, the obvious omitted variable problem is wreaking havoc in the identification strategy.

However, this proposition must be nuanced since all regressions except for the one of long-run BBI on identity 4 dummies, show a joint significance of coefficients with 95% confidence. This is actually a very valuable indication of the role that the monetary and exchange rate institutions appear to play in the boom-bust cycle of the stock market. As indicated in part 3, just this fact provides evidence in favor of the leaning against the wind approach to financial crises, which, as Freixas et. al., (2015) indicate, is a job not only for monetary authorities but for the whole institutional apparatus (central banks, regulators and financial institutions).

Studying Table 21, we find that the regime with the lowest BBI for any of the three time horizon or the two identities is the lax peg regime. In the case of the short-run BBI, it is interesting to find no evidence of any difference between the gold exchange standard and the EMU because, as we indicated in Part 2, Bordo & James (2015) propose these two systems are actually quite close. Our results provide evidence in the same direction.

In the short-run, when using a lax definition of the free floating regime we fin it is more prone to crises than the EMU, however when we use the strict definition or look at different time periods this difference does not hold. Finally, the effect of being the gold exchange standard appears to be solely a short-run effect, as it is impossible to draw inference on the DGESL or DGESS coefficients for the long-run or equally weighted definitions of the BBIs.

Table 22: Ranking of institutional regime by value of the BBI using granular identities

		Ranking of institutional regimes by statistical significant coefficients - Granular identities						
	Value of BBI	**Short Run BBI**			**Long-Run BBI**		**Equally-Weighted BBI**	
		Lowest	*Higher*	*Highest*	*Lowest*	*Highest*	*Lowest*	*Highest*
Identity 2	*Ranking*	DMF	DGESL DEPGS	DEMU DFFS	DPEGS	DFFS	DPEGS	DFFS DEMU
	Joint significance	YES			YES		YES	
Identity 4	*Ranking*	DMF DPEGS	DGESS DFFL	DEMU	DPEGS	DFFL	DPEGS	DFFL DEMU
	Joint significance	YES			NO		YES	

Analyzing the results from the more granular regressions, we find that when we use the strict definition of a free float regime (identity 2), the managed float is more prone to crises that the peg rate system. This, of course is interesting as it nuances the findings from the previous table. When the definition of the free float regime is relaxed the difference between the managed float and the pegged rate regimes disappears. This provides an important indication about the importance of specifying the dummies correctly and defining, very clearly, what each dummy represents.

It is also interesting that both the EMU and the strict free floating regimes have the stronger propensity to accumulate imbalances (booms). This is actually not surprising since they both have free movement of capital flows, which may play a role in the excessive growth of asset prices through foreign direct investment and credit. Of course, this proposition is not new, but it usually

applies to emerging market countries and this database includes only developed Western European countries. This invites further studies and analysis.

Finally, looking at the possibility of model over-determination (including too many variables or alternative specifications with low added value), we find our ranking of the gold exchange standard does not change whether we use the strict definition in DGESS (only *de jure*) or the broad definition in DGESL (both *de jure* and *de facto*). However, identity 4 shows that separating the lax definition of a peg regime in DPEGL into a managed float (DMS) and a strict peg (DPEGS) does increase our understanding as the former is statistically more prone to short-run busts than the latter. In that sense we could drop the results from identity 1 since they are contained in the other three specifications.

Discussion: Caveats to this analysis

Of course this analysis is not exempt form criticisms and issues to be resolved in the future. A first element to take into account has to do with the interpretability of coefficients from the regressions. The BBI methodology is contingent on an arbitrary grading based on the distance of each observation, measured in standard deviations, from the mean observation. This grading, which is useful since it allows the measure to be bounded in the interval [-10, 10] complicates the measure as the distance from 10 to 9 is not interpretable as a decrease in one standard deviation. For that reason we have avoided doing such analysis. However, it would be useful to construct the BBI in such a way that the dimension of the coefficient was not only ordinal but cardinal as to facilitate interpretation and policy design.

Second, issues can arise from the use of stock market variables rather than series for some other asset. Even though stock market wealth is very important today, both as a percentage of GDP and as percentage of wealth for agents in the economy[4] (Forero-Laverde 2016), this might not be true for the first half of the twentieth century. In that sense a robustness check for these results begs for the use of housing prices or some other variables. The tradeoff, of course, is the loss of observations due to lower frequency in the data and the increased measurement error in new asset price series.

A third issue has to do with omitted control variables. It may be true that the effect that we have found of the monetary regime on the asset cycle is really contained in variables outside of this analysis, such as unemployment, *per capita* GDP, or some other macroeconomic measure that is uncorrelated to the monetary regime and thus remains in the error coefficient. The inclusion of control variables is a relevant robustness check for these results and will be included in future versions of this paper.

A final issue has to do with causality. Even though we found that there is a relation between changes in the monetary regime and differences in the behavior of the stock market, this relationship need not be causal. To prove causality we need to include trilemma variables that

[4] Recall that every employee who has a pension plan, state managed or privately held, is, at least in some portion, invested in the stock market. A stock market crash, with the subsequent loss in his aggregate wealth will necessarily affect his investment-consumption decisions for the future, altering both aggregate demand and economic growth.

proxy for monetary policy, exchange rates and capital flows. Even if there is no proof of causality, the results of this paper are interesting, and their contributions to the literature motivate further research.

Part 9. Conclusion and future research

The results presented in parts 7 an 8 indicate there is a role for the monetary regime on the evolution of asset prices. This is clear from the joint significant coefficients for all specifications of the regressions with 90% confidence. This implies that BBIs behave differently in mean according to the regime in place. Even if we have more information about a short-run relationship than for long-run effects (for now), we can say that the peg regime, by any definition, is more prone to crises than any of the other regimes. We can also state that both the free float and the EMU regimes are more prone to short-run booms, while long term effects only show differences between a prone-to-crises peg and a prone-to-booms free floating regime. Additionally, the short run effect of the regime on the short run boom-bust cycle of the stock market is statistically the same for the EMU and any definition of the gold exchange standard.

Some future extensions of this paper may include, for example, changes in the dependent variables so as to make them easier to interpret as changes in standard deviations. Additionally, we should exploit the added variability in transitioning from dependent dummy variables to continuous variables by performing time series analysis for each country to confirm or nuance the results.

From a methodological standpoint, future research could study not only the differences in means but also in variances across regimes. This is important since variance is a measure of risk, and more stable BBIs under a given regime would imply it is safer or at least less elastic in the sense described by Borio & Lowe (2014). This further analysis may majorly alter the findings from this paper and we cannot infer the direction of the result from the available data.

As indicated in the previous section, one of the larger caveats of this paper has to do with causality. The most relevant future research would have to do with widening the panel by including both control and trilemma variables both contemporaneous and with lags in order to determine if the effect of the regime on the asset cycle runs, as expected, through the mechanisms presented at the end of part 3.

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